Jg. 3 · Heft 1 · November 2022

Research Journal for Applied Management

Inhalt

Herausgeber: Prof. Dr. Ingo Böckenholt,
Prof. Dr. Kai Rommel

Research Journal for Applied Management
Jg. 3, Heft 1

ISM International School of Management
Prof. Dr. Ingo Böckenholt; Prof. Dr. Kai Rommel (Hg.)

Um aus dieser Publikation zu zitieren, verwenden Sie bitte diesen DOI Link:
https://doi.org/10.22602/IQ.9783745870886

Bibliografische Information der Deutschen Nationalbibliothek:
Die Deutsche Nationalbibliothek verzeichnet diese Publikation in der Deutschen Nationalbibliografie; detaillierte bibliografische Daten sind im Internet über dnb.dnb.de abrufbar.

publIQation
ACADEMIC PUBLISHING

PubliQation – Wissenschaft veröffentlichen

Ein Imprint der Books on Demand GmbH, In de Tarpen 42, 22848 Norderstedt

Chefredaktion: Robinson Nittke
Gestaltung: Sabine Pillath-Günthner
Vorsitz Wissenschaftlicher Beirat: Prof. Dr. Kai Rommel

Herstellung und Verlag: BoD – Books on Demand GmbH
In de Tarpen 42, 22848 Norderstedt

ISBN Print 978-3-745-870-862
E-Book-ISBN 978-3-745-870-886

Inhalt

Editorial

Das **Research Journal for Applied Management** (RJAM) stellt auch in der Ausgabe 1/2022 aktuelle Ergebnisse aus der praxisorientierten Forschung zu verschiedenen Managementthemen vor. Die Beiträge dieser Ausgabe behandeln Forschungsthemen aus den Bereichen Marketing, Customer Lifetime Value, Customer Journey Management, Investment-Management und der Analyse von Konsumentenpräferenzen.

Sonja Klose und Ngoc Anh Truong untersuchen die Wirksamkeit von In-Game-Werbung in Handy-Spielen. Die Ergebnisse dieser Studie geben Antworten auf unentdeckte In-Game-Werbewirksamkeit im Mobile-Gaming-Umfeld. Als solches trägt diese wesentlich zum Gesamtbild der Werbung in digitalen Spielen bei und kontextualisiert die Verknüpfungen von Markeneinstellung, Markenwert und allgemeinem Engagement.

Ronit Patel, Jens Perret und Eyden Samunderu untersuchen mit dem Datensatz eines repräsentativen britischen Einzelhändlers das Phänomen der Klumpenbildung im Kaufverhalten (Clumpiness). Mit einer Clusteranalyse werden Kunden mit ähnlichen Verhaltensmerkmalen identifiziert und auf diese Weise ein existentes Maß für Klumpenbildung bestätigt. Für dieses Maß wird zusätzlich ein Test konzipiert, um gezielt Kunden identifizieren zu können, die von Natur aus ein hohes Potenzial aufweisen, derartige Verhaltensweisen an den Tag zu legen.

Christian Duncker und Jens Perret beschäftigen sich mit den Wechselwirkungen entlang der Customer Journey. Die bisher weitgehend getrennt betrachteten Bereiche Customer Journey Management, Customer Relationship Management und Customer Experience Management werden dabei zu einem umfassenden Framework zusammengefasst. Sie analysieren die Zusammenhänge zwischen den Stufen der Customer Journey am Beispiel des Produktbereichs Damenunterwäsche.

Ob und inwieweit sich aktive Investitionen in Pensionskassen lohnen und wie sich Renditen entwickeln können und was Manager daran verdienen, wird von **Joshua Traut, Alexander Simonov und Matthias Meitner** am Beispiel eines konkreten Fonds diskutiert. Diese Inhalte sind insbesondere für die Performancebewertung und die Aktiv-Passiv-Debatte zu festverzinslichen Wertpapieren relevant.

Kai Rommel und Julian Sagebiel schätzen in Ihrem Beitrag die marginale Zahlungsbereitschaft für schnelllebige Konsumgüter mit einem Discrete Choice Experiment. Mit den Ergebnissen einer Online-Befragung in Deutschland ermitteln sie auch die sozioökonomischen Determinanten und leiten aus den Ergebnissen Empfehlungen für das Marketing im Einzelhandel ab.

Herzlich bedanken möchten wir uns bei Gutachterinnen und Gutachter dieser Ausgabe und dem Editorial Board für die inhaltliche Bewertung der eingereichten Beiträge. Auch beim Team der ISM-Bibliothek und den Mitarbeiterinnen des Forschungsdekanats möchten wir uns für die erfolgreiche Umsetzung des Research Journal for Applied Management bedanken. Beim Lesen dieser Ausgabe wünschen

wir allen Leserinnen und Lesern viel Spaß und freuen uns über die Einreichung von Beiträgen für die nächste Ausgabe des Research Journal for Applied Management. Diese können bei robinson.nittke@ism.de eingereicht werden. Sämtliche Ausgaben des Research Journal for Applied Management und der Call for Paper können auf diesem Link heruntergeladen werden: http://ism.de/research/research-activities).

Herausgeber: Prof. Dr. Ingo Böckenholt (Präsident), Prof. Dr. Kai Rommel (Vizepräsident Forschung)

Redaktionelle Leitung: Prof. Dr. Kai Rommel

Dortmund im Dezember 2022

Editorial

The **Research Journal for Applied Management** (RJAM) presents current results from practice-oriented research on various management topics in issue 1/2022. The articles in this issue deal with research topics from the fields of marketing, customer lifetime value, customer journey management, investment management and the analysis of consumer preferences.

Sonja Klose and Ngoc Anh Truong investigate the effectiveness of in-game advertising in mobile games. The results of this study provide answers to undiscovered in-game advertising effectiveness in the mobile gaming environment. As such, it contributes significantly to the overall picture of advertising in digital games and contextualizes the links between brand attitude, brand equity and overall engagement.

Ronit Patel, Jens Perret and Eyden Samunderu use the data set from a representative British retailer to investigate the phenomenon of clumpiness in consumers' buying behaviour. With a cluster analysis, customers with similar behavioural characteristics are identified, affirming a respective measure. For this measure a test is considered to identify customers who are inherently clumpi in their behaviour.

Christian Duncker and Jens Perret deal with the interactions along the customer journey. The previously largely separate areas of customer journey management, customer relationship management and customer experience management are combined to form a comprehensive framework. They analyse the relations between the different stages of the customer journey using the example of the women lingerie.

Joshua Traut, Alexander Simonov and Matthias Meitner use the example of a specific fund to discuss whether and to what extent active investments in pension funds are worthwhile and how returns can develop and what managers earn from it. This content is particularly relevant for performance evaluation and the active-liability debate on fixed income securities.

In their contribution, **Kai Rommel and Julian Sagebiel** estimate the marginal willingness to pay for fast-moving consumer goods using a discrete choice experiment. With the results of an online survey in Germany, they also determine the socio-economic determinants and derive recommendations for retail marketing from the results.

Dortmund, December 2022

Klose, Sonja; Truong, Ngoc Anh

The effectiveness of in-game advertising in mobile games

Highlights

- In-game advertising can be an alternative to traditional mass media
- In-game advertising positively influences gamers attitudes towards the ad
- In-game advertising exerts positive influence on brand equity
- In-game advertising has a positive impact on brand awareness and brand image
- In-game advertising positively influences perceived quality and brand loyalty

Abstract

Purpose: This study aims to investigate the effectiveness of branding through mobile games with in-game advertising (IGA). The concept of in-game advertising will be linked with game experience, game engagement, brand attitude, and brand equity to demonstrate its effectiveness empirically.
Design/Methodology/Approach: An online survey is conducted to help collect attitudinal responses of gamers about the collaboration between a mobile game and a beverage brand. The conclusion is drawn based on hypotheses testing using the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique.
Findings: The results show that in-game advertising positively influences player experience and game engagement of players as well as brand attitude and brand equity. Further, brand attitude plays an important mediating role in the relationship between in-game advertising and brand equity.
Research implications: In-game advertising is a potential alternative to traditional media. For game publishers, in-game advertising can help improve player retention by enhancing the enjoyment, hedonism, and realism of their gameplays. For brands, in-game advertising possibly improves brand equity by positively influence people's attitude towards the brand.
Limitations/Future research: The research contains some limitations regarding the scope of the study, stimuli selections, and sample size. Researchers can consider some possible directions for their future research about in-game advertising, such as examining its influence on gamers' behaviors, investigating its influence in different contexts or on different perspectives.
Originality/Value: The results of this study provide answers to the undiscovered effectiveness of in-game advertising in mobile game contexts. Thus, it makes a significant contribution to the holistic picture of advertising in digital games.

Keywords: in-game advertising, iga, mobile games, consumer-based brand equity, brand equity, game experience, game engagement

1 Introduction

Gaming, and mobile gaming, in particular, has continuously achieved meteoric growth in the past few years. While many industries are suffering and struggling to survive the impact of Covid-19, the global game market is expected to generate $175.8 billion in 2021 and reach $218.7 billion in 2024 (Newzoo, 2021) with a Compound Annual Growth Rate (CAGR) of 7.5%. Furthermore, the number of people spending time on digital games is also increasing more than ever before with 2.96 billion players worldwide by the end of 2021, which means more than one-third of the world population was involved in digital games at that time (Newzoo, 2021).

Over the past decade, mobile gaming has dramatically surpassed all other gaming segments to become the biggest segment in terms of revenue and players. Market research experts claimed that mobile gaming would continue to be the most dominant and fastest-growing game segment in the upcoming years. Revenue generated by mobile games was predicted to hit $90.7 billion by the end of 2021, with a year-on-year growth of 4.4% (Newzoo, 2021). Furthermore, people's appetite for mobile games is also reflected by the fact that mobile E-sports has entered the upper echelon and is expected to take over the previously dominated PC market (Wijman, 2021). However, game-based marketing still received little attention from marketers despite the fact that it can be an alternative digital marketing strategy that offers marketers and advertisers more opportunities to enhance digital consumer experience or enjoyment (Smith, 2020; Yoon, 2019).

The most common approach of advertising when it comes to mobile applications is in-app advertising. Nevertheless, in-app advertising has always been interruptive in nature, which can in turn spoil the user experience (Paddon, 2019). Further, with the decision to grant users the choice to block the Identifier for Advertisers (IDFA) in the iOS14 update (September 2019), Apple has significantly restricted advertisers from tracking user data for customizing in-app ads and measuring advertising effectiveness (Emery, 2021). Consequently, many titles that predominantly monetize through in-app ads have been severely impacted as their business model relies on these revenue streams as opposed to charging users for playing the game (Schöber & Stadtmann 2020). In this context, in-game advertising (IGA) appears as a more sophisticated advertising practice because of its strong first-party data pools; targeting customers with relevant messages and content can become so much more efficient – without relying on identifiers and third-party data (Sondhi 2021). One direction IGA is heading is contextual targeting to maintain relevance with customers. Contextual targeting’s ability to connect in a relevant way with players based on what they are viewing, versus their personal data, will continue to be a safe targeting alternative amid a quickly evolving privacy landscape (Roy 2022). Apart from providing a seamless gaming experience to players, IGA also allows titles to swell profit with many collaborative opportunities. This practice is especially relevant for games that value user experience and do not exploit revenue from in-app advertising. For marketers, in-game advertising cannot only promote the brand directly to players but also place an indirect effect on millions of E-sports fans or viewers of content creation platforms such as Twitch, Facebook streaming, Youtube, or Tiktok (Seo et al., 2018).

With these advantages, branding through mobile games with IGA can become a trend in the future. However, IGA is still an uncharted territory in both practice and research (Terlutter and Capella, 2013). Just a few studies have looked at the impact of IGA on customers in the literature. Further, research to date concentrated only on computer and console games. Studies focusing on advertising in mobile games have been substantially neglected.

With the primary purpose of investigating the effectiveness of the branding strategy that leverages blended advertisements in mobile games, this paper will attempt to address the following research questions using the research model depicted in Figure 1. Firstly, how IGA influences players' attitudinal responses with regard to their game experience, game engagement and brand attitude. Secondly, how IGA influences player evaluation towards the integrated brand by examining the players' responses towards brand equity.

2 Theoretical framework

2.1 In-game advertising (IGA)

IGA refers to the incorporation of product or brand images into the digital game environment in either a subtle or a prominent manner (Terlutter and Capella, 2013). The most important feature distinguishing in-game ads from in-app ads is that they are not clickable and do not lead users to any landing pages or apps outside the current game environment (Yerukhimovich, 2020). IGA can be implemented under various forms such as sponsorship deals, real-world analogs, brand placements, branded music and sounds, branded characters, and brand-related cheat codes.

Many advertisers and scholars have expressed confidence in the superiority of IGA compared to other advertising media. IGA has the advantage of appearing time, which means players are exposed to brand images in the game longer than in typical video commercials (Yang et al., 2006). Moreover, the average time that gamers invest in one game title is 30 hours (Nelson et al., 2004), which is much longer than in a movie. With the benefit of high replay value, the frequency of advertising repetitions in each game session is considerable (Herrewijn and Poels, 2017). Apart from that, IGA possesses an outstanding advantage of brand placements that is not disrupting the player's experience, unlike the other interruptive advertisements. Moreover, gamers reported that they appreciated the presence of authentic brands because they brought a sense of familiarity, added authenticity to the game scenarios, and enhanced the entertainment value (Nelson et al., 2004). Thus, IGA is considered an element that offers some added verisimilitude to the virtual environment of games (Thomas and Stammermann, 2007; Nelson et al., 2004). Finally, interactivity is the key characteristic that makes games stand out from the traditional means of communication. In games, people can feel, control, and interact with a brand (Nelson, 2002). Past studies have discovered that such interactivity has a substantial impact on IGA efficacy (Nelson, 2002) and benefits brand attitude and brand awareness (Escalas, 2004; Herrewijn and Poels, 2017).

Attitude toward ads has been regarded as a standard measure of advertisement effectiveness as it determines the consumer's likelihood of considering, committing to, and purchasing a brand (Eastin and Lee, 2020). Attitude towards advertisements is also described as an individual's inclination to respond in a favorable or unfavorable way to a particular advertising content (Muehling and Laczniak, 1988). For years, research has been carried out to examine player attitudes towards ads in general and IGA in particular. In a study in 2002, Nelson confirmed that IGA was generally viewed positively by gamers. Furthermore, participants in her study also agreed that IGA contributes to the game's realism and that they did not find it misleading or invasive. Additionally, people who have a negative attitude towards general advertisements seem to present a favorable attitude towards ads purposefully programmed into games (Molesworth, 2006).

The effectiveness of IGA on games and integrated brands has been studied for years and has presented contradictory results. For example, in an attempt to examine the effectiveness of interactive brand placement in an online role-playing game, Reijmersdal et al. (2010) found that children's attitude toward the game is positively affected by interactive brand placements. This finding was contrary to the prior research by Mau et al. (2008). When trying to discover the effects of IGA on familiar and unfamiliar brands in a first-person shooter game, they surprisingly found that in both cases, IGA negatively affects players' attitudes towards the game. The player's attitude towards the game will then correspondingly affect the player's attitude towards the advertised brand.

2.2 Game Experience

All famous and successful game titles share a common point: a large player base. A good gaming experience is an imperative element in convincing players to continue with a game (Choi and Kim, 2004). Furthermore, positive emotional experience has been proven to foster player engagement and increase player loyalty (Su et al., 2016). In addition, research by Cheung et al. (2021) suggested that game owners are able to strengthen not only loyalty but also in-game purchase intentions by enhancing the in-game experience. Reversely, when players' expectations about optimal experience are not fulfilled, they can easily surrender, switch to competitions or even boycott the title (Pelsmacker et al., 2019). For those reasons, optimizing the player experience is always the top priority of all game companies.

Lately, gaming experience or player experience (PX) has been widely used in studies about games. It refers to the experience that a player has during the process of playing games. Evaluating experience entails assessing the user's subjective opinion because it is characterized as personal and subjective (Calvillo-Gámez et al., 2010). Pleasure, arousal, and frustration are some of the most common emotions possibly evoked by digital games (Herrewijn and Poels, 2013). However, playing games is expected to bring a joyful experience (Calvillo-Gámez et al., 2010). Therefore, game enjoyment is a concept that has received much attention in research and practice to serve the purpose of examining and improving the player experience. Enjoyment is also considered as a factor that contributes to the success of IGA. In particular, understanding and managing variables that make the game more enjoyable would help improve the effectiveness of IGA, which may consequently lead to good sentiments toward the integrated brands (Moulard et al., 2019). Most game studies agree that the hedonic aspect of the game is an essential factor in determining enjoyment (Moulard et al., 2019).

Past advertising studies already showed that player experience affects the way people process the in-game ad. For instance, Coulter (1998) documented that players in high involving and arousing game contexts will have lower brand recall and recognition. The positive game experience was presented to have a positive influence on brand attitude (Owolabi, 2009), recall of brand (Lee and Sternthal, 1999), or IGA effectiveness (Herrewijn and Poels, 2013). However, studies investigating the influence of IGA on player experience are still neglected. One of the few studies considering this aspect is Nielsen's research stating that IGA barely affects game experience. 82% of the respondents agreed that games were exactly as entertaining with advertisements as they were without them, and over 60% felt the ads caught their attention, made games more realistic, did not interrupt the game experience, and were promoting relevant products (GamesIndustry International, 2008). In terms of attitudes, however, a study conducted by Kim et al. (2016) found that high prominence ads within mobile games produced more negative effects on attitudes toward the game. This study aims to further examine the impact of IGA on game experience with the following hypothesis:

H1:	*IGA has a positive effect on game experience.*

2.3 Game engagement

Engagement in digital games is a broad topic that covers a diverse range of studies, including subjective experience, physiological responses, motives for playing games, game usage, game market and player loyalty, and the impact of game-playing on life satisfaction (Boyle et al., 2012). These categories focus on different stages in the engagement process, so the proposed concepts are also very diverse and different. Among them, the concept related to the subjective experience of people when playing games is most prevalent. However, this study will consider game engagement as the player's commitment to the game. This approach avoids conceptual duplication with game experience and is essential in helping game publishers evaluate the effect of IGA on the appealingness of their product.

Nojima (as cited in Shibuya et al., 2017) suggested that a game service consists of three stages that are vital to its success: the hook, retention, and monetization. The hook concerns how the game attracts new players and can be measured by individual game download counts (Che and Ip, 2017). Retention refers to the ability that the game can keep the player playing continuously (Nojima, as cited in Shibuya et al., 2017). Monetization relates to how well the title can generate revenue for game publishers (Che and Ip, 2017). Depending on the characteristics of the game, game publishers will apply different business models such as freemium, premium, ad-supported, or hybrid. However, their primary stream of revenue is derived from two groups: gamers (via game purchases and in-game goodies purchases) and advertisers (via advertisements) (Scolastici and Nolte, 2013).

It is clear that IGA does not have a direct effect on the download rate of a game because the players can only interact with in-game ads after having the game downloaded and experiencing it. Therefore, the download rate will not be examined in the latter parts. The effect of IGA on player retention can be assessed through mobile game usage in terms of frequency of playing, time, and effort that players would invest in the title. There is a commonsense assumption that the more people love playing games, the longer they play (Boyle et al., 2012). In addition, the impact of IGA on a game's profitability will be evaluated through players' purchase intentions of branded items. Research to date only examined the influence of well-executed advergames on player experience and future intention to play (Peter and Leshner, 2013). Studies on such effect of IGA is missing. While the influence of IGA on general attitude towards games is still debatable, analyzing its influence on more detailed aspects such as player experience, game usage, and purchase intention will provide valuable insights for both researchers and practitioners. The hypothesis of IGA influence on game engagement is formulated as follows:

H2: IGA has a positive influence on game engagement.

2.4 Brand attitude

Attitude towards a brand or brand attitude was described as an individual's inclination to respond to a particular brand in a favorable or unfavorable way. Consumers tend to purchase items for which they have positive sentiments (Muehling and Laczniak, 1988). Studying the influence of IGA on brand attitudes has sparked tremendous attention from the academic community. The influence of IGA on brand attitude was investigated with a multitude of approaches, such as attitude towards ads (Mackay et al., 2009; Nelson et al., 2004), game-product congruity *(Peters and Leshner, 2013),* placement proximity *(Peters and Leshner,* 2013), ads characteristics and formats (Reijmersdal et al., 2010; Herrewijn and Poels, 2017; Herrewijn and Poels, 2018), game difficulty (Herrewijn and Poels, 2013), brand familiarity (Mau et al., 2008; Herrewijn and Poels, 2018), and so on. In general, the results of the above studies are consistent in presenting a positive effect of IGA on brand attitude. This finding implies that the practice of integrating brands in games possibly enables companies to achieve a bifocal goal of acquiring new customers and retaining existing ones. Based on what was discussed, it can be hypothesized that:

H3: IGA has a positive influence on brand attitude.

2.5 Brand equity

David Aaker (1991) definition of brand equity as "a set of brand assets and liabilities linked to a brand, its name, and symbol," has gained significant attention from academia. He also mentioned that the set consists of brand loyalty, name awareness, perceived quality, brand associations, and other proprietary brand assets that can augment or depreciate the value given by a product or service to a company and/or its consumers (Aaker, 1991). Although there are many different views and approaches, brand equity is approached based on two main perspectives: financial perspective and consumer-based perspective (Kim et al., 2003). In particular, when the financial perspective underlines the "financial value that brand equity provides to the firm" (Nguyen et al., 2013), the consumer-based perspective aims "to determine how consumers respond to a brand" (Hanaysha et al., 2013). Based on consumer perspective, brand equity has been defined by Keller (1993) as "the differential effect of brand knowledge on consumer response to the marketing of the brand." Adopting consumer-based brand equity (CBBE) in research does not mean recognizing the financial value of a brand is unnecessary, but understanding how consumers respond to the company's marketing efforts would provide more practical insights for the management board (Faircloth et al., 2001). Thus, the term brand equity used in this study from now on will refer to CBBE.

Simply said, brand equity can be viewed as an individual biased behavior towards an object, and brand attitude is his/her summary evaluation of that object (Faircloth et al., 2001). Farquhar (1989), Aaker (1991), and Keller (1993) believed that brand equity is positively influenced by favorable brand evaluations or attitudes. However, in an attempt to test these arguments from the above scholars about the effect of brand attitude on brand equity, Faircloth et al. (2001) found that brand attitude had no direct effect on brand equity. Instead, there is a possibility that brand attitude affected brand equity indirectly through brand image (Faircloth et al., 2001). This result may be affected by the author's use of purchase intention as a measure of brand equity rather than other common constructs suggested by other scholars such as brand awareness, brand image, perceived quality, brand loyalty (Aaker, 1991; Keller, 1993; Yoo and Donthu, 2001). Purchase intention is the final purpose of transmitting any marketing efforts (Lee et al., 2017). Nevertheless, the relationship between brand attitude and purchase intention is not always clear (Spears and Singh, 2004). For that reason, this research will measure brand equity as a multidimensional construct that consists of brand awareness, brand image, perceived quality, and brand loyalty.

2.6 Brand Awareness

Among the studies on the influence of IGA on gamer's evaluations, the number of studies focusing on brand awareness outnumbers the others. Brand awareness is defined as consumers' ability to recall or recognize a brand under different circumstances (Keller, 2013). Similar to brand placements in television and movies, one of IGA's objectives is to enhance brand familiarity within the target audience so that they will be more likely to remember it (Nelson, 2002). In the context of IGA, studies often examine the IGA's effect on brand awareness under three primary constructs: brand recognition, brand recall, and brand memory. Assessing the effect of IGA on brand memory is also relevant because recognition and recall of a brand occur as a result of storing and retrieving data in one's memory (Johnstone and Dodd, 2000). For instance, Yang et al. (2006) confirmed the influence of IGA on brand memory by comparing the ability to complete the word-fragment test about the brand's names between people playing a soccer game, racing game, and not playing any games. On the other hand, when exploring the player's ability to recall brand under different settings, Nelson (2002) found that the game players are able to recall brands in both short- (25 - 30% of the brands) and long-term (10 - 15% of the brands). This is also true for those who played the game for the first time and in a short period. Consistent with Nelson's study, the research of Mackay et al. (2009) and Herrewijn and Poels (2017) also agreed that engaging with a brand while playing a game improves one's ability to recall and recognize that brand when requested.

However, a project by Chaney et al. (2004) demonstrated a fairly low recall rate among their respondents (5 - 20% of people can recall). This result can be explained by a model of Lang (2009) called LC4MP or the Limited Capacity Model of Motivated Mediated Message Processing. This model contends that a person's capacity to comprehend information is limited because he/she only has access to a finite pool of cognitive resources at a time (Lang, 2009). This model suggests a significant implication for studying the impact of IGA on brand awareness. In a digital game environment, players are often overwhelmed with a plethora of tasks and stimuli that simultaneously vie for their attention. Obviously, players usually dedicate their cognitive resources to activities that are most important to them (i.e., enjoy the gameplay, control the characters, etc.), namely their primary task. Hence, getting a brand recognized and stored in mind is not easy in such an engrossing gaming context. Given these conflicting findings, it is interesting to extend the study of such an influence of IGA on brand perception in a mobile game context.

2.7 Brand Image

Brand image is a customer's impression about the brand and is reflected by a set of brand associations that they stored in mind (Aaker, 1991; Keller, 1993). A brand association is anything linked to a brand that stays in one's memory, such as brand attributes (price information, packaging, etc.), brand benefits (functional benefits, experiential benefits, and symbolic benefits), and brand attitudes (as described in the above section) (Aaker, 1991; Keller, 1993). The reason for including brand image as a component of brand equity arises from its important role in determining the differential reaction that creates brand value (Kim et al., 2003). Further, a strong brand image will support a brand positioning in creating a competitively attractive position (Aaker, 1991).

The number of studies exploring the effect of brand placement in general and IGA in particular on brand image is significantly scarce. However, researching in the context of television brand placement, Reijmersdal et al. (2007) found that placing a branded item in a television program can have an influence on that brand's image. In addition, the level of influence depends on the frequency of brand exposure. In line with this finding, a study by Reijmersdal et al. (2010) showed that interactive brand placement in an online game resulted in more positive attitudes toward the game, higher top of mind awareness of the brand, more positive brand images, and more favorable behavioral intentions.

2.8 Perceived Quality

Perceived quality is the perception of customers about the overall quality of products or services of a brand without any knowledge of detailed information. A brand that achieved a satisfactory level of perceived quality will have an advantage over its competitors, especially when consumers do not have enough motivation or are not able to search and compare alternatives (Aaker, 1991). More specific, perceived quality is a factor that has a significant impact on consumers' purchasing decisions. Thus, high perceived quality is a sign of effective marketing and advertising practices (Aaker, 1991).

Similar to the case of brand image, research focusing on perceived quality in the IGA context is sparse. With an intention to examine the influence of IGA on brand equity, Yang et al. (2015) inspected IGA influence on perceived quality as one of four brand equity dimensions, together with brand awareness, brand association, and brand loyalty. By comparing the outcomes of two groups of people playing a game on a social network with IGA and without IGA, the authors validated the consequential impact of IGA on perceived quality.

2.9 Brand Loyalty

Brand loyalty is a consistent and robust commitment to purchase or repatronize a product or service that belongs to a preferred brand in the future (Oliver, 1997). It can be said that brand loyalty makes customers refuse to switch to other competing brands under situations such as price changed or product features changed, thereby increasing brand equity (Aaker, 1991; Yoo et al., 2000). Moreover, existing customers may support in acquiring new ones by recommending a brand to friends and family (Bobâlcă et al. 2012). In addition, brand loyalty can help companies predict future revenue streams based on habitual buyers and thus can be a measure of future profitability and a brand's success (Aaker, 1996). However, unlike the other dimensions of brand equity, brand loyalty is qualitatively distinct because of its close link to consumer's use experience. While brand awareness, brand image, and perceived quality of a brand are the dimensions that customers can roughly evaluate from the very first encounter, brand loyalty is impossible to achieve without prior use experience (Aaker, 1991).

Although the literature has presented that brand loyalty cannot occur when customers have not bought and used the brand's products, many studies from various areas have indicated that a positive attitude towards a brand can exert an influence on brand loyalty (Liu et al., 2012; Krystallis and Chrysochou, 2014; Bozbay et al., 2018). Attitude towards a brand can be developed not only from cumulative gratification during usage occasions (Oliver, 1997) but also from evaluations towards brand associations (such as symbols, slogans, or advertisements, etc.) (Aaker, 1991), which do not necessarily happen during the usage phases of the products. Analyzing brand attitude and brand loyalty from this perspective has a special significance for research about IGA because it will help evaluate the effectiveness of the practice on current customers but also on potential customers who have not had any prior experience with the integrated brands. Unfortunately, research investigating the influence of IGA on brand loyalty is also lacking attention. Yang et al.'s (2015) study is one of the few studies that take brand loyalty into account when investigating IGA's efficacy. However, the results show that IGA has no positive effect on brand loyalty.

Upon the review of past research, it appears that there is a lack of investigation on the influence of IGA on brand equity as a whole, whereas the influence of IGA on partial constructs of brand equity such as brand awareness has been investigated (Yang et al., 2006; Herrewijn and Poels, 2018; Chaney et al., 2018). However, as evidence from literature specifies that IGA positively influences player's attitudes towards advertised brands and brand attitudes can influence brand equity in a favorable manner, it is expected that brand attitude will play a mediating role in the relationship between IGA and brand equity. Mediation occurs when the effect of the independent variable on the dependent variable is transmitted via an intermediate variable or mediator. We propose IGA to have a direct effect on brand equity as well as an indirect one via brand attitude as the mediator which will add up to a total effect, represented by the sum of indirect and direct effects.

Hence, the fourth and fifth hypotheses are proposed as follows:

H4:	*Brand attitude has a positive influence on brand equity.*

H5:	Brand attitude has a mediating effect on the relationship between IGA and brand equity.

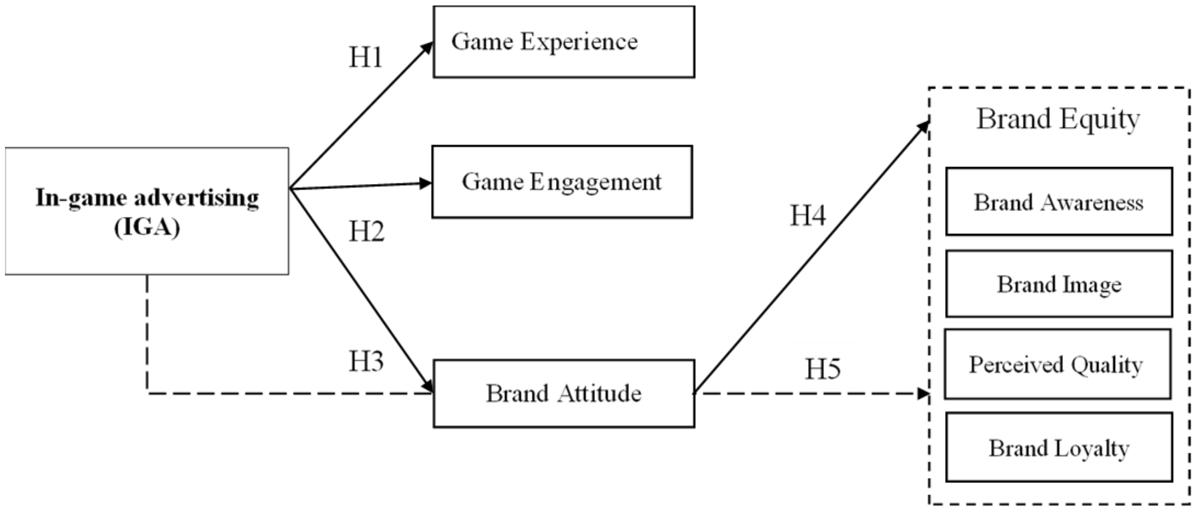


Figure 1: *Research model*
Source: *own illustration*

3 Methodology

The current study is exploratory research since it seeks to explore the influences of IGA on player experience, game usage, in-game purchase intention, brand attitude, as well as brand equity, particularly in the mobile game context. Because the main idea is to provide insights from the customer perspective, a quantitative survey approach was employed to collect gamers' opinions. The collaboration between PlayerUnknown's Battlegrounds Mobile (PUBGM) and Mountain Dew (Mtn Dew) was used as the stimulus for the empirical research. Mountain Dew is a global soft drink brand under PepsiCo Inc. (Mountain Dew n. d.). Games have been an integral part of Mountain Dew's marketing strategy since they recognized the need to consume caffeinated drinks to replenish the energy of gamers who are gaming throughout the night (Gamefuel 2022, Hitt 2020). Within the PUBGM-collaboration, the campaign "Do the Dew" was launched with several events both inside and outside the game. By collecting the Mountain Dew cans at virtual Mountain Dew vending machines, players could redeem in-game goodies such as branded t-shirts, branded parachutes, coupons, and an amount of in-game currency (Sengupta, 2020). Before the "Do the Dew" campaign, Mountain Dew used to be the platinum sponsor of the PUBG Mobile Pro League South Asia 06/2020 and later continued sponsoring for PUBG Mobile Global Championship 11/2020 (Ahmed 2020).

3.1 Research design

A questionnaire was developed to collect primary data directly from PUBGM players (see Appendix A). After consenting to the privacy declaration and accepting to participate, the respondents were directed to the demographic part with four questions about their nationalities, genders, age ranges, and current employment status. After completing the question about prior brand knowledge, participants were moved to the next part with information about PUBGM and Mountain Dew's collaboration. The event was described concisely with text and illustration images. This part is necessary as it is intended to remind gamers who have participated in the event and supplement information for gamers who started playing the game after the event. Subsequently, participants were forwarded to more in-depth questions about their attitudes towards the game and the brand. The promotion of Mountain Dew in the game was done in a subtle and complex way through an in-game event containing branded items, in-game props, and a variety of interactive activities to foster player engagement. For that reason, player's responses towards IGA will be referred to their evaluation towards this in-game event. In order to build an effective survey, the questions were mainly created utilizing pre-existing scales.

3.2 Measurements

In-game advertising (IGA): Player attitude towards IGA was measured using the Personal Involvement Inventory (PII) developed by Zaichkowsky (1994). PII is a tool used to measure “A person’s perceived relevance of the advertisement based on inherent needs, values, and interests” (Zaichkowsky 1994) and is applicable for all types of advertisements. PII covers both affective and cognitive involvement. Affective involvement is a term used to describe an individual's feelings and achievements of particular emotional states. Cognitive involvement addresses the utilitarian motive and can be understood as "the degree of personal relevance of message contents or issue" (Zaichkowsky, 1994). The scale consists of 10 items which can be grouped as follows: interesting, appealing, fascinating, exciting and involving represent the affective involvement according to Zaichkowski (1994), and important, relevant, valuable, means a lot to me and needed might be described as more rational or cognitive in nature. Zaichkowsky (1994) suggests the scale might be divided into two subscales. In order to ensure the compactness and efficiency of this study’s questionnaire, only five out of the ten items from Zaichkowsky's (1994) scale were adopted, representing the affective as well as the cognitive aspect. Participants replied on a semantic differential scale as follows: unexciting/exciting, unappealing/appealing, irrelevant/relevant, unimportant/important, not needed/needed.

Except for the independent variable, all dependent variables were measured using a 5-point Likert scale, ranging from strongly disagree to strongly agree.

Game Experience (GE): Since there were no suitable scales available for measuring this variable, the items were built based on the objective of measuring customers' consensus toward their overall experience. Hedonism is a crucial factor determining player enjoyment. Therefore, one question about IGA's ability to improve the hedonism of the game is also included. Eventually, PUBGM is a highly appreciated and popular game because of the realistic combat experience it brings to players. Thus, the final item was developed to examine whether IGA contributes to the verisimilitude of the game.

Game engagement (EN): This variable was measured by four items, of which three items belong to game usage, and one is for in-game purchase intention. The first item is intended to explore if players are willing to spend more time playing PUBGM during this event. Along with the duration of play, the frequency of play also reflects the effectiveness of customer retention. Thus, the second item measuring the effect of IGA on the frequency of playing the game was added. The third item examines the impact of IGA on player engagement by seeing how much more effort players make to win event rewards. Finally, appealing branded items can generate revenue for the game publisher. The last question will inspect player's purchase intention towards these items.

Brand attitude (BA): Three items were used to measure player attitude towards the brand Mountain Dew. The first item was adapted from the 7-point bipolar scale of Fishbein and Ajzen (as cited in Muehling and Laczniak, 1988), which is "My attitude toward the brand X is negative/positive." The second item was inspired by Yoo and Donthu (2001), who measure brand attitude on a 5-point bipolar scale with "extremely likable" and "extremely unlikable." The last item was inherited from the scale of Sengupta and Johar (2002), which is "My opinion of X is very favorable."

In order to measure consumer-based brand equity, dimensions from different scales were selected according to the study context and then united. However, there are still certain inconsistencies when applying widely accepted scales to the survey. For instance, it makes no sense to ask someone who has zero prior knowledge about Mountain Dew whether he or she considers himself/herself to be loyal to Mountain Dew. Therefore, some items were removed, modified, and added to the survey.

Brand equity (BE): As mentioned before, this research will measure brand equity as a multidimensional construct that consists of brand awareness, brand image, perceived quality, and brand loyalty.

Brand awareness (AW): Two items developed by Yoo and Donthu (2001) were used to measure this variable, including "I can recognize Mountain Dew among other competing brands" and "I am aware of Mountain Dew," respectively.

Brand image (BI): Since brand image was established from a set of brand associations, Yoo and Donthu's (2001) scale for measuring brand association was employed to measure this variable. Players were asked to what extent do they agree with the three following statements: "Some characteristics of Mountain Dew come to my mind quickly," "I can quickly recall the symbol or logo of Mountain Dew," and "I have difficulty in imagining Mountain Dew in my mind." The last item is reverse scored.

Perceived quality (PQ): Three items were used to measure players' perception of the quality of Mountain Dew soda drink. Two first items were adopted from the scale of Yoo and Donthu (2001) with minor adjustments to fit with the context of the survey. The last item was added to measure the perceived quality of Mountain Dew in comparison with other soft drinks.

Brand loyalty (BL): Brand loyalty was measured using four items. The first item stems from the action loyalty scale of Bobâlcă et al. (2012) which in turn is based on the scale of Zeithaml, Berry and Parasuraman (1996). It asks how likely it is that the customers recommend this brand to their friends. The second item was selected from Yoo and Donthu's (2001) scale to ask participants whether they would consider Mountain Dew as their first choice when looking for a soft drink. The third item was also adopted from Yoo and Donthu's (2001) scale to examine the priority choice of gamers. Finally, the last item was developed to gain insights into the customer's possibility of choosing Mountain Dew instead of a similar product.

3.3 Data Collection

The survey is limited to PUBGM players only because players who have a good understanding of PUBGM will be able to recall or imagine how the brand is promoted more clearly than those who have never played. Furthermore, the purpose of this study was to explore the impact of IGA on gamers in general, so it is unnecessary to include subjects who shared other specific similarities.

The questionnaire was administrated in two versions, including the Vietnamese version for Vietnamese gamers and the English version for global gamers. The survey was conducted online, using Google Forms and distributed directly in-game as well as via gaming platforms such as PUBGM Facebook groups and Discord communities with a total of 20 public posts across 19 communities. The survey finished with 330 participants, of which 10.3% are international players and the remaining 89.7% are Vietnamese players. Among 330 participants, it is clear that male players still make up the majority with 56.7 %, followed by female players with 39.7%, LGBT 2.7%, and about 0.9% do not want to mention their gender. In terms of age, the majority of players are Gen Z (people born from 1995 - 2010) with approximately 89.4%. Besides, millennials are made up of 10.3%, and 0.3% are Gen Xers (Francis and Hoefel, 2018). Students account for the vast majority of respondents with 69.1% and follow by employees with 21.5%. In addition, the data also shows that the majority of participants are veteran gamers who have been with the game for more than one year (83%). Their gaming frequency is also very intensive, with 76.1% playing on a daily basis. Based on the data, it can be inferred that Mountain Dew is a well-known brand among the participants since 72.7% of people already knew the brand. More details about sample demographics can be found in Table 1.

Table 1: Sample demographics

Sample size = 330	Number	Percentage
Gender		
Male	187	56.7%
Female	131	39.7%
LGBT	9	2.7%
Prefer not to say	3	0.9%
Age		
Under 18	86	26.1%
18 - 25	209	63.3%
26 - 40	34	10.3%

41 - 60	1	0.3%
Above 60	0	0.0%
Status of employment		
Student	228	69.1%
Employee	71	21.5%
Unemployed	16	4.8%
Entrepreneur/Self-employed	14	4.2%
Retired	1	0.3%
Other	0	0.0%
Nationality		
Vietnamese	296	89.7%
Other nationalities	34	10.3%
Know Mountain Dew		
Yes	240	72.7%
No	90	27.3%
Playing PUBGM for		
Less than 1 week	7	2.1%
Less than 1 month	7	2.1%
1 - 6 months	20	6.1%
6 months - 1 year	22	6.7%
More than 1 year	274	83.0%
Frequency of playing PUBGM		
Less than 1 time a month	11	3.3%
1 - 3 times per month	19	5.8%
Once a week	8	2.4%
2 - 5 times per week	41	12.4%
Everyday	251	76.1%

Source: own table

4 Results

All hypotheses in the research model were examined using the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique. The procedure of evaluating PLS-SEM results consists of two main parts, namely, examining the measurement models and assessing the structural models. Examining the measurement model includes examining the indicator loadings, internal consistency reliability, convergent and discriminant validity of each construct (Garson, 2016; Hair et al., 2019). Assessing structural model entails multicollinearity, the coefficient of determination (R^2), and structural path coefficients (Garson, 2016).

In the reflective model, the focus is on outer model loadings instead of outer model weights, and the acceptable loadings range is from 0.708 to 1 (Garson, 2016). The analyzed result showed that all items have sufficient loadings except BI3 (=-0.538) (see Appendix B). A possible reason for that might be the reversed scoring of this single item. BI3 was thus removed from the data set. Next, the reliability of scales was examined by Cronbach's alpha and composite reliability. Because measuring items were inherited and combined from different existing scales or developed based on literature review, these indices will help ensure the reliability of the new scales by eliminating inconsonant items. Cronbach's alpha is a statistic used to measure the internal consistency of all observable items within a construct (Taber, 2018). Composite reliability is an alternative to Cronbach's alpha and is favored by academics in PLS-based research. Generally, the acceptable values of Cronbach's alpha and composite reliability are greater than 0.7 (Nunnally and Bernstein, 1994; Taber, 2018; Garson, 2016). Accordingly, the scales of all variables fulfilled the requirements. The summary of construct measurements is shown in Table 2.

Table 2: Construct measurement summary

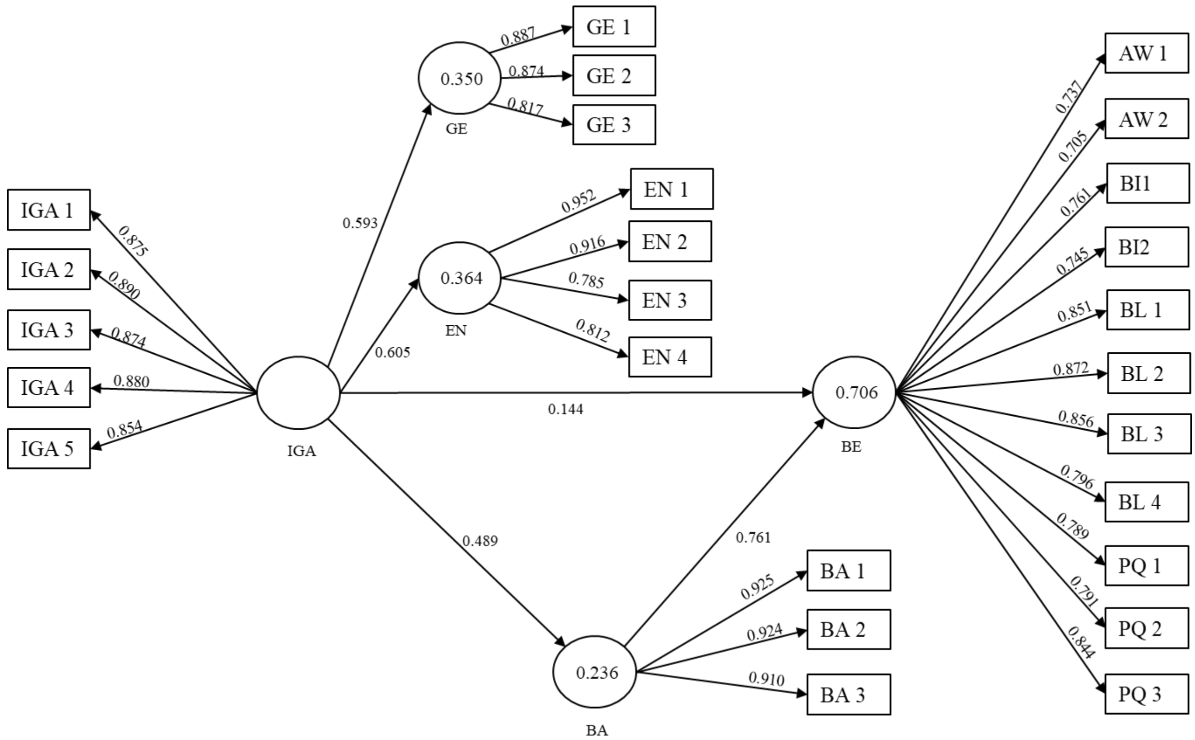
Variable	Item	Loadings	Composite Reliability	Cronbach's alpha	AVE
IGA	IGA1	0.875	0.942	0.923	0.765
	IGA2	0.890			
	IGA3	0.874			
	IGA4	0.880			
	IGA5	0.854			
GE	GE1	0.887	0.895	0.825	0.739
	GE2	0.874			
	GE3	0.817			
EN	EN1	0.925	0.920	0.883	0.743
	EN2	0.916			
	EN3	0.785			
	EN4	0.812			
BA	BA1	0.925	0.943	0.909	0.846
	BA2	0.924			
	BA3	0.910			
BE	AW1	0.737	0.950	0.942	0.635
	AW2	0.705			
	BI1	0.761			
	BI2	0.745			
	BL1	0.851			

	BL2	0.872
	BL3	0.856
	BL4	0.796
	PQ1	0.789
	PQ2	0.791
	PQ3	0.844

Source: own table

In addition to the construct reliability, the result of the PLS algorithm also allowed for checking the construct validity with average variance extracted (AVE) and discriminant validity. All constructs in the research model have AVE values that exceeded the requirement of 0.5, implying that factors can explain more than half the variance of their respective indicators (Garson, 2016). Discriminant validity in SmartPLS was assessed using three indicators: the Fornell-Larcker criterion, cross-loading, and Heterotrait-Monotrait (HTMT) ratio (see Appendix B). Although satisfying most of the requirements for discriminant validity, the HTMT ratio of GE and EN (=0.92) is higher than the cutoff of 0.90 (Gold et al., 2001; Henseler et al., 2015). However, the requirement of an HTMT ratio for a well-fit model is below 1.0 (Garson, 2016); thus, none of the constructs was changed.

After ensuring the measurement model fulfilled expectations, it was proceeded with assessing the structural model. In the reflective model, variance inflation factors (VIF) are presented by the “Inner VIF Values” and should not be higher than 4.0 (Garson, 2016). Therefore, it can be concluded that there is no collinearity in the current model because the VIF only reached values between 1.000 and 1.341 (see Appendix).



Inner model: Path coefficients; Outer model: Outer loadings; Constructs: R square adjusted

Figure 2: Structural equation model
Source: own illustration

The coefficient of determination (R^2) is a measure of the fit of the linear model. As shown in Figure 2, IGA can explain 35%, 36.4%, and 23.6% of GE, EN, and BA variance, respectively. Similarly, 70.6% of the variance in BE is explained by IGA and BA. The explanatory powers of independent variables are considered substantial, moderate, and weak if R^2 values are 0.75, 0.50, and 0.25 respectively (Hair et al., 2019).

Table 3: Summary of path coefficients and hypotheses evaluation

Hypotheses	Original Sample (O)	P Values	Result
H1: IGA -> GE	0.593	0.000	Preliminary not rejected
H2: IGA -> EN	0.605	0.000	Preliminary not rejected
H3: IGA -> BA	0.489	0.000	Preliminary not rejected
H4: BA_ -> BE	0.761	0.000	Preliminary not rejected
H5: IGA -> BA -> BE	0.372	0.000	Preliminary not rejected

Source: own table

Before examining the structural path coefficients, bootstrapping technique was executed with 1,000 subsamples. Results in Table 3 demonstrate the direct effects of independent variables on endogenous variables. Accordingly, IGA exerted the most potent effect on EN (=0.605), followed by GE (=0.593) and

BA (=0.489). Similarly, BA exerted a significant influence on BE (=0.761). With significance levels of 0.000 (smaller than the threshold of 0.05) (Garson, 2016), none of the hypotheses H1, H2, H3, and H4 were preliminarily rejected. It is noticeable that IGA can have a slight direct effect on BE (=0.144). The analysis also calculated the indirect effect of IGA on BE through BA by multiplying the path coefficient of IGA -> BA (=0.489) with the path coefficient of BA -> BE (=0.761). As a result, the indirect effect of IGA -> BA -> BE has a value of 0.372 and is statistically significant with a p-value of 0.000. The direct and indirect effects of IGA on BE together made up a considerable total effect of IGA on BE (=0.516). Explicitly, most of the IGA's influence on BE is achieved through BA. Thus, the hypothesis about the mediating role of BA in H5 is also supported.

Further in-depth analysis of the impact of IGA and BA on each brand equity's dimension was also carried out with a similar process of accessing measurement model and structural model. All loadings vary from 0.785 to 0.954, fulfilled the requirement of minimum loadings of 0.708. The reliability and validity of each dimension also satisfied the approval criteria. Furthermore, no multicollinearity was detected in this analysis, with all VIF values smaller than 4.0. (see Appendix C). In regard to the influence of IGA on each dimension, the result indicated that IGA does not have any direct effect on PQ (=0.062), AW (=-0.048), and BI (=0.055) with p-values greater than 5%. However, IGA was demonstrated to have a moderate direct influence on BL (=0.281; p-value = 0.000). In contrast, the influence of BA on all dimensions of BE is explicitly confirmed with appropriate significance levels of all path coefficients. More specifically, BA exerted a substantial influence on PQ (=0.757). The influence of BA on other dimensions is slightly weaker but still can be considered significant (AW=0.699; BI=0.645; BL=0.599). Besides testing for direct effects, bootstrapping results also examined the indirect effects of IGA on four dimensions of brand equity. In general, all influences are statistically relevant with significant values of 0.000. Therefore, although there is no direct effect, the total effect of IGA on brand equity's dimensions is considerable, especially on BL (=0.573).

Table 4: Summary of control factors' influences

Variable	**IGA**	**GE**	**EN**	**BA**	**PQ**	**AW**	**BI**	**BL**	**BE**
Nationality		✓	✓	✓	✓	✓			✓
Brand knowledge						✓	✓		✓
Gender								✓	
Age									
Employment Stt	✓								
Playing period									
Playing frequency	✓		✓		✓				

Source: own table

In addition to examining the impact of IGA on gamers' evaluation towards PUBGM and Mountain Dew, the influence of control factors on the outcomes was also tested by the independent sample t-test and one-way ANOVA (ANOVA).

In sum, there is no discrepancy in people’s evaluations towards the game and advertised brand between different age groups and between individuals who have started playing the game for a long or short period of time. On the other side of the spectrum, the opinions of players from Vietnam and players from other countries are different in the majority of aspects, except in IGA and BL. In all cases, Vietnamese players tended to show a more positive attitude than players from other nationalities. Especially, while Vietnamese players seemed to agree that IGA helps improve their gaming experience (Mean=3.730), the other players slightly disagreed (Mean=2.941).

It is also worth noting that prior knowledge of the advertised brand leads to more favorable attitudes towards BE, particularly in AW, BI. Additionally, the more frequently people play PUBGM, the higher level of involvement with IGA they held. Among five levels of playing frequency, people playing the game on a daily basis tended to engage with the game more than people who play the game occasionally. Their perception of the quality of the integrated product is also more favorable. Besides, gender differences also lead to differences in evaluations towards BL. In particular, male gamers show a slightly higher loyalty to the advertised brand than female gamers. Finally, a difference in the mean of IGA between students and self-employed people was also reported. Entrepreneur and self-employed people expressed a higher level of involvement with IGA than students did.

5 Discussion

The results of this study demonstrate that IGA has a positive influence on player experience, player engagement, brand attitude, and brand equity. In addition, statistical evidence from the analysis also supports that brand attitude plays a crucial mediating role in the influence of IGA on brand equity. This study successfully provided answers to the research questions raised at the beginning. In a nutshell, IGA positively affects games and promoted brands, thus bringing mutual advantages to game publishers, brands, as well as players.

5.1 Advantages for game publishers

For game publishers, positive responses to advertising are seen as a very beneficial token. An exemplary implementation of a few "pioneer" ads will be a preliminary to persuade potential clients to invest in more IGA campaigns even with a grander scale. Consequently, game companies can expect a growing revenue stream from IGA to help them subsidize marketing costs, reinvest in game development to improve user experience, expand the user base, increase retention, and drive more in-game purchases (Herrewijn and Poel, 2014).

Although proven to be effective, it should be noted that the outcomes of the execution depend on several other factors. Importantly, while the evidence that incorporating real-life brands allows for greater immersion into a more realistic game world is undeniable, realism is not appreciated in fantasy games (Poels et al., 2013). Thus, optimizing IGA for fantasy games is a challenging task that needs further consideration by academics and practitioners to ensure that the inconsistency between game environment and ads which tends to ruin player experience cannot occur. In sum, it is vital for game developers to design and implement ads carefully, meticulously, and creatively. Additionally, keeping track of the gamer's feedback towards executed IGA is also an important task that can help generate many valuable insights for future improvements.

5.2 Advantages for Brands

For brands, IGA can be seen as a new approach with many exceptional advantages. The vivid and interactive nature of IGA allows customers not only to see but also to interact with the brand or product in their gameplays, thereby provoking their affection for the brand as well as help them remember it easily (Herrewijn and Poel, 2014). The placement of the product and brand in games influences customer's assessment of its quality. Therefore, brands should find ways to present the product's features tactfully and let customers experience it through interaction. Doing this can further strengthen customer trust and perception of the brand. Mau et al. (2010) also found that game outcomes will influence player evaluations towards the integrated brand. Therefore, to minimize the detrimental impacts of bad gaming outcomes, branded items could be used as an enabler to help players overcome challenges and win the game more easily.

Attesting to the positive influence of IGA on brand attitude reinforced the findings of previous studies. Players' attitudes towards the promoted brand were relatively consistent across different subject groups except nationality. As this study used a single brand as a research stimulus, some effects such as product/brand differences, congruity between product/brand and the game were omitted. However, integrating a brand into a gaming environment requires these considerations to achieve the optimal level of affection which can, in turn, prompt beneficial consumer behavior or enhance brand equity (Nelson et al., 2004). Reijmersdal et al. (2010) and Herrewijn and Poel (2018) discovered that brands that were integrated in an interactive way attained a higher favorite level compared to brands that were integrated passively. It was also proven that player's attitudes towards embedded brands would be positive in positive game contexts and vice versa (Yoo and Eastin, 2017). Although determining the congruity between a title and a brand is not an easy task, it is critical since many studies confirmed that game-product congruity positively affects people's attitudes towards the brand. Reversely, the perceived incongruity between game and brand will lead to negative responses (Lee and Faber, 2007; Peters and Leshner, 2013). Finally, Mau et al. (2008) presented a surprising finding that IGA did not benefit familiar brands. In their research, players showed a favorable inclination towards unfamiliar brands, but their opinions towards familiar brands deteriorate. Another research by Yang et al.

(2015) also highlighted a similar finding that the lower the level of brand familiarity, the greater the effect of IGA; on the other hand, the higher the level of brand familiarity, the smaller the influence of IGA.

5.3 Advantages for players

The reasons people play games are to escape reality, relieve boredom, reduce pressure, and generally to have fun (Youn and Lee, 2003). When an individual is immersed in a digital world with a high feeling of presence, they will experience a more significant impact of the events in that world, including the influence of any persuasive message (Herrewijn and Poel, 2014). In this study, IGA was displayed to have a positive effect on player experience by enhancing hedonism and adding a touch of reality to the game environment. IGA is also a kind of non-disruptive advertising as it goes with the flow of the gameplays, so game developers can leverage IGA as a tactic for bringing players a refreshing experience.

Evidence from the analysis also proved that IGA helps improve the appealingness of games by positively influencing the players' commitments to the title they play. According to Lucas and Sherry (2004), the top-rated motivation for playing a game is challenge. By creating novel challenges and rewarding with in-game goodies, the ads implemented in the form of short-term events successfully triggered players' ambition to receive rewards by accomplishing all event-related tasks. It also, in turn, galvanized players to spend more time as well as to play the game with higher frequency. Although a previous study indicated that virtual rewards and perceived playfulness are the drivers of in-game purchase intention (Cheung et al., 2021), the result of this study showed that the majority of players were not willing to pay for a branded item. Purchase intention, however, is a complicated behavior that needs both ability and motivation (Balakrishnan and Griffiths, 2018). Purchase of virtual items in-game is predicted by aesthetic design, sense of authenticity (Wu and Hsu, 2018), competitive price, and game loyalty (Cheung et al., 2021). Therefore, a possible explanation for this could be that a player's purchasing decision is more determined by other factors rather than the influence of IGA.

In the current study, players expressed a relatively high involvement with IGA. It suggested that they found the practice is interesting, appealing, relevant, important, and needed. It can be inferred that the attitude of players towards the advertisements is positive since the involvement was assessed under both affective and cognitive angles. The result also revealed that the more frequently people play the game, the more favorable their attitude towards IGA will be. These findings are in line with previous studies (Nelson, 2002; Poels et al., 2013) in proving that IGA could be a promising alternative to traditional mass media advertising.

6 Conclusions and outlook

As one of the few studies that investigated the impact of IGA on brand equity, this study demonstrated that IGA could exert a moderate influence on brand equity as well as its dimensions. However, it should be noted that the direct effect of IGA on brand equity is very fair. IGA's influence on brand equity is mainly achieved through brand attitude. The more the players are involved with IGA, the more favorable their attitude towards the brand will be, and thus a company’s brand equity can be improved. Likewise, IGA not only helps the brand strengthen its brand awareness and makes the brand image stay in the customer's mind but also helps potential customers appreciate product quality. Despite the fact that brand loyalty is a challenging aspect to assess when prior usage experience is not guaranteed, it was also positively influenced by IGA. It is worth mentioning that prioritizing the purchase of the advertised product does not receive as much agreement as recommending that product to others. The reason for this result may be that people tend to say positive words about as well as recommend their favorite brands to others (Bozbay et al., 2018) while purchase decision requires more complex considerations (Balakrishnan and Griffiths, 2018).

This study contributes to the holistic picture of advertising in digital games by filling a present knowledge gap in the field of strategy, making it relevant to both academia and businesses. However, it must be noted that apart from increasing brand awareness and changing brand perceptions, the ultimate goal of marketing communication is driving key behavioral outcomes (Kotler and Keller, 2015). As the impact of IGA on customer behavior has not been thoroughly investigated in this study, future studies are expected to extend knowledge in this direction.

Additionally, further investigation on other game genres besides shooting games would be very valuable. Added to that, the difference between free-to-play (F2P) and pay-to-play (P2P) games should be regarded in future studies, for players who had to pay for the game in the first place might be less accepting when it comes to IGA.

Also, the selection of the stimulus product and ad categories can be expanded. This study not just used a single category (beverages), but also a single product within this category as the stimulus for the survey. This way, the effects of product or brand differences as well as existing brand preferences were omitted. Moreover, the congruity between product or brand and the game has been emphasized in many studies. For that reason, comparisons between different products or brands in the same game context are needed in future studies to find out which ones are suitable for IGA. In addition, as mentioned earlier, the implementation of advertising in the game environment is exceptionally dynamic and flexible in terms of advertising forms. In addition to brand placements, the effectiveness of other categories such as sponsorship deals, real-world analogs, branded music and sounds, branded characters, and brand-related cheat codes are also worth investigating.

Although video games are traditionally seen as a hobby for the young and for males, there are suggestions that gamers are a much more diverse group nowadays. Further investigations should consider this fact, widening the focus from this traditional view and include other genders and age groups.

As gaming is a worldwide phenomenon, similar studies are encouraged to be carried out in other markets to better present the global picture of IGA in mobile games. In addition, the differences in assessment between different cultures presented in this study need to be considered more thoroughly by further cross-cultural research to draw a firmer conclusion about the influence of these factors.

Research about IGA often derives from the consumer perspective. Understanding consumer behavior and attitudes are vital in providing significant implications for the academic and business domain. However, the current body of literature largely lacks research that considers the perspective of game publishers and brands towards the feasibility of this strategy. Sharings about the barriers that parties may face when implementing IGA, aspects that need to be considered to create effective campaigns or comparing the effectiveness of IGA with other marketing communication strategies would help complete the holistic picture of IGA.

References

Aaker, D.A. (1996). Measuring brand equity across products and markets. *California Management Review,* Vol. 38, Spring, pp. 102-120.

Aaker, D.A., (1991). *Managing brand equity: capitalizing on the value of a brand name*. Free Press; Maxwell Macmillan Canada; Maxwell Macmillan International, New York: Toronto: New York. Pp. 18 – 106.

Ahmed, W. (2020, Sep 22). *Here are the locations of Mountain Dew vending machines in PUBG Mobile.* Retrieved from https://dotesports.com/news/here-are-the-locations-of-mountain-dew-vending-machines-in-pubg-mobile. Accessed on 26.07.2022.

Balakrishnan, J. & Griffiths, M.D. (2018). Loyalty towards online games, gaming addiction, and purchase intention towards online mobile in-game features. *Computers in Human Behavior*, 87, 238-246. https://doi.org/10.1016/j.chb.2018.06.002.

Bobâlcă, C., Gătej(Bradu), C., & Ciobanu, O. (2012). Developing a Scale to Measure Customer Loyalty. *Procedia Economics and Finance,* 3, 623–628. https://doi.org/10.1016/S2212-5671(12)00205-5.

Boyle, E.A., Connolly, T., Hainey, T., & Boyle, J.M. (2012). Engagement in digital entertainment games: A systematic review. *Computers in Human Behavior*, 28, 771-780. https://doi.org/10.1016/j.chb.2011.11.020.

Bozbay, Z. & Karami, A. & Arghashi, V. (2018). *The Relationship between Brand Love and Brand Attitude*. 2nd International Conference on Management and Business, Tebriz, Iran, 8-9.

Calvillo-Gámez, E.H., Cairns, P., & Cox, A.L. (2010). Assessing the Core Elements of the Gaming Experience. In Bernhaupt, R. (Ed.), *Evaluating User Experience in Games*. Human-Computer Interaction Series. Springer, London. https://doi.org/10.1007/978-1-84882-963-3_4.

Chaney, I., Hosany, S., Wu, M. S., Chen, C. S., & Nguyen, B. (2018). Size does matter: Effects of in-game advertising stimuli on brand recall and brand recognition. *Computers in Human Behavior*, 86, 311-318. https://doi.org/10.1016/j.chb.2018.05.007.

Chaney, I., Lin, K. & Chaney, J. (2004). The Effect of Billboards within the Gaming Environment. *Journal of Interactive Advertising*, 5(1), 37-45. https://doi.org/10.1080/15252019.2004.10722092.

Che, X. & Ip, B. (2017). Mobile Games in China: Development and Current Status. In Jin, D. (Ed.), *Mobile Gaming in Asia.* Mobile Communication in Asia: Local Insights, Global Implications. Springer, Dordrecht. https://doi.org/10.1007/978-94-024-0826-3_9.

Cheung, M., Leung, W., Chang, L., & Shi, S. (2021). Driving loyalty intentions of mobile games: a motivation theory perspective. *Quality & Quantity*. https://doi.org/10.1007/s11135-021-01120-y.

Choi, D., & Kim, J. (2004). Why people continue to play online games: In search of critical design factors to increase customer loyalty to online contents. *Cyberpsychology & Behavior*, *7*, 11–24. https://doi.org/10.1089/109493104322820066.

Coulter, K.S. (1998). The effects of affective responses to media context on advertising evaluations. *Journal of Advertising*, 27(4), 41–51. https://doi.org/10.1080/00913367.1998.10673568.

Eastin, M.S. and Lee, J.A. (2020). Attitudes Toward Advertisements and Brands. In Bulck, J. (Ed.), *The International Encyclopedia of Media Psychology.* https://doi.org/10.1002/9781119011071.iemp0187

Emery L. (2021, Apr 20). *What is an IDFA (and How Will Apple's iOS 14 Update Impact Advertisers)*? Retrieved from https://tinuiti.com/blog/data-privacy/apple-ios-idfa-guide/. Accessed on 07.05.2021.

Escalas, J. E. 2004. Imagine Yourself in the Product: Mental Simulation, narrative Transportation, and Persuasion. *Journal of Advertising*, 33 (2): 37–48. https://doi.org/10.1080/00913367.2004.10639163.

Faircloth, J., Capella, L., & Alford, B. (2001). The Effect of Brand Attitude and Brand Image on Brand Equity. *Journal of Marketing Theory and Practice, 9* (3), 61-75.

Farquhar, P.H. (1989). Managing Brand Equity. *Marketing Research,* 1, 24-33.

Francis, T. & Hoefel, F. (2018, Nov 18). *'True Gen': Generation Z and its implications for companies*. Retrieved from https://www.mckinsey.com/industries/consumer-packaged-goods/our-insights/true-gen-generation-z-and-its-implications-for-companies. Accessed on 20.08.2021.

Gamefuel (2022). Retrieved from https://gamefuel.com/. Accessed on 26.07.2022.

GamesIndustry International (2008, Jun 17). *Landmark IGA-Nielsen Study*. Retrieved from https://www.gamesindustry.biz/articles/landmark-iga-nielsen-study. Accessed on 05.07.2021.

Garson, G. D. (2016). *Partial Least Squares: Regression and Structural Equation Models*. Asheboro, NC: Statistical Associates Publishers.

Gold, A. H., Malhotra, A., & Segars, A. H. (2001). Knowledge management: An organizational capabilities perspective. *Journal of Management Information Systems* 18(1), 185–214. https://doi.org/10.1080/07421222.2001.11045669.

Hair, J.F., Risher, J.J., Sarstedt, M. & Ringle, C.M. (2019). When to use and how to report the results of PLS-SEM", *European Business Review*, 31(1), 2-24. https://doi.org/10.1108/EBR-11-2018-0203.

Hanaysha, J., Abdullah, H.H., & Ghani, N.H. (2013). Assessing the literature on brand equity: From past, present to future. *Australian Journal of Basic and Applied Sciences,* 7(14), 488-499.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science* 43(1), 115-135. https://doi.org/10.1007/s11747-014-0403-8.

Herrewijn, L. & Poels, K. (2013). Putting brands into play. *International Journal of Advertising: The Review of Marketing Communications*, 32(1), 17-44. https://doi.org/10.2501/IJA-32-1-017-044.

Herrewijn, L. & Poels, K. (2014). Rated A for Advertising: A Critical Reflection on In-Game Advertising. In Angelides, M.C. and Agius, H. (Eds.). *Handbook of Digital Games*. https://doi.org/10.1002/9781118796443.ch11.

Herrewijn, L. & Poels, K. (2017). Exploring player responses toward in-game advertising : the impact of interactivity. In Rodgers, S. & Thorson, E. (Eds.). *Digital Advertising.* https://doi.org/10.4324/9781315623252-18.

Herrewijn, L. & Poels, K. (2018). The Effectiveness of In-Game Advertising: Examining the Influence of Ad Format. In Cauberghe, V., Hudders, L. & Eisend M. (Eds.). *Advances in Advertising Research IX.* European Advertising Academy. Springer Gabler, Wiesbaden. https://doi.org/10.1007/978-3-658-22681-7_7.

Hitt, C. (2020, Aug 13). *The Highly Caffeinated & Super-Interesting History of Mountain Dew.* Retrieved from https://www.thrillist.com/news/nation/history-of-mountain-dew-origin-facts. Accessed on 26.07.2022.

Johnstone, E. & Dodd, C. A. (2000). Placements as mediators of brand salience within a UK cinema audience. *Journal of Marketing Communications*, 6(3), 141-158. https://doi.org/10.1080/13527260050118649.

Keller, K. L. (1993). Conceptualizing, Measuring, and Managing Customer-Based Brand Equity. *Journal of Marketing,* 57(1), 1-22. https://doi.org/10.2307/1252054.

Keller, K. L. (2013). *Strategic Brand Management: Building, Measuring, and Managing Brand Equity* (4th ed.). Pearson.

Kim, H., Kim, W. & An, J. (2003). The effect of consumer-based brand equity on firms' financial performance. *Journal of Consumer Marketing*, 20, 335–351. https://doi.org/10.1108/07363760310483694.

Kim, S., Lee, J., Hwang, Y. & Jeong, S. (2016). Effects of prominent in-game advertising in mobile media: cognitive, affective, and behavioural outcomes and the moderating role of persuasion knowledge. *International Journal of Mobile Communications,* 14(3), 203-225.

Kotler, P. & Keller, K. L. (2015). *Marketing Management* (15th Ed.). Pearson.

Krystallis, A. & Chrysochou, P. (2014). The effects of service brand dimensions on brand loyalty. *Journal of Retailing and Consumer Services*, 21(2), 139-147. https://doi.org/10.1016/j.jretconser.2013.07.009.

Lang, A. (2009). The Limited Capacity Model of Motivated Mediated Message Processing. In Nabi, R. L. & Olive, M. B. (Eds.). *The SAGE Handbook of Media Processes and Effects,* 193-204. Thousand Oaks, CA: Sage Publications.

Lee, A. Y., & Sternthal, B. (1999). The effects of positive mood on memory. *Journal of Consumer Research*, 26(2), 115–127. https://doi.org/10.1086/209554.

Lee, E., Lee, S., & Yang, C. (2017). The influences of advertisement attitude and brand attitude on purchase intention of smartphone advertising. *Industrial Management & Data Systems*, 117(6). http://dx.doi.org/10.1108/IMDS-06-2016-0229.

Lee, M., & Faber, R. J. (2007). Effects of Product Placement in On-line Games on Brand Memory. *Journal of Advertising*, 36(4), 75-90. https://doi.org/10.2753/JOA0091-3367360406.

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

Lucas, K., & Sherry, J. L. (2004). Sex Differences in Video Game Play: A Communication-Based Explanation. *Communication Research*, 31(5), 499–523. https://doi.org/10.1177/0093650204267930.

Mackay, T., Ewing, M., Newton, F., & Windisch, L. (2009). The effect of product placement in computer games on brand attitude and recall. *International Journal of Advertising,* 28(3), 423-438. https://doi.org/10.2501/S0265048709200680.

Mau G., Silberer G., & Gödecke J. (2010). Game Outcome and In-Game Advertising Effects. In Terlutter, R., Diehl, S., Okazaki, S. (Eds.). *Advances in Advertising Research (Vol. 1)*. Gabler. https://doi.org/10.1007/978-3-8349-6006-1_11.

Mau, G., Silberer, G., & Constien, C. (2008). Communicating brands playfully. *International Journal of Advertising*, 27(5), 827-851. https://doi.org/10.2501/S0265048708080293.

Molesworth, M. (2006), Real brands in imaginary worlds: investigating players' experiences of brand placement in digital games. *Journal of Consumer Behaviour*, 5, 355-366. https://doi.org/10.1002/cb.186.

Moulard, J. G., Kroff, M., Pounders, K. & Ditt C. (2019). The Role of Suspense in Gaming: Inducing Consumers' Game Enjoyment. *Journal of Interactive Advertising*, 19(3), 219-235. https://doi.org/10.1080/15252019.2019.1689208.

Mountain Dew (n.d.). Home page. Retrieved from https://www.mountaindew.com. Accessed on 26.07.2022.

Muehling, D. D. & Laczniak, R. N. (1988). Advertising's Immediate and Delayed Influence on Brand Attitudes: Considerations Across Message-Involvement Levels. *Journal of Advertising*, 17(4), 23-34. https://doi.org/10.1080/00913367.1988.10673126.

Nelson, M. R. (2002). Recall of brand placements in computer/video games. *Journal of Advertising Research,* 42(2), 80-92. https://doi.org/10.2501/JAR-42-2-80-92.

Nelson, M.R., Keum, H., & Yaros, R. A. (2004). Advertainment or Adcreep Game Players' Attitudes toward Advertising and Product Placements in Computer Games. *Journal of Interactive Advertising*, 5(1), 3-21. https://doi.org/10.1080/15252019.2004.10722090.

Newzoo (2021, Jul 21). *Newzoo Global Games Market Report 2021 | Free Version*. Retrieved from https://newzoo.com/insights/trend-reports/newzoo-global-games-market-report-2021-free-version/. Accessed on 20.07.2021.

Nguyen, T., Dadzie, C. & Davari, A. (2013). *Does Brand Equity Mean Brand Equity? An Empirical Study of Consumer Based Brand Equity and Financial Based Brand Equity.* AMA Summer Educators' Conference, Bosten, MA.

Nunnally, J. and Bernstein, I. (1994). *Psychometric Theory (3rd edition)*. New York: McGraw-Hill.

Oliver, R.L., (1997). *Satisfaction: A Behavioral Perspective on the Consumer*. Routledge. https://doi.org/10.4324/9781315700892.

Owolabi, A. B. (2009). Effect of Consumers Mood on Advertising Effectiveness. *Europe's Journal of Psychology,* 5(4), 118-127. https://doi.org/10.5964/ejop.v5i4.243.

Paddon, R. (2019, Mar 19). *Pros and Cons of in-app advertisement for money making*. Retrieved from http://www.adotas.com/2019/03/pros-cons-app-advertisement-money-making/, Accessed on 01.03.2021.

Pelsmacker, P.D., Dens, N., & Verberckmoes, S. (2019). How Ad Congruity and Interactivity Affect Fantasy Game Players' Attitude towards In-Game Advertising. *Journal of Electronic Commerce Research*, 20, 55.

Peters, S. & Leshner, G. (2013). Get in the Game: The Effects of Game-Product Congruity and Product Placement Proximity on Game Players' Processing of Brands Embedded in Advergames. *Journal of Advertising*, 42(2-3), 113-130. https://doi.org/10.1080/00913367.2013.774584.

Poels, K., Janssens, W., & Herrewijn, L. (2013). Play Buddies or Space Invaders? Players' Attitudes Toward In-Game Advertising. *Journal of Advertising*, 42(2-3), 204-218. https://doi.org/10.1080/00913367.2013.774600.

Reijmersdal, E., Jansz, J., Peters, O., & Noort, G. (2010). The effects of interactive brand placements in online games on children's cognitive, affective, and conative brand responses. *Computers in Human Behavior*, 26(6), 1787-1794. https://doi.org/10.1016/j.chb.2010.07.006.

Reijmersdal, E.A., Neijens, P.C. & Smit, E.G. (2007). Effects of television brand placement on brand image. *Psychology & Marketing*, 24, 403-420. https://doi.org/10.1002/mar.20166.

Roy, A. T. (2022, Jan 03). *Contextual: What's All the Fuss About.* Retrieved from https://verve.com/blog/contextual-whats-all-the-fuss-about/. Accessed on 26.07.2022.

Schöber, T./Stadtmann, G. (2020). Fortnite: The Business Model Pattern Behind the Scene. *Die Unternehmung,* 74(4), 426-444. https://doi.org/10.5771/0042-059X-2020-4.

Scolastici, C. & Nolte, D. (2013). *Mobile game design essentials*. Packt Publishing, 283 – 285.

Sengupta, J., & Johar, G. V. (2002). Effects of inconsistent attribute information on the predictive value of product attitudes: Toward a resolution of opposing perspectives. *Journal of Consumer Research*, *29*(1), 39–56. http://dx.doi.org/10.1086/339920.

Sengupta, S. (2020, Sep 24). *Mountain Dew Announces Expanded Partnership With PUBG Mobile.* https://archive.esportsobserver.com/mountain-dew-pubg-mobile-sept2020/. Accessed on 04.04.2021.

Seo, Y.N., Kim, M., Lee, D., & Jung, Y. (2018). Attention to eSports advertisement : effects of ad animation and in-game dynamics on viewers' visual attention. *Behaviour and Information Technology*, 37(12), 1194-1202. https://doi.org/10.1080/0144929X.2018.1488993.

Shibuya, A., Teramoto, M. & Shoun, A. (2017). Toward Individualistic Cooperative Play: A Systematic Analysis of Mobile Social Games in Japan. In Jin, D. Y. (Ed.). *Mobile Gaming in Asia*. *Local Insights, Global Implications.* Springer, Dordrecht. https://doi.org/10.1007/978-94-024-0826-3_14.

Smith, J. (2020, Oct 20). *Why in-game advertising now represents a powerful performance as well as a branding channel*. Retrieved from https://www.thedrum.com/profile/the-digital-voice/news/why-in-game-advertising-now-represents-a-powerful-performance-as-well-as-a-branding-channel. Accessed on 01.03.2021.

Smith, M., Sutherland, J., Mackie, B., & Sun, S. (2014). In-Game Advertising influencing factors: a Systematic Literature Review and meta-analysis. *The Computer Games Journal,* 3(2), 102-131.

Sondhi, S. (2021, Dec 05). *The Games People Play... Create Opportunities.* Retrieved from https://verve.com/blog/the-games-people-playcreate-opportunities/. Accessed on 26.07.2022.

Spears, N. & Singh, S. (2004). Measuring Attitude Toward the Brand and Purchase Intentions. *Journal of Current Issues and Research in Advertising*. 26, 53-66. https://doi.org/10.1080/10641734.2004.10505164.

Su, Y., Chiang, W., Lee, C. J., & Chang, H. (2016). The effect of flow experience on player loyalty in mobile game application. *Computers in Human Behavior*, 63, 240-248. https://doi.org/10.1016/j.chb.2016.05.049.

Taber, K. S. (2018). The Use of Cronbach's Alpha When Developing and Reporting Research Instruments in Science Education. *Res Sci Educ* 48**,** 1273–1296. https://doi.org/10.1007/s11165-016-9602-2.

Terlutter, R. & Capella, M. L. (2013). The Gamification of Advertising: Analysis and Research Directions of In-Game Advertising, Advergames, and Advertising in Social Network Games. *Journal of Advertising*, 42(2-3), 95-112. https://doi.org/10.1080/00913367.2013.774610.

Thomas, W. & Stammermann, L. (2007). *In-Game Advertising – Werbung in Computerspielen*, Gabler.

Wijman, T. (2021, Feb 4). *Newzoo's Trends to Watch in 2021 (Games, Esports and Mobile)*. Retrieved from https://newzoo.com/insights/articles/newzoos-trends-to-watch-in-2021games-esports-and-mobile/. Accessed on 07.05.2021.

Wu, S.-L., & Hsu, C.-P. (2018). Role of authenticity in massively multiplayer online role playing games (MMORPs): Determinants of virtual item purchase intention. *Journal of Business Research*, 92, 242–249. https://doi.org/10.1016/j.jbusres.2018.07.035.

Yang J., Zhang M., & Zou. Z. (2015). The effect of In-game Advertising in SNS on Brand Equity. *Journal of Service Science and Management*, 8(1). http://dx.doi.org/10.4236/jssm.2015.81013.

Yang, M., Ewoldsen, D., Dinu, L., & Arpan, L. (2006). The Effectiveness of "in-Game" Advertising: Comparing College Students' Explicit and Implicit Memory for Brand Names. *Journal of Advertising*. 35, 143-152. https://doi.org/10.2753/JOA0091-3367350410.

Yerukhimovich, A. (2020, Aug 17). *In-app Ads and In-game Ads: What's the Difference?*. Retrieved from https://www.businessofapps.com/insights/in-app-ads-vs-in-game-ads/. Accessed on 01.03.2021.

Yoo, B. & Donthu, N. (2001). Developing and Validating a Multidimensional Consumer-Based Brand Equity Scale. *Journal of Business Research*. 52, 1–14. https://doi.org/10.1016/S0148-2963(99)00098-3.

Yoo, B., Donthu, N. & Lee, S. (2000). An Examination of Selected Marketing Mix Elements and Brand Equity. *Journal of the Academy of Marketing Science*. 28, 195–211. https://doi.org/10.1177/0092070300282002.

Yoo, S. & Eastin, M. (2017). Contextual advertising in games: Impacts of game context on a player's memory and evaluation of brands in video games. *Journal of Marketing Communications*, 23(6), 614–631. https://doi.org/10.1080/13527266.2016.1155074.

Yoon, G. (2019). Advertising in Digital Games: A Bibliometric Review. *Journal of Interactive Advertising*, 19(3), 204-218. https://doi.org/10.1080/15252019.2019.1699208.

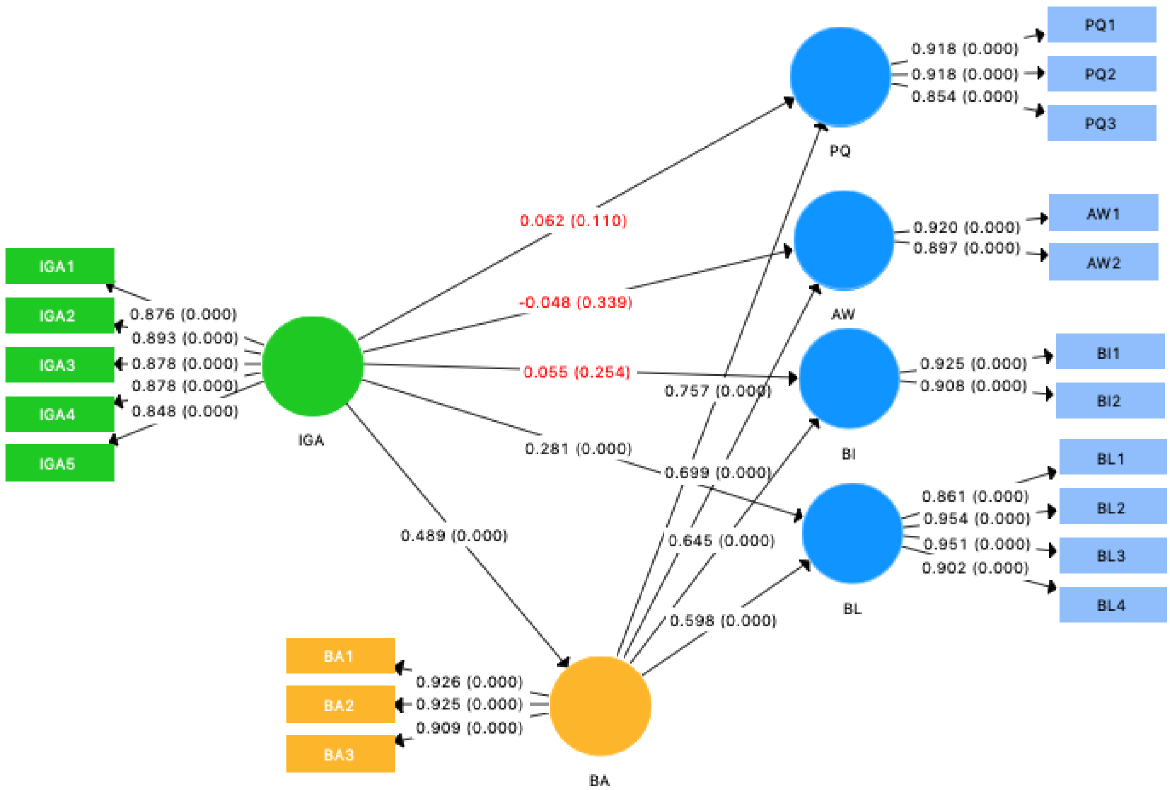
Youn, S., & Lee, M. (2003). *Antecedents and consequences of attitude toward the advergame in commercial web sites*. Proceedings of the 2003 Conference of the American Academy of Advertising, Pullman, WA: American Academy of Advertising, 128.

Zaichkowsky, J. L. (1994). The Personal Involvement Inventory: Reduction, Revision, and Application to Advertising, *Journal of Advertising*, 23(4), 59-70. https://doi.org/10.1080/00913367.1943.10673459.

Zeithaml, V., Berry, L., Parasuraman, A., 1996. The Behavioral Consequences of Service Quality*, Journal of Marketing,* 60(2), 31-46.

Appendix: PLS-SEM Analysis of IGA and BA influence on BE dimensions

1. Influence of IGA and BA on BE dimensions



Inner model: Path coefficients and p-values; Outer model: Outer loadings and p-values

2. Outer Loadings

	BA_	BE	EN	GE	IGA
AW1		0.737			
AW2		0.705			
BA1	0.925				
BA2	0.924				
BA3	0.910				
BI1		0.761			
BI2		0.745			
BL1		0.851			
BL2		0.872			
BL3		0.856			

BL4		0.796			
EN1			0.925		
EN2			0.916		
EN3			0.785		
EN4			0.812		
GE1				0.887	
GE2				0.874	
GE3				0.817	
IGA1					0.875
IGA2					0.890
IGA3					0.874
IGA4					0.880
IGA5					0.854
PQ1		0.789			
PQ2		0.791			
PQ3		0.844			

3. Construct Reliability and Validity

	Cronbach's Alpha	rho_A	Composite Reliability	AVE
AW	0.7886	0.7962	0.9041	0.8250
BA	0.9092	0.9096	0.9429	0.8463
BI	0.8101	0.8151	0.9131	0.8401
BL	0.9371	0.9391	0.9553	0.8426
EN	0.8832	0.9018	0.9199	0.7425
GE	0.8254	0.8526	0.8945	0.7389
IGA	0.9233	0.9241	0.9422	0.7652
PQ	0.8782	0.8818	0.9251	0.8048

4. Discriminant Validity

Heterotrait-Monotrait Ratio (HTMT)

	AW	BA	BI	BL	EN	GE	IGA	PQ
AW								
BA	0.7950							
BI	0.8808	0.7811						
BL	0.6717	0.7934	0.7793					
EN	0.5918	0.7602	0.6694	0.8362				
GE	0.6182	0.8094	0.6695	0.7688	0.9200			
IGA	0.3408	0.5318	0.4222	0.6162	0.6632	0.6654		
PQ	0.8105	0.8788	0.7358	0.8359	0.7259	0.7583	0.4809	

Fornell-Larcker Criterion

	AW	BA	BI	BL	EN	GE	IGA	PQ
AW	0.9083							
BA	0.6754	0.9200						
BI	0.7024	0.6716	0.9166					
BL	0.5806	0.7359	0.6820	0.9179				
EN	0.4846	0.6741	0.5632	0.7587	0.8617			
GE	0.4926	0.7006	0.5464	0.6811	0.7866	0.8596		
IGA	0.2932	0.4886	0.3698	0.5733	0.6047	0.5929	0.8748	
PQ	0.6764	0.7870	0.6186	0.7563	0.6333	0.6422	0.4314	0.8971

Cross Loadings

	AW	BA	BI	BL	EN	GE	IGA	PQ
AW1	0.9195	0.6482	0.6201	0.5416	0.4758	0.4845	0.2888	0.6474
AW2	0.8970	0.5754	0.6590	0.5121	0.4007	0.4065	0.2413	0.5781
BA1	0.6418	0.9256	0.6116	0.6528	0.6058	0.6619	0.4532	0.7306
BA2	0.6092	0.9248	0.6172	0.6611	0.6211	0.6214	0.4257	0.6894
BA3	0.6127	0.9094	0.6243	0.7152	0.6327	0.6491	0.4682	0.7501
BI1	0.6445	0.6384	0.9247	0.6473	0.5737	0.5478	0.4115	0.5541
BI2	0.6436	0.5910	0.9084	0.6012	0.4534	0.4496	0.2597	0.5816
BL1	0.6254	0.7336	0.6465	0.8611	0.6528	0.6308	0.4792	0.7200
BL2	0.5126	0.6929	0.6425	0.9541	0.7353	0.6635	0.5470	0.7285
BL3	0.5208	0.6735	0.6450	0.9509	0.7084	0.6351	0.5409	0.6786
BL4	0.4625	0.5896	0.5612	0.9025	0.6871	0.5630	0.5385	0.6413
EN1	0.3887	0.5891	0.4913	0.6769	0.9248	0.7208	0.5675	0.5833
EN2	0.3951	0.5819	0.5002	0.6792	0.9164	0.7197	0.5874	0.5626
EN3	0.5262	0.6284	0.5347	0.6180	0.7849	0.6546	0.4135	0.5619
EN4	0.3978	0.5461	0.4325	0.6449	0.8118	0.6164	0.4932	0.4834
GE1	0.3569	0.5982	0.4502	0.6157	0.7088	0.8868	0.6027	0.5434
GE2	0.5148	0.6414	0.5015	0.5898	0.6774	0.8736	0.4724	0.5713
GE3	0.4219	0.5723	0.4681	0.5456	0.6375	0.8168	0.4261	0.5500
IGA1	0.2498	0.4105	0.3255	0.4675	0.4998	0.5086	0.8750	0.3367
IGA2	0.2460	0.4372	0.3292	0.5123	0.4989	0.5156	0.8911	0.3930
IGA3	0.3067	0.4712	0.3754	0.5235	0.5220	0.5481	0.8753	0.3978
IGA4	0.2504	0.4082	0.3072	0.5231	0.5692	0.4801	0.8796	0.3913
IGA5	0.2253	0.4062	0.2764	0.4777	0.5545	0.5391	0.8524	0.3649
PQ1	0.6123	0.7515	0.5365	0.6293	0.5409	0.5721	0.3551	0.9176
PQ2	0.6331	0.6994	0.5653	0.6116	0.5020	0.5551	0.3470	0.9183
PQ3	0.5745	0.6636	0.5657	0.8039	0.6679	0.6035	0.4649	0.8540

5. Collinearity Statistics (VIF)

Inner VIF Values

	AW	BA	BI	BL	EN	GE	IGA	PQ
AW								
BA	1.3136		1.3136	1.3136				1.3136
BI								
BL								
EN								
GE								
IGA	1.3136	1.0000	1.3136	1.3136	1.0000	1.0000		1.3136
PQ								

6. R Square

	R Square	R Square Adjusted
AW	0.4580	0.4547
BA	0.2387	0.2364
BI	0.4534	0.4500
BL	0.6015	0.5991
EN	0.3657	0.3638
GE	0.3515	0.3496
PQ	0.6223	0.6200

7. f Square

	AW	BA	BI	BL	EN	GE	IGA	PQ
AW								
BA	0.6865		0.5791	0.6847				1.1548
BI								
BL								
EN								
GE								
IGA	0.0033	0.3136	0.0042	0.1506	0.5765	0.5421		0.0076
PQ								

8. Path Coefficients

Mean, STDEV, T-Values, P-Values

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
BA -> AW	0.6991	0.6960	0.0490	14.2703	**0.0000**
BA -> BI	0.6449	0.6467	0.0464	13.9006	**0.0000**
BA -> BL	0.5987	0.5975	0.0432	13.8619	**0.0000**
BA -> PQ	0.7569	0.7550	0.0399	18.9515	**0.0000**
IGA -> AW	-0.0484	-0.0446	0.0473	1.0231	**0.3065**
IGA -> BA	0.4886	0.4914	0.0561	8.7040	**0.0000**
IGA -> BI	0.0548	0.0537	0.0476	1.1493	**0.2507**
IGA -> BL	0.2808	0.2796	0.0427	6.5732	**0.0000**
IGA -> EN	0.6047	0.6057	0.0436	13.8565	**0.0000**
IGA -> GE	0.5929	0.5958	0.0456	12.9985	**0.0000**
IGA -> PQ	0.0616	0.0635	0.0394	1.5642	**0.1181**

9. Total Effects

Mean, STDEV, T-Values, P-Values

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
BA -> AW	0.6991	0.6960	0.0490	14.2703	**0.0000**
BA -> BI	0.6449	0.6467	0.0464	13.9006	**0.0000**
BA -> BL	0.5987	0.5975	0.0432	13.8619	**0.0000**
BA -> PQ	0.7569	0.7550	0.0399	18.9515	**0.0000**
IGA -> AW	0.2932	0.2966	0.0553	5.3016	**0.0000**
IGA -> BA	0.4886	0.4914	0.0561	8.7040	**0.0000**
IGA -> BI	0.3698	0.3711	0.0492	7.5123	**0.0000**
IGA -> BL	0.5733	0.5722	0.0450	12.7280	**0.0000**
IGA -> EN	0.6047	0.6057	0.0436	13.8565	**0.0000**
IGA -> GE	0.5929	0.5958	0.0456	12.9985	**0.0000**
IGA -> PQ	0.4314	0.4337	0.0522	8.2731	**0.0000**

10. Specific Indirect Effects

Mean, STDEV, T-Values, P-Values

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
IGA -> BA -> BL	0.2925	0.2926	0.0318	9.1916	**0.0000**
IGA -> BA -> AW	0.3416	0.3412	0.0400	8.5299	**0.0000**
IGA -> BA -> BI	0.3151	0.3174	0.0400	7.8758	**0.0000**
IGA -> BA -> PQ	0.3698	0.3702	0.0397	9.3149	**0.0000**

Authors

Prof. Dr. Sonja **Klose** earned her Ph.D. in Marketing at the WHU – Otto Beisheim School of Management in 2007. Afterwards, she worked for several start-ups as director of marketing before she became Professor of Marketing in 2017, first at FOM university, now at the Berlin School of Economics and Law (HWR Berlin). She has practical as well as academic experience in the following fields: Online and Offline Marketing, Serices Marketing, CRM, B2C and B2B Marketing.

Ngoc Anh **Truong** earned her Master's Degree in International Marketing Management at Berlin School of Economics and Law in 2021. She has more than six years experience working in B2B and B2C marketing with a focus on data analytics, digital marketing, and brand management. She is currently employed by a young F&B company in Berlin

Patel, Ronit; Perret, Jens K.; Samunderu Eyden

Unbundling CRM – A RFMC Perspective

Abstract

Customer lifetime value (CLV) has been gaining increasing importance in many areas but the (RFM – recency, frequency, monetary) segmentation framework is the most commonly used due to the availability of customer data as well as ease of calculation. One of the drawbacks of the RFM segmentation framework is that it is unable to identify behavior correctly in the face of customers that show hot and cold periods of visiting and buying (binge buying). This kind of phenomenon is called clumpiness (C).

One of the empirical findings of this study is that such a kind of behavior is quite prevalent and clumpy customers generate (if not significantly) more revenues than customers who are non-clumpy. Even if clumpiness does not account for high revenue customers, this study shows by use of a correlation and cluster analysis that the clumpiness statistic significantly adds to the RFM framework making the establishment of an RFMC framework immanent.

The clumpiness phenomenon is studied by performing a detailed empirical analysis on a representative UK based retailer's dataset. Regression and neural network analysis were implemented to identify the main drivers for clumpiness. Cluster Analysis was used to identify customers that have similar behavioral characteristics and to sort them in small groups so that targeting a group of customers is possible. Thus, clumpiness can detect customers that are high potential and high risk in nature, which were previously unseen.

1 Introduction

The retail sector is essential to the world economy, as it provides a substantial amount of employment to skilled and unskilled labor. The retail industry has been growing from the 19th century onwards and with the advancement of new e-commerce, there has been immense as well as tough competition. While the industry continues to undergo constant change at a rapid rate, amid all changes what remains constant are the consumers and their growing demand. Consumers are becoming more powerful, with the decision of purchase lying within them. To stay competitive in the market, many retailers have shifted their investment as well as business strategies over the past decades. Organizations have moved from growth via new stores to developing new business models.

To adjust to changing conditions, organizations have to adopt customer-centric strategies, helping the organization to retain loyal customers and increase repeat purchases as well as the monetary value thereof. To maintain relationships with their customers, organizations have invested heavily in IT infrastructure by creating databases that can store a large amount of customer as well as transaction-related data. For each customer, many data points are collected, ranging from name to gender to transaction amount, etc., allowing to analyze the customer's complete purchasing history (so-called

360° customer view). However, the information obtained is seldom integrated into other business functions, such as customer relationship management (CRM) or Enterprise resource planning (ERP).

In this context, this study aims to develop a methodology to support Analytical CRM in the retail industry, such that the relationship between organizations and their customers can be reinforced. This research focuses on customer identification, attraction, development, and retention by applying data mining techniques to extract knowledge from large databases to build a customer lifetime value (CLV), model.

Traditionally, recency, frequency, and monetary value (RFM) models have been and are still used by many organizations to determine the CLV of a customer. But this methodology doesn't fully explain the critical aspects of customer behavior. Zhang et al. (2015) propose a new individual-level measure of a customer's history known as clumpiness (C), which is defined as the degree of nonconformity to equal spacing. Hence, this study continues the work by Zhang et al. (2015) and provides a framework for analyzing customer data.

In a first step the analysis of Zhang et al. (2015) is replicated for a UK based retailer's dataset. In particular using Monte Carlo Simulations the distribution of the clumpiness indicator is estimated to develop a statistical test for clumpiness. For a number of significance levels the test is then applied to the dataset to determine the customers reporting clumpiness in their shopping behavior. Based on this classification of test is conducted whether a significant difference exists between clumpy and non-clumpy customers in regard to the revenue they generate, with the test showing that clumpiness as an indicator does not add to the detection of more valuable customers. A succeeding correlation analysis, however, determines that the clumpiness statistic as such contributes to the RFM framework and it is not simply a new concept which is already covered by the three existing components. This result is later backed by cluster analysis as well. Based on the assumption that an RFMC framework is superior to an RFM framework using an analytical hierachical process is used to determine weights for all four components of the new RFMC framework. Finally, cluster analysis is used to test the robustness of the previous results regarding the value added by clumpiness to the RFM framework and the determination of weights and using an artificial neural networks approach impact factors of customers ranked as clumpy are determined.

Note, that the analysis take place based on an empirical foundation and not on a set of a priori assumptions. Thus, it can be seen as a case study on the process of analyzing purchasing data regarding the RFMC framework. The study concludes in the fifth and final chapter with a discussion of the practical implication of this study.

2 Combining CRM and Customer Analytics

Customer Relationship Management (CRM) on the one hand is a strategic process of recognizing the most profitable customers which an organization can serve and how they can develop interactions (Payne & Frow, 2005). It is divided into three components: Strategic, Operational, and Analytical. Analytical CRM – the focus of this study - consists of the Information management process, which focuses on the development, creation, and exploitation of customer-related data for the organization's strategy. It focuses on the mining of customer data for accomplishing the objective of a company's strategy and operational goals (Iriana & Buttle, 2007).

Customer analytics on the other hand is a process by which data mining techniques are used to extract information regarding customer behavior via profiling, segmentation, clustering or the development of predictive models. Grouping can help organizations to optimize their campaigns and target the right customers with the right offers. Customer analytics helps organizations in acquiring customer insights.

The essence of acquiring customer knowledge is knowing who the customers are (customer profiling) with the capability to identify strategically significant customers or groups of customers. Customer Analytics predicts the possible actions that are likely to be taken by customers based on their previous behavior patterns. It can guide staff that has direct contact with customers as to which offers can improve their buying rate, satisfaction, and make real-time recommendations on the best offers available. Moreover, customer analytics can help organizations to allocate their resources differently for individual customers based on their customer lifetime value (Kumar & Reinartz, 2018, 50 ff.).

The use of customer analytics has a positive impact on an organization's performance. With the use of customer analytics, extensive use of data and models and fact-based management drive decision and actions, where data and models are defined at the customer level. However, most analytical models developed focus on customer transactions alone (Bijmolt et al., 2010). Therefore, organizations need to develop customer metrics that they can trace over a span of time. Customer behavior needs to be continuously observed in order to recognize behavior patterns and trends and to distinguish any abnormal behavior or emerging patterns. Monitoring and tracking should be based on predefined criteria to supervise on what and how to observe, and what results to anticipate.

To propose an effective Customer Relationship Management (CRM) - Data Mining framework for the prediction of customer behavior in the area of retail - one can refer to the process introduced by Bahari and Elayidom (2015).

3 The RFMC Framework

While the previous chapter motivated in general the necessity of CRM Analytics and related methods it has to be detailled inhowfar especially loyalty management can profit data-driven analytical tools. In this regard the classic RFM framework approach is detailled. While the RFM framework is an established marketing tool since more than two decades already (Hughes, 1996) studies like Kaul (2020), Maraghi et al. (2020) and Sun et al. (2020) illustrate the relevance it still plays in current research as well as in current research endeavors. Nevertheless, The framework approach did not remain unchanged over the years. Studies like Zhang et al. (2015), Josep (2020) and Oztaysi and Kavi (2020) show that the framework is continuously advanced still.

Oztaysi and Kavi (2020) introduce the use of a fuzzy k-means algorithm as part of the framework as such and is representative for studies that advance the RMF approach via the introduction of more sophisticated tools that are applied in the course of the basic framework itself. Josep (2020) on the other hand introduces the aspect of activating customers as an additional aspect considered in the course of the framework. It is representative for the class of studies that shift the focus of the pure RFM framework into including additional information that promise insights on customer behavior. By focussing on customer activation, the aspect added by Josep (2020), the study, however, is extended by a factor not of original customer behavior but by the potential customer reactions. Finally, Zhang et al. (2015) incorporates the purely customer driven concept of clumpiness (Zhang et al., 2013) into the RFM framework. It is for this reason that the present study follows the approach initiated by (Zhang et al., 2015).

To alleviate the overall understandability, this chapter introduces the RFM framework as such followed by a deduction of the concept of clumpiness and a discussion of its general benefits in the context of the RFM framework.

3.1 The RFM Framework

The RFM model incorporates the three aspects recency, frequency, and monetary value. It employs three metrics to evaluate customer behavior and customer value and is frequently used in practice.

1. Recency – How much time has passed since the customer's last order.
2. Frequency - How often a customer orders from the company in a certain pre-defined period.
3. Monetary value - The amount that the customer spends on average per transaction.

The general idea of RFM is to group customers based on their RFM scores. The resulting groups of customers are associated with their purchase behavior, e.g. the possibility of a customer reacting to a marketing campaign. RFM closely follows the transition matrix path in that it also traces customer behavior over a period of time in what is called a state space. The higher the RFM score of the customer, the more valuable he is for the organization. In recent studies, authors suggested using a weighted RFM score - instead of an RFM score with equal weights. They assigned weights to R, F, and M. depending upon the characteristics of different industries.

The measurement of CLV via the RFM framework is one of the most common methods (Khayvand et al., 2011). RFM has been used for many years in direct marketing to predict customer behavior and to generate customer segments. If an organization has a database of its customers, which includes their purchase history, the firm can perform an RFM analysis at practically no cost. From a behavioral perspective, the RFM method evaluates the relationship between the organization and its customers (Shih & Liu, 2003). Customers who purchased recently, frequently, and spent large amounts of money are more inclined to react to mailings and therefore represent more attractive candidates for future marketing campaigns (Coussement et al., 2014).

3.2 Clumpiness

According to Zhang et al. (2013), Clumpiness is defined as the degree of nonconformity to equal spacing and demonstrates an essential component in a better understanding of recognizing a profitable customer. To better capture clumpiness, Zhang et al. (2013) provides a rich analysis of this issue and proposes a new class of clumpiness measures that are shown to have larger statistical power in extensive simulations under a wide variety of data-generating mechanisms (alternative hypotheses as compared to the null of stationarity). Although details are provided in Zhang et al. (2013), the central properties of such measures are:

- Minimum – The measure should be at its minimum if the events are equally spaced.
- Maximum - The measure should be at its maximum if all the events are gathered together.
- Continuity - Shifting event times by a small amount should only change the measure by a small amount.
- Convergence. As events move closer (further apart), the measure should increase (decrease).

These four features provide a comprehensive description of any clumpiness measure.

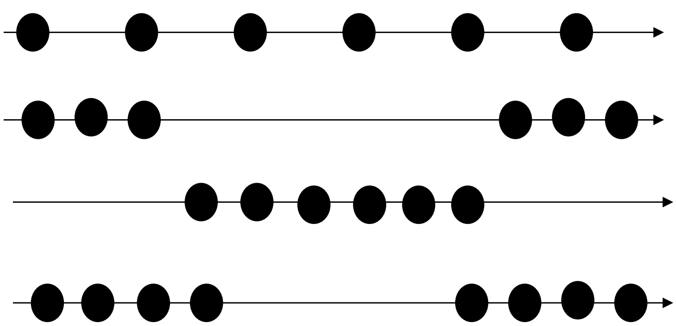


Figure 1: Exemplary Cases of Customer Behavior
Source: Zhang et al. (2015)

Figure 1 shows possible situations of customer behavior. While the first and third situation are not considered clumpy the second and fourth are.

According to Zhang et al. (2015), a clumpiness measure is a formal statistical test that is needed to determine the importance of an observed clumpiness value. Assuming the null hypothesis is random sampling without replacement, where *n* (the number of events) and *N* (number of trials) are known Monte Carlo simulation is applied and the z-table, the table of critical values, can be estimated. To measure clumpiness, H_p, an individual level entropy measure (metric) from the class of convex and symmetric IET statistics is chosen. It can be written as:

$$H_p = 1 + \frac{\sum_{i=1}^{n+1} \log(x_i) * x_i}{\log{(n+1)}}$$

with x_i = *N*+1 at the i-th event (this is done to control the length of the observation period).

In an information system, entropy is a measure of uncertainty. It quantifies the expected value of the information contained in a message. Although it is intended to represent a different story, its characterization and profound indication of disorder can provide a great measure for clumpiness.

A distinguishing feature of using this type of clumpiness measure is that a given percentage variation in any of the IETs has the same effect on the measure itself. Hence, it “normalizes” the ranges being aggregated (Zhang et al., 2013). Since the clumpiness measure is calculated by using scaled inter-event times (i.e., dividing by *N*+1), it is conceptually invariant to the scaling of time units. However, the timeframe should not be too long; otherwise, the data points would be aggregated, and information about inter-event times (IETs) would be wasted. On the other hand, a too-short timeframe would give rise to over-fitted patterns.

Steps required for computation of clumpiness

1. Convert the individual-level (purchase/visitation) data into incidence data (0/1).
2. Compute the inter-event times (IETs), specifically x_i, x_{i-1},..., where the x_i represent the time occurrence of i-th visitation.
3. Rescale the IETs. Divide IETs by N+1.
4. Compute the entropy given by the formula
$$H_p = 1 + \frac{\sum_{i=1}^{n+1} \log(x_i) * x_i}{\log{(n+1)}}$$
5. Create a cut-off table (critical values) using Monte Carlo simulation at different significance levels and find the corresponding value based on frequency
6. Determine the significance of clumpiness by comparing the clumpiness values with the critical cut-off point. If H_p is larger than the critical value then the customer is considered as a clumpy customer else the customer is not clumpy.

4 Empirical Analysis

Since clumpiness is a metric based approach, Zhang et al. (2015) hints that the customer lifetime value framework should be transformed from the traditional RFM model to a newer model of RFMC. Where the C, i.e. clumpiness, adds additional predictive power to the RFM model in recognizing valuable customers. Hence, this study proceeds with the recommendation suggested by (Zhang et al., 2015)

After checking whether clumpiness is present in the dataset that is used in this study and determining how many customers are clumpy it is tested whether they are generating higher revenues than non-clumpy customers. Secondly, a weighted RFMC model where the weights are determined through an analytical hierarchical process (AHP) is conceived. Subsequently, data mining techniques such as clustering are implemented to identify groups of customers that are valuable to an organization. Finally, artificial neural networks are used to check which of the variables of the RFMC framework, if any, is the most important in predicting clumpy behavior per se.

4.1 Description and Pre-processing of the Dataset

The dataset that is used in this research work was obtained from Kaggle, an online community that allows users to publish datasets, explore, and build models in a web-based data science environment. The dataset contained transactions between 01/12/2010 and 09/12/2011 from a UK based and registered non-store online retailer. The company sells unique all occasion gifts, and many of the organization's customers are wholesalers. The variables included in the dataset are Invoice No, Quantity, InvoiceDate, Unit Price, Customer ID, Country to which they belonged. Since this data stems from a UK retailer, it is safe to assume that the unit prices are measured in Pounds Sterling. However, as long as all purchases are in the same currency the calculations are not affected.

The dataset contains 541,909 transactions. Since some entries for the unit prices and the quantity were less than or equal to zero, those transactions were eliminated. After performing this cleaning task, the number of transactions is reduced to 168,631.

While the time of purchase is not required for determining the CLV of a customer through RFMC Analysis the date of purchase is. Additionally, for RFMC analysis, another variable is required that is the total price. The total price results as the product of quantity and unit price. Hence, both variables are replaced by the total price. As sales were recorded product-wise but an invoice usually consists of different positions to generate the total costs of an order all positions with the same invoice n umber were summed up resulting in a total of 7,961 orders for the years 2010 and 2011. As the majority of orders occurred in 2011 which is covered in full as compared to 2010 this study limited to only these orders yielding a final set of 7,070 orders in 2011 by 2,821 unique customers.

4.2 Clumpiness as a Valuable Complement to the RFM Framework

While Table 1 summarizes the core statistics for the four indicators of the RFMC framework, Table 5 in the appendix summarizes the critical values for the clumpiness statistic in dependence on the frequency score. Using this z-table in conjunction with the clumpiness scores of the 2,821 different customers depending on different margins of error Table 2 is constructed showing the number of clumpy customers as well as the average worth of their orders.

Table 1: Core Statistics for RFMC

	R	F	M	C
Mean	151.8245	2.5041	458.6717	0.2538
Standard Deviation	98.8776	3.5469	3213.0330	0.2238
Minimum	22.0000	1.0000	5.9000	-0.0012
Maximum	364.0000	83.0000	168,469.6000	0.9689

Source: Own calculations

Table 2: Classification of clumpy and non-clumpy customers

Significance Level	Number of - Clumpy customers	Number of - Non-clumpy customers	Average revenue of Clumpy customers	Average revenue of Non-Clumpy customers	% increase in revenue	% clumpy customers	% non- clumpy customer
90%	411	2410	522.72	447.75	14%	17.06	82.94
95%	263	2558	620.41	442.04	29%	10.28	89.72
99%	85	2736	662.69	452.33	32%	3.11	96.89
99.5%	52	2769	781.11	457.82	41%	1.88	98.12

Source: Own calculations

The table clearly indicates that clumpiness is present in the implemented dataset even in the very conservative case of allowing only for an α of less than 0.5% as margin of error. It is this conservative case that is of particular interest as in this case no clumpy customers with a frequency of 1 exist anymore. (Customers with a frequency of 1 skew the analysis as in their case clumpiness is solely determined by the date of the purchase.) The table also motivates that on average clumpy customers generate higher revenues as compared to non-clumpy customers.

Using a Shapiro-Wilk-test to check for normality in the clumpiness statistic little does it surprise that the clumpiness scores in the sample are not normally distributed but significantly rightwards skewed. Considering that this characteristic will hold for the population as well a U-test instead of a t-test is used to compare the revenues via clumpy and non-clumpy customers. It turns out that although the values for the two groups as reported in Table 2 considerably differ, these differences are not significantly different from zero (accepting a margin of error of 5%).

Considering the results from Table 1 that all statistics are measured on different scales, it is imperative for the ongoing analysis to z-standardize them first. To account for severe outliers from the outset all customers whose z-standardized score exceed the range from -3 to +3 are excluded from the analysis reducing the dataset to only 2,735 customers.

To get a better impression of the structure of the four variables of the RFMC model correlations between them are calculated. Due to the issue with normality which persists with the R, F and M variables as well a Spearman test is implemented here:

Table 3: Correlations between the parts of the RFMC framework

	R	F	M	C
R	-	0.449 (0.000)	0.117 (0.000)	0.027 (0.145)
F	0.449 (0.000)	-	0.141 (0.000)	0.109 (0.000)
M	0.117 (0.000)	0.141 (0.000)	-	0.031 (0.103)
C	0.027 (0.145)	0.109 (0.000)	0.031 (0.103)	-

Source: Own calculations

Table 3 reports for all pairwise correlations the correlation coefficient as well as the significance level in parentheses. While the three parts of the original RFM framework are highly correlated with each other, the clumpiness variable is highly correlated only with frequency but not with the other two. This can be interpreted in such a way that clumpiness integrates into the CLV framework but at the same time provides additional valuable insights not yet covered by the original framework. This insight could be replicated via a factor analysis design strengthening it in this regard. A factor analysis, however, is not explicitly conducted at this point. As mentioned above it cannot be assured that the four variables are normally distributed across the sample or the population.

4.3 Determination of RFMC Weights

While there have been various combinations, and weightings proposed, judging and weighting of RFMC variables remains highly subjective (Shih & Liu, 2003). This study uses the Analytical Hierarchy Process (AHP) to evaluate the weight of each RFMC variable by ranking them according to the importance for all customers. This process is explained in detail in Shih and Liu (2003).

Before the AHP can be applied the dataset needs to be re-standardized as the AHP requires non-negative values. The formula that is used for normalization in this context is:

$$X' = \frac{X - X_s}{X_l - X_s}$$

Where X' is the value after standardization, X is the value that is related to the variable, X_l, and X_s are the maximum and minimum values of the variable.

Using the approach described by Shih and Liu (2003) yields a 4x4 (each column or row representing one variable of the RFMC framework) matrix of pairwise comparisons. The matrix is then column-normalized by dividing the column score by the row score. After column-wise normalization and averaging across rows (which in this case are all identical) the relative weights can be calculated for each customer. Averaging the relative weights for all customers results in the following values:

$w_R = 0.38$ $w_F = 0.15$ $w_M = 0.15$ $w_C = 0.32$

This shows not only that clumpiness is a critical part of the RFMC framework – as suspected from the correlation analysis already – but with an average relative weight of 0.32 it is the second most important aspect and close in its weight to the first most important part recency.

4.4 Clustering as a Stability Test

The AHP in the previous section resulted in individual relative weights for each customer. Thus, to determine which customers behave similarly a clustering analysis in regard to the determined weights is conducted. This allows to detect groups of customers that share similar behavior patterns. In this study a k-means approach as implemented in the SPSS 23 package is used for clustering. As the k-means algorithm requires an ex-ante fixed number of clusters an analysis is conducted for two and three clusters. Since the two cluster solution does not provide suitable answers only the results for the three cluster approach are discussed below. Using more than three clusters at this stage has been deemed irrelevant as the three clusters approach already provides satisfactory answers. The cluster centers of the three cluster solution are summarized in Table 4

Table 4: Cluster Centers - 3 Cluster Solution

Cluster	1	2	3
R	0.0527	0.3389	0.1987
F	0.0052	0.0297	0.0091
M	0.0096	0.0102	0.0087
C	0.1629	0.0883	0.0323

Source: Own calculations

Of the 2,735 valid cases 380 are assigned to cluster 1, 1,148 to cluster 2 and the remaining 1,207 to cluster 3. To additionally assure that the clusters not only with regard to all four parts of the RFMC framework considered at the same but for each part by itself represent a powerful separation a Kruskal-Wallis-H-test has been performed. The four H-tests all turned out highly significant showing that the three clusters represent groups that are distinctly different with regard to all four aspects of the RFMC framework. In all four cases the difference between the groups has been highly significant. With a significance level of only 0.008 the monetary variable is the weakest of the four variables of the RFMC framework. Considering the results in Table 4 this result does not surprise.

Cluster 1 represents those customers that are mainly described by their clumpy behavior. In cluster 2 there are those customers that have a high RFM score. Finally, in Cluster 3 there are primarily customers with a high weight for recency. While clusters 2 and 3 would have been covered by the RFM framework. The presence of the small but still pronounced Cluster 1 with roughly 14% of all customers stresses once more the relevance of clumpiness as an essential part in a comprehensive RFMC framework. Comparing the results in Table 2 and Table 4 it shows that the size of the cluster of primarily clumpy customers roughly coincides with the group of clumpy customers at a margin of error of 90%. The arguments given above in favor of using on the group defined by using a margin of error of 0.5% can thus be considered a very conservative one.

4.5 The RFMC Framework as a Predictor for Clumpy Customers

To test whether adding the clumpiness statistic to the RFM framework extending it to the RFMC framework helps in detecting clumpy customers an artificial neural network (ANN) approach has been considered. The advantage of ANNs over rigid regression models is that they act more flexible with regard to non-linearities in the underlying relation. Additionally, as shown in Table 3 the four variables are strongly correlated with each other. In a regression model this would have resulted in a severe problem with multi-collinearity. Also, the absence of normality in all four variables does not pose a critical problem in an ANN approach.

To realize the ANN model a multilevel perceptron is estimated. The variables resulting from Table 2 - at a margin of error of 10% as well as of 0.5% - that measure whether a customer is clumpy (value of 1) or not (value of 0) are used as dependent variables and the four indicator variables measuring the z-standardized score for recency, frequency, monetary value and clumpiness are used as independent variables. Additionally, an ANN with only a single layer has been estimated as trials with using two layers revealed that it does not significantly decrease the relative error.

In this context the discussion of Table 2 can be recalled in that a high clumpiness score not necessarily results in clumpy behavior if the frequency score is 1. Thus, this part of the overall analysis is not self-evident. This can also be evidenced from the results of the estimation of the ANN. In this study a learning design for estimating the ANN has been selected where roughly 70% of the sample are used to estimate the synaptic weights while the remaining 30% are using to test the quality of the estimated model. This approach not only allows to get an estimate of the out-of-sample performance of the resulting model it also assures – as the assignment of cases to the estimation and the testing set is randomized - that a lucky assignment generates biased results. However, to get a representative impression of the true quality of the results the analysis has to be performed multiple times with the results of all results being averaged. In the context of this study for each of the two dependent variables the estimation has been repeated twenty times.

When using the more relaxed version of clumpiness, i.e. the variant with a 10% margin of error, the relative error of the models turns out to be 1.075% for the estimation set and 1.005% for the testing set. It is interesting to note that the model actually works better out-of-sample than in-sample. With regard to the four variables of the RFMC framework clumpiness and frequency play the most important role, whereas in most cases clumpiness is the most important variable.

In contrast, if the more conservative version of clumpiness is used, i.e. the variant with a 0.5% relative error, decreases to 0.805% for the estimation set and to 0.785% for the testing set. Again, the model performs slightly better out-of-sample than in-sample. With regard to the RFMC framework it is again the frequency and clumpiness that report the major importance, however, where before clumpiness has been the most important variable, here it is frequency.

That clumpiness and frequency both play a major role in determining whether a customer is truly clumpy seems only reasonable following the discussion of Table 2 where it has been stated that clumpiness can also be an effect of infrequency, in particular of one-time shoppers. Thus, the results of the $\alpha = 0.5\%$ case might be more relevant than those of the $\alpha = 10\%$ case as in the 0.5% case no clumpy customers report a frequency score of 1 anymore. While an error of 1% or less can be considered marginal at best it still might signify that between 5% to 10% of the clumpy customers remain undetected as the model on average generates more false negatives than false positives; in particular in the testing sets. Nevertheless, an overall error of roughly 1% shows that the RFMC framework has forecasting quality and can significantly help companies in detecting highly valuable clumpy customers.

5 Conclusions

5.1 General Insights

CRM is an important issue to improve an organization's competitiveness in today's changing environment in the retail industry. This study contributes to the field of CRM by contributing innovative analytical models backed by data mining techniques. The models introduced herein are adapted to real-world problems motivated by the difficulties faced in identifying customer behavior. This study is an example of application-driven theory, which is considered of the highest importance in the field of customer relationship management and data analytics. The contributions of the study can be summarized as follows:

- Replication of previous studies on clumpiness to ensure the validity of the implemented dataset.
- Segmentation of customers according to them being clumpy or not does not help in the determination of a customer group that generates significantly higher revenues.
- Exemplification that the clumpiness statistic though correlated with the frequency statistic does provide additional insights and can thus be used to expand the RFM framework.
- The model makes use of an analytical hierarchical process (AHP) to determine the weights of the four components of the RFMC framework.
- Identification of customer groups that behave in similar patterns by making use of clustering techniques.
- Identification of the important variables concerning clumpy customers through artificial neural networks.

Summarizing, aside from adding to the literature on clumpiness, the study provided an empirically driven outline on analyzing purchasing data in the context of the expanded RFMC framework.

5.2 Managerial Applications

Since clumpiness is a phenomenon of identifying customer behavior, in campaign building it suggests the retailer perform a trigger-based dynamic campaign. For example, a customer could be shopping only on the days that the retailer is providing huge discounts, so the clumpiness methodology could help the retailer to identify such customers and then target them accordingly. This could help the retailer to check whether clumpy customers respond to the trigger based dynamic campaign. To deepen insights on such a customer, the retailer could identify the categories that the customer has purchased during the past discount day and target the customer with cross-selling or up-selling categories.

Since clumpiness is observing the buying pattern of the customer, it makes clumpiness an important parameter for retailers' loyalty programs. According to (Kumar, 2009, 16), the Loyalty program, in contrast to other marketing efforts, has more effect on average purchase frequency than on penetration. From the empirical analysis, it was observed that frequency was one of the main drivers of clumpiness; hence clumpiness is an important factor when deciding customer loyalty. This is the main reason why loyalty programs are most engaging with existing and heavy buyers.

High-frequency behavior tends to increase the share of requirements asked by the customers and therefore tends to increase the effort spent on them. An increase in loyalty could also help the retailer to improve the brand penetration level. This means that the brand will have a higher average purchase frequency than would be expected, given the level of penetration. Finally, the retailer's main aim is to increase the profitability of the company, and since clumpy customers are more profitable in nature (i.e., clumpy customers generate 40% additional revenue as compared to non-clumpy customers). Therefore, it is important to integrate clumpy customers in the loyalty program.

5.3 Limitations and Outlook

The main limitation of the present study is that it is based solely on purchasing data for a single year from a single UK retailer. Thus, any generalization of the study might be precluded from the outset. Since the study successfully replicated part of previous studies and their results for US retailers (Zhang et al., 2015), it is, however, highly likely that similar results will present themselves if purchasing data from other retailers for from other countries is implemented. Nevertheless, a replication of this study in different sectoral or regional contexts is highly advised. Additionally, the RFM framework, even though mainly implemented in retail, is a general purpose CRM approach which requires the replication of this study as well in the context of different industries.

Since there is no correct way of predicting whether customers will return in the future, it would be appropriate to build a churn model for the clumpy customer that could help the UK based retailer to identify all potential churners. The Bayesian learning or Markov model could be an excellent methodology to develop such a new churn prediction model. For future research, it would be worthwhile to extend the work developed in this study to support the company's direct marketing initiatives. It would be appropriate to create a model to predict customer's responses to direct marketing campaigns.

Additionally, it would be insightful to analyze the buying patterns of clumpy customers. It could be possible that there are some categories that are brought by the clumpy customers in huge categories, and these categories are influencing the clumpy behavior of the customer. Since the UK based retailer considered herein is selling its products to international customers, it would be interesting to identify whether international customers or domestic customers are more clumpy in their behavior. This would help the retailer to target its marketing actions more efficiently.

As future research, it would be interesting to compare the different customer lifetime value (CLV) models to identify which CLV model would be best suited for a UK based retailer. The retailer could then develop a retention model (loyalty program) that can predict accurately to what level and how much a customer will consume in a visit, day, or a year. This ability can aid the retailer with developing strategies to retain clumpy customers by making them feel like a privileged customer; privilege could lead to the customer being more loyal. Such types of loyalty programs for the retailer would help to provide valued customers with valuable rewards, all with the intent of keeping them being clumpy in nature and spending more money with the organization over the competitors. The information gathered would result in a lifetime loyalty and thereby profit the organization in the long term.

The research methodologies proposed in this study could be applied to other business environments in which customer relationship management (CRM) is crucial to guarantee an organization's competitiveness and success in the business environment. Fields that could be studied in the future cover, for example, banking, insurance, media & entertainment, and telecommunications, etc. Finally, the study focused on a UK online retailer. It still remains to be analyzed in how far the results of this study hold for offline retailers from different sectors and countries.

References

Bahari, T. F., & Elayidom, M. S. (2015). An Efficient CRM-Data Mining Framework for the Prediction of Customer Behaviour. Procedia Computer Science, 46, 725–731.

Bijmolt, T.H.A., Leeflang, P.S.H., Block, F., Eisenbeiss, M., Hardie, B.G.S., Lemmens, A., & Saffert, P. (2010). Analytics for Customer Engagement. Journal of Service Research, 13(3), 341–356.

Coussement, K., van den Bossche, F.A.M., & Bock, K. W. de (2014). Data Accuracy's Impact on Segmentation Performance: Benchmarking RFM Analysis, Logistic Regression, and Decision Trees. Journal of Business Research, 67(1), 2751–2758.

Hughes, A. M. (1996). Boosting Response with RFM. Marketing Tools, 5, 4–10.

Iriana, R., & Buttle, F. (2007). Strategic, Operational, and Analytical Customer Relationship Management. Journal of Relationship Marketing, 5(4), 23–42.

Josep, A. V. (2020). Predicting Customer Behavior With Activation Loyalty per Period. From RFM to RFMAP. Esic Market Economics and Business Journal, 51(3), 609–637.

Kaul, S. (2020). Customer Segmentation Through Rfm (Recency, Frequency, Monetary) Model In Retail Sector. Solid State Technology, 63(2), 8918–8931.

Khayvand, M., Zolfaghar, L., Ashoori, S., & Alizadeh, S. (2011). Estimating Customer Lifetime Value Based on RFM Analysis of Customer Purchase Behavior: Case Study. Procedia Computer Science, 3, 57–63.

Kumar, V. (2009). Managing Customers for Profit: Strategies to Increase Profits and Build Loyalty. Pearson Prentice Hall.

Kumar, V., & Reinartz, W. J. (2018). Customer Relationship Management: Concepts, Strategy, and Tools. Springer.

Maraghi, M., Adibi, M. A., & Mehdizadeh, E. (2020). Using RFM Model and Market Basket Analysis for Segmenting Customers and Assigning Marketing Strategies to Resulted Segments. Journal or Applied Intelligent Systems & Information Sciences, 1(1), 35–43.

Oztaysi, B., & Kavi, M. (2020). Fuzzy RFM Analysis: An Application in E-Commerce. In C. Kahraman, S. C. Onar, B. Oztaysi, I. U. Sari, S. Cebi, & A. C. Tolga (Eds.), Intelligent and Fuzzy Techniques: Smart and Innovative Solutions: Proceedings of the INFUS 2020 Conference (1225–1232). Springer.

Payne, A., & Frow, P. (2005). A Strategic Framework for Customer Relationship Management. Journal of Marketing, 69(4), 167–176.

Shih, Y.-Y., & Liu, C.-Y. (2003). A Method for Customer Lifetime Value Ranking - Combining the Analytic Hierarchy Process and Clustering Analysis. Journal of Database Marketing & Customer Strategy Management, 11(2), 159–172.

Sun, G., Xie, X. F., Zeng, J., Jiang, W., Lin, M., & Huang, Y. X. (2020). Using improved RFM Model to classify Consumer in big data Environment. International Journal of Embedded Systems, 14(1), 54–64.

Zhang, Y., Bradlow, E. T., & Small, D. S. (2013). New Measures of Clumpiness for Incidence Data. Journal of Applied Statistics, 40(11), 2533–2548.

Zhang, Y., Bradlow, E. T., & Small, D. S. (2015). Predicting Customer Value Using Clumpiness: From RFM to RFMC. Marketing Science, 34(2), 195–208.

Appendix:

Table 5: Cut-off table (z-table) for different significance level at different frequencies

Frequency	Cut-off value - 95%	Cut-off Value - 90%	Cut-off value - 99%	Cut-off Value - 99.5%
1	0.8335	0.7055	0.9511	0.9728
2	0.5846	0.4842	0.7701	0.8173
3	0.4698	0.4045	0.6363	0.6866
4	0.4098	0.3501	0.5336	0.5874
5	0.3663	0.3151	0.4722	0.5132
6	0.3320	0.2897	0.4292	0.4658
7	0.3070	0.2696	0.3898	0.4216
8	0.2877	0.2543	0.3594	0.3936
9	0.2674	0.2406	0.3416	0.3682
10	0.2568	0.2285	0.3217	0.3482
11	0.2457	0.2193	0.3018	0.3257
12	0.2337	0.2103	0.2881	0.3077
13	0.2249	0.2024	0.2771	0.2968
14	0.2168	0.1958	0.2638	0.2825
15	0.2103	0.1895	0.2541	0.2716
16	0.2045	0.1843	0.2467	0.2635
17	0.1977	0.1801	0.2387	0.2540
18	0.1921	0.1748	0.2287	0.2433
19	0.1867	0.1703	0.2231	0.2377
20	0.1839	0.1668	0.2178	0.2322
23	0.1706	0.1570	0.2004	0.2122
24	0.1681	0.1544	0.1963	0.2081
25	0.1637	0.1503	0.1916	0.2035
27	0.1579	0.1455	0.1836	0.1943
28	0.1548	0.1428	0.1797	0.1891
30	0.1508	0.1396	0.1748	0.1837
32	0.1457	0.1348	0.1671	0.1761
34	0.1411	0.1311	0.1626	0.1726
35	0.1385	0.1295	0.1590	0.1667
37	0.1362	0.1263	0.1542	0.1615
49	0.1174	0.1106	0.1328	0.1388
66	0.1004	0.0948	0.1110	0.1155
83	0.0873	0.0830	0.0962	0.1002

Source: Own calculations

Authors

Ronit **Patel**, M.A. studied Engineering at the Dwarkadas J Sanghvi College of Engineering in Mumbai and International Business at the International School of Management in Dortmund. Before his post-graduate studies Mr. Patel worked with an Indian Consultancy as senior data analyst. Currently he is employeed by a major German insurance company focussing on project management in IT service lines. His research interests include data analytics in the context of customer relationship management.

Prof. Dr. Jens K. **Perret** studied business mathematics and economics at the University of Wuppertal. He received his doctorate in economics from the University of Wuppertal with a thesis on the knowledge society in Russia. For more than a decade Mr. Perret worked at the European Institute for International Economic Relations and at the Chair of Macroeconomic Theory and Policy at the University of Wuppertal. He was a lecturer at the Technical University of Kaliningrad. Since September 2016 he holds a professorship for Economics and Statistics at the International School of Management in Cologne.

Prof. Dr Eyden **Samunderu** is a leading expert in the area of air transport with extensive consulting experience. He holds a PhD in Strategic Management and is a Program Director for a Master´s program at the International School of Management in Dortmund Germany. He is also sitting as an Board Advisor at Africa Aviation Partners (London). His research interests include: aviation, multimarket contact, strategic groups and competition dynamics, container logistics and maritime economics.

Duncker, Christian; Perret, Jens K.

Beyond Linearity - An Analysis of the Interdependencies across the Customer Journey

Abstract

This study analyzes the various stages of the customer journey (CJ) concept using the example of the lingerie product area. The fields of Customer Journey Management, Customer Relationship Management, and Customer Experience Management, which have so far been largely considered separately, are summarized into a comprehensive framework.

In the second part, the study uses a representative survey of 1,050 women of generation X to establish the validity of the model empirically. It additionally analyzes in how far the data requires the expansion of the model by a secondary vertical meta-level to capture interlinkages not considered within a purely linear model of the CJ. The result, a two-dimensional network structure of the CJ, illustrates the links between different parts of the CJ and the requirement of a multidimensional approach towards the customer journey.

Finally, the study presents an approach on how to model the willingness-to-pay as the central part of the CJ by implementing an artificial neural network (ANN) approach. The results show the ANN is ideally suited for such a complex background. The resulting model combines high explanatory power with the potential to increase it further by successively including newly available customer data, thus offering additional benefits for practitioners.

Keywords:

Customer journey; CRM; customer experience; artificial neural network; survey data

1 Introduction

1.1 Customer journey research – an introduction

The concept of the customer journey (CJ) has been experiencing a real boom for several years (for a first overview see Lemon and Verhoef (2016, p. 69) and Folstad and Kvale (2018)). Especially within digital media sciences, an attempt is being made to understand the consumer's journey towards brand offerings (Anderl et al., 2016; Muret, 2013). The main focus here is on the use of database systems to understand the customer from the first contact with the brand in the digital space, in order to guide and accompany him in a goal-oriented manner from the very first moment. However, business administration and the communication sciences are also trying to understand how companies can best reach and retain their consumers (Edelman & Singer, 2015) – particularly across different types of online and offline touchpoints.

In all three fields of science, an attempt is being made to understand the journey of the consumer from the first contact with the brand (awareness phase), through different described decision levels, to the repurchase and recommendation (loyalty). Many models have been developed for this purpose in recent years (Folstad & Kvale, 2018). Their aim is to depict a causality of different levels, as well as their legitimacy. Most models are based on the assumption of a certain linearity of the processes over predefined levels, which, depending on the authors, have different numbers.

Upon closer examination, the majority of CJ models are related, directly or indirectly, to the approach of the Customer Experience (CE) (Lemon & Verhoef, 2016, p. 69). McKinsey research with more than 200 companies (Edelman & Singer, 2015) showed the operational relevance of the CJ for marketing: On the one hand, well-designed CJs offer such added value that customers remain loyal to the company not only because of brand performance, but also because the CJ is perfectly designed. On the other hand, well-designed CJs also offer the opportunity to gain a real competitive advantage - especially in times of increasingly interchangeable product offers.

The constructs CE and CJ have been discussed in detail for several years both in science (e.g. Verhoef et al., 2009; Homburg et al., 2017) and business practice (e.g. Edelman & Singer, 2015; Rosenbaum et al., 2016; Schwarz, 2019). On closer examination, both concepts are closely related to each other: When used correctly, a CJ map helps to optimise the costumer experience - and this in relation to the large number of all brand-specific touch points (Lemon & Verhoef, 2016, p. 74; Richardson, 2010). This is the reason, why improving CJs, and in the result optimal CEs, are one of the most important strategic topics in a lot of companies (Accenture, 2015): Big players like Google, Amazon or KPMG install the position of a CE vice president, chief CE officer or similar managing positions in their companies. In recent years, numerous models and schemes have been developed. As a result, linear flow diagrams and cyclic models, such as the Loyalty Loop from the management consultancy McKinsey (Court et al., 2009), are being developed.

The various publications provide different definitions of the term CE. For the following explanations, the interpretation of Verhoef et al. (2009) will be followed. The authors define the CE as the customer's cognitive, affective, emotional and physical responses of a company's offer (Verhoef et al., 2009). Accordingly, consumers are also the focus of the subsequent considerations of the CJ. Only this perspective makes it possible to understand the different CJ approaches and finally to reflect critically.

In this context, two distinct research gaps can be made out:

(1) What is certain is that the main weaknesses of these models are the fact that (a.) phenomena, such as the unreflective spontaneous purchase and (b.) the strength of the connections between the various influencing factors have not yet been sufficiently analyzed (Lemon & Verhoef, 2016, p. 88).
(2) Another scientific gap is the fact that the majority of CJ models come from the field of digital sciences. Lemon and Verhoef (2016, p. 88) therefore demand: "This work should be extended in the offline-world. For example, researchers could examine not only sales effects but also how distinct touchpoints (brand, customer, partner and social/external) simultaneously contribute to the CE in different phases of the CJ".

In particular for the fashion, footwear and accessories sector, it should also be noted that most of the customers decisions are not taken on a rational level. On the contrary, they are largely highly emotional. It is precisely the goods of this economic sector that serve consumers to present their identity and personality to the outside world (Loussaief et al., 2019). Based on Maslow's pyramid of needs (Maslow, 1987, p. 150), branded clothes and accessories in particular are most of the time used to satisfy social needs and the desire for recognition (Krämer & Schmutz, 2020). We are at the higher levels of the pyramid, the satisfaction of growth needs. Purchasing decisions in this area are usually not made on the basis of functional-objective criteria, but far more on the basis of emotional purchasing criteria.

In the past decades, a wide range of studies have been conducted that go far beyond the above considerations at "Maslow-level" (Pham & Lee, 2019).

1.2 Research questions

Correspondingly, the purchase decision process itself is usually comparatively irrational and emotional - even under the condition of limited resources like money, space etc. (Hamilton et al., 2019). In the field of fashion and accessories, therefore, CJs and experiences are usually strongly discourse-oriented, as consumers make their decisions dependent on a number of external factors, in particular on conscious or unconscious exchanges with third parties like opinion leaders, influencers, friends, acquaintances and others (Hughes et al., 2019).

This is only one example of the fact that consumer research should not only analyze the temporally logical sequence of customer contacts. Another example is the pricing policy of a brand: here the rule of thumb is that the higher the price positioning of a brand, the stronger the social and psychological purchase motives (Krämer & Schmutz, 2020). The majority of existing CJ and CE models only superficially consider these factors, because they are more social-psychological than chronological. However, the importance of these factors cannot be denied. In behavioral economics, these anchor effects are discussed in detail (Furnham & Boo, 2011; Wansink et al., 1998).

The present study analyzes whether, in addition to the causal-logical processes of the various CJ and experience models, further explanatory patterns exist as to how a consumer from an initial contact with a brand ultimately becomes a consumer and later a repeat buyer. In particular, it will be investigated in how far the different stages of the CJ exert influence on each other (Lemon & Verhoef, 2016) even though to differing degrees.

This leads to the formulation of three research questions guiding the process of this study:

- RQ_1: Can the temporally logical sequence of the CJ be supplemented by further dimensions?
- RQ_2: Can the temporal sequential approach of the CJ be expanded into a secondary vertical dimension by considering non-linear relationships based on empirical data?
- RQ_3: Can customer purchase decisions be modelled in a non-linear environment? If so, what are the main determinants thereof?

Based on a comprehensive theoretical model of the CJ, deduced in the second section of this study, these three questions are in the third section studied empirically for a representative dataset of 1050 women. The fifth section concludes on derives recommendations for practitioners.

Note: The informed reader might skip the section 2.1 through 2.3 that provide a background on CJM, CRM and CEM as summarized by the Triple-C-Model in section 2.4.

2 Theoretical Background and Literature Review

2.1 Customer Journey Management (CJM) and related models

From the marketing perspective, there are distinct fields of CJ research. One strand of research considered the customers' decision process from becoming aware of a brand or product to making the purchase decision (Lee, 2010) while other strands focus more on loyalty (Buttle, 2006; Court et al., 2009). In this perspective, the experiences and behavior of customers are primary analyzed according to a predefined process, structures in steps like awareness, familiarity, consideration, purchase and loyalty (e.g. Court et al., 2009). Other publications work with different process-concepts and define a three-step model with a "pre-purchase", "purchase" and "post-purchase" model (Lemon & Verhoef, 2016; Rosenbaum et al., 2016). In the world of marketing, the different models are labeled as "buying-", "purchase-", or "brand-funnel" too (e.g. Jansen & Schuster, 2011). It is obvious: in science and practice, there are many labels for the same topic.

The oldest concept is the well known AIDA-formula (Lavidge & Steiner, 1961) or its newer variation the ASIDAS-formula (Brysch, 2017, p. 39; Opresnik & Yilmaz, 2016, p. 18). The CJ-, and brand funnel-concepts (Dierks, 2017, p. 17) are further developments of the AIDA formula too. Folstad and Kvale (2018) offer a good and in-depth overview about this. The McKinsey Loyalty Loop was one of the first approaches that led to a serious further development of the CJ concept (Court et al., 2009).

Therefore, the idea of CJs and the related field of CEs is not new. Lemon and Verhoef (2016, p. 71) identified in their study the development of the CE across the last six decades. From decade to decade, the focus moved deeper into the decision-making process of the customer, as well as in the necessary marketing structures and processes inside the brand companies. For the present study, the focus is on the decision-making process of the customers and its determinate variables.

Table 1: Comparison of the Relevant Models - A Symbolic Overview

Author & model	Pre-purchase-stage				Purchase	Post-purchase-stage			
Rosenbaum et al., 2016: CJ map	pre-service				service	post-service			
Lavidge & Steiner, 1961: AIDA	awareness		interest	desire	action				
Dierks, 2017: CJ	awareness	familiarity	consideration		purchase	loyalty			
Opresnik & Yilmaz, 2016: ASIDAS	attention	search	interest	desire	action	share			
Court et al., 2009: Loyalty loop	(awareness)	consider	evaluate		buy	enjoy	advocate	bond	(loop)

Source: Own Table

Table 1 compares the different models in summary form. Their structure is oriented towards the specific complexity of the models: from top to bottom, the differentiation into sub-steps, and thus the number of variables analyzed, increases line by line.

Only some exemplary alternative models are presented in Table 1. Studies with a specialization on this subject (e.g. Folstad & Kvale, 2018 or Lemon and Verhoef (2016)) show that many alternative models and representations have been published in recent years. However, providing such an all-encompassing overview is not the aim of the present study. However, it is important to note that the different models have three central phases: the pre-purchase stage, the purchase stage and the post-purchase stage. In the subsidiary individual steps, however, they already differ (zero to four differentiating steps). In the meantime, there are so many alternative models that Rosenbaum et al. (2016) called their introductory section of their article "the customer journey map confusion". They point out that so many and varying concepts are now available, that neither science nor practice are able to determine the "best" CJ map (p. 2).

They identified the differentiation of CJs into a *horizontal* (1) and a *vertical* (2) level as a particular challenge. While the determination of the horizontal presentation, i.e. the actual process model, is relatively simple, the main challenge is the determination of the vertical presentation. Some authors use this axis to reflect sociopsychological factors like feelings, attitudes, values (e.g. Lingqvist et al., 2015). Other authors locate here the brand touchpoints, communication and distribution channels, or design alternatives (e.g. Court et al., 2009; Skinner, 2010).

At the latest, from this level of differentiation onwards, the confusion among managers and scientists is quite understandable. Rosenbaum et al. (2016) offer an alternative: In their study "how to create a realistic CJ map" they use the example of services at one of the world's largest shopping malls in the USA, the Highland Park Mall, to show which alternative strategic service activities (vertical axis) can be used at which touchpoint (horizontal axis) to generate a maximum of success via the individual CJ of a customer (pp. 5).

This study does not deal with services rather than brand products in the lingerie sector, making this model not an ideal basis for an empirical study. However, it is important to note the finding of Rosenbaum et al. (2016) that various influencing factors correlate with one another, especially on the vertical axis - and this in different combinations and intensities (p. 7).

The models mentioned above have one thing in common: They declare a (chrono-)logical and linear relationship between the different process steps (horizontal level). However, they do not specifically declare the determining variables of the decision-making process and, above all, the strength of the influence of individual variables on potential purchasing behavior. From the perspective of the scientifically thinking practitioner, Richardson (2010, p. 3)Klicken oder tippen Sie hier, um Text einzugeben. therefore pleads to expand the one-dimensional linear view of CJs by the following perspectives:

- *"Actions*: What is the customer doing at each stage? What actions are they taking to move themselves on to the next stage?
- *Motivations*: Why is the customer motivated to keep going to the next stage? What emotions are they feeling? Why do they care?
- *Questions*: What are the uncertainties, jargon, or other issues preventing the customer from moving to the next stage?
- *Barriers*: What structural, process, cost, implementation, or other barriers stand in the way of moving on to the next stage?"

In relation to these questions, the present publication attempts to gain further insights, especially regarding the strength of the influence of the areas of *action* and *motivation* on the buying action in general and willingness-to-pay in particular.

2.2 The Customer Relationship Management approach

The Customer-Relationship-Management (CRM) is strictly speaking a continuation of the CJM approach (Lemon & Verhoef, 2016). Like the CJM approach, CRM has been viewed from various perspectives since its introduction at the turn of the millennium. Customer acquisition and long-term customer retention were the main perspective of earlier CRM definitions (Ling & Yen, 2001; Winer, 2001). In the 1990s CRM gained importance and was really popular among IT vendors (Payne & Frow, 2005). Some authors have defined CRM as a business strategy (Jackson, 2005). However, other authors have referred to CRM as a data-driven approach that aids in examining the customers' existing needs and profitability (Fitzgibbon & While, 2005).

In the literature, different points in time can be found from which stage of the CJ an organization's active CRM is used: customer acquisition (Cambra-Fierroa et al., 2017; Winer, 2001), customer qualification, or, in most publications, the customer retention/loyalty (see overview in Sota et al. (2018)). We will follow the definition of Cambra-Fierroa et al. (2017): "From a practical point of view, managing successful customer relationships begins with identifying and acquiring the right customers". We share this view that "true" CRM begins with the acquisition of the "right customer", i.e. the one who fits the specific offer/brand. This statement is important for the derivation of the model presented later thus, our model shown in Figure 1 also does not begin with any kind of customer qualification, but rather with the first phase of customer contact - the generation of awareness. n this sense, CRM is a customer-centric approach that cannot be assigned exclusively to the marketing department. Rather, it must be seen as a holistic approach in which the company's units of sales and service in particular must also be integrated.

As the study results of John (2018) show, CRM based on IT solutions can be divided into the following categories: operational CRM, analytical CRM and collaborative CRM. The current study focuses primarily on operational CRM. The corresponding IT applications have the goal to integrate all information about the (potential) customers from "the front" to "the back office". These solutions can help in the automation of key business processes (marketing, sales, and customer service), so that all these processes can be made more efficient and effective (Venturini & Benito, 2015).

2.3 The Customer Experience Management (CEM) approach

In science and practice, there are many definitions and derivations of the terms Customer Experience (CE) and Customer Experience Management (CEM) (Homburg et al., 2017). Presenting and discussing the alternatives is beyond the scope of this study. Therefore, for the following steps of this paper, a holistic definition of CE (based on Brakus et al. (2009) and Verhoef et al. (2009)) will be used, which summarizes the essential characteristics: "CE is the involvement of a person's sensorial, affective, cognitive, relational, and behavioral responses to a firm or brand by living through a journey of touchpoints along prepurchase, purchase, and postpurchase situations and continually judging this journey against response thresholds of co-occurring experiences in a person's related environment. In this regard, a touchpoint represents any verbal (e.g., advertising) or nonverbal (e.g., product usage) incident a person perceives and consciously relates to a given firm or brand" (Duncan & Moriarty, 2006). Within this definition, the overlaps with the concept of the Customer Journey Management (CJM) are clearly visible.

However, there are some core differences discussed too: Meyer and Schwager (2007) differentiate CRM from the perspective of "knowing customers and leveraging that data" from CEM from "the perspective of knowing about customers reactions and behave" in real time and leveraging that data. Payne and Frow (2005), however, consider these two aspects as included in a strategic perspective on CRM, which helps determine whether the "value proposition is likely to result in a superior CE." These overlaps have also became evident in practice, and Davey (2012), managing editor of MyCustomer.com, was asking, "is CEM the new CRM?".

2.4 The connection between the three different groups of "customer" models

In the above explanations, various concepts are listed that place the consumer at the center of strategic considerations of brand and fashion management. In summary, there are implicit and explicit links between the concepts discussed above

- Customer Journey Management (CJM)
- Customer Relationship Management (CRM), and
- Customer Experience Management (CEM),

These models are often isolated or distinguished from each other in the literature. It is questionable whether these areas of science really need to be separated from each other, or whether there are central overlaps (Lemon & Verhoef, 2016). Meyer and Schwager (2007) have already noted that CRM, for example, focuses on the knowledge about the consumer. From their point of view, CEM, on the other hand, focuses on knowledge regarding the reactions of consumers, and thus their behavior. In this perspective, CEM would mean a deepening of the knowledge of CRM. Homburg et al. (2017) suggest differentiating between the two approaches. According to their findings (see Table 2), CEM is characterized above all by a higher dynamism and individualization of the measures than CRM.

Table 2: Demarcation of CRM and CEM

	CRM	CEM
Cultural Mindsets	-	Experiential response, touchpoint journey, and alliance orientation
Strategic directions	Multichannel integration and personalized customer interactions as key elements of profitable customer relationship	Thematic cohesion, consistency, context-sensitivity, and connectivity of touchpoint journeys as key elements of loyalty-driving CE
Firm capabilities	Effective use of market data through the periodic planning, implementation, and monitoring of customer relationship	Effective use of market data through the continual design, prioritization, monitoring, and proactive adaptation of CE
Primary goals	Customer retention and profit maximization	Customer loyalty and long-term growth

Source: Shortened version of (Homburg et al., 2017)

Additionally, as Homburg et al. (2017) found in their qualitative study, successful CEM concepts are based on the following capabilities of companies: Developing a touchpoint journey design, touchpoint prioritization, continuous touchpoint journey monitoring and touchpoint adaptation based on this. In the context of the present study, the above findings of CRM and CEM research are accordingly supplemented by the findings of CJM research. As a result of this combination, we have developed the innovative "Triple-C-Model" (Figure 1) described below.

The Triple-C-Model puts the three approaches in a logical context. The starting point is the findings of the scientific field of CJM (see Table 1). The models assigned here define the fundamental and chronological steps of the consumer from the first contact with a fashion brand (awareness) to the re-use/re-purchase of this brand (loyalty). For the Triple-C-Model, it is initially not relevant which CJM model is used. Much more important is the fact that there is a logical process sequence that can be used as a template for both CRM and CEM.

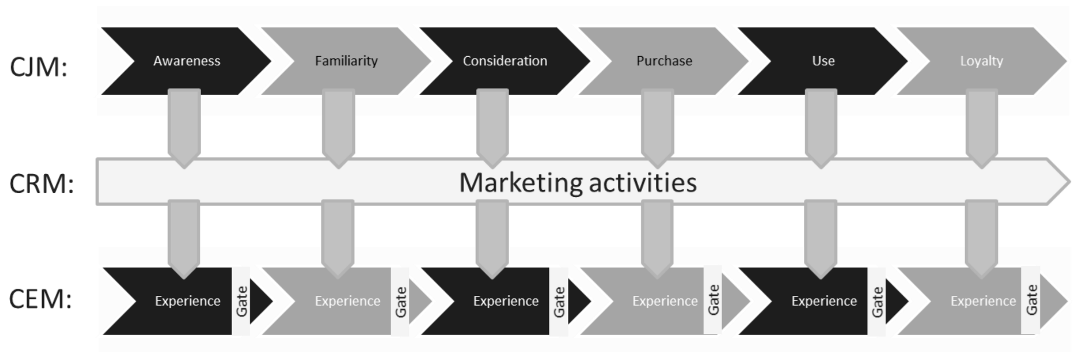


Figure 1 Relationship between CJM, CRM & CEM – the „Triple-C-Model“

Source: Own Figure

Based on this perspective, specific marketing tools with specific offers must be used in each stage of the CJ to maximize the customer relationship. From this perspective, "real" relationship management is not just a digital line in a database (customer master data). From this perspective, CRM is a holistic management approach, with the objective of understanding the customer from the beginning in order to target them through different marketing tools along the CJ (e.g. Barcelo-Valenzuela et al., 2018).

However, as shown in section 2.2, there is currently no single definition of CRM. One main reason for this is that it is defined from different perspectives (for an overview see Cambra-Fierroa et al., 2017, p. 318). Nevertheless, two central commonalities exist:

- CRM is the management of long-term customer relationships (e.g. Gummesson, 2004; Payne & Frow, 2005; Zablah et al., 2004).
- CRM aims to achieve a real competitive advantage by managing profitable customer relationships.

Both can only be realized if the customer has a positive *experience* with the brand at every touchpoint.

This is where the CEM in the "Triple-C-Model" comes in. The following basic assumption is important at this point: According to the model, the CE is the result of a contact (touchpoint) with a brand. In this perspective, CEM pursues the central goal that all active CRM measures in every phase of the CJ also ensure brand-compliant, and above all, positive experiences. According to the "Triple-C-Model", these experiences act like a gatekeeper: only if the consumer has had a positive experience with the brand's appearance at a specific touchpoint, he or she will take a step further in the CJ.

Overall, the "Triple-C-Model" shows the linearity of a chronology already mentioned - especially the CJ in its primarily horizontal representation. We see the other two models (CRM & CEM) as complementary perspectives: they are also fundamentally based on a chronological assumption, but here the focus is on the factual alternatives for realizing each CJ process step. This is, as a second basic assumption of our model, the *vertical perspective* (see Lingqvist et al. (2015); Court et al. (2009) and Skinner (2010)). This means: within the framework of CRM, marketing management has various instruments at its disposal at the same time (communication and sales channels, product and pricing policy, service concepts, …). These instruments can also be designed differently (design, tonality, exclusivity, ...). On this vertical level, the entire range of marketing instruments can be used - suitable for the specific stage of the CJ.

Table 3: Exemplary representation of the interrelationships between the three levels of the "Triple C Model”

CJM	Awareness	Familiarity	Consideration	Purchase	Use	Loyalty
CRM (touchpoints to be managed)	• Mass media • POS • SEO / SEM • Banner advert. • Social Media • Paid content • OOH • …	• Mass media • POS • SEO / SEM • Banner advert. • Google search • Social Media • Paid content • OOH • Website • …	• Own website • Google search • Brochures • Distribution concepts • Product & • Pricing policies • Online & Offline communities …	• Distribution concepts & • Availability (sales channels) • POS concepts • Sales staff • Selling process • Product & • Pricing policies • Packaging • …	• Quality & • Benefit & • usability of the product • Product related services • Product related Apps • Availability of accessories • …	• Value Added services • Newsletter • Loyalty programs • Service units • Call Center • Apps • Recycling services • …
CEM (dimensions of experiences)	• Conformity with symbolic & • functional needs	• Conformity with symbolic & • functional needs	• Conformity with lifestyle & • Fashion design preferences • Value for money (symbolic & functional)	• Style of goods presentation • Handover style • Speed of process • Tonality • Willingness to pay	• Real experiences using the brand offer • Feedback of the social environment	• Appreciation • Quality & • speed of reaction • Event experience
	Gate	Gate	Gate	Gate	Gate	

Source: Own Table

Table 3 shows the logic of the Triple-C-model by using selected CRM tools: Different marketing tools (touchpoints) can/must be developed and launched for each stage of the CJ. The design of these tools must be able to ensure that the *experience* of each (potential) customer is positive (CEM). This means that the measures and their design must be chosen in a way that latent, abstract and/or rational needs are addressed. If this is not the case, if the consumer's experience is either neutral, or even negative, the specific "gate" is not passed through. In this case, the consumers' probability of purchase and use of a specific underwear brand is very low. In this sense, the three different C-models do not have to be distinguished from each other. Quite the opposite: in our Triple-C-model, they are rather a mutual complement that shows a stronger specification of goals and measures from level to level. Marketing managers who are aware of these interrelationships are also in a position to achieve optimal sales success - and not only in the area of underwear brands.

The following explanations therefore deal with the central question of which vertical factors have the greatest influence on a customer's decision to buy/use a product, and thus on the probability of purchase and the willingness to pay. Different factors of a classic marketing concept that the CEs within the framework of his individual CJ are considered. These management parameters must not be considered in isolation. Rather, the present study attempts to work out the strength of the interrelationships between the different levels. For example, the influence of the material properties of the lingerie or even brand knowledge on the customer's willingness to pay will be investigated.

3 Analytical Framework

Building on the implementation of the „Triple-C-Model“ in Figure 1 there are six conceptual units. In the course of this analysis, only the first five are considered – the loyalty aspect is excluded as it is tackled by other theoretical approaches like the RFM framework (Patel et al., 2021). Of these five units, three are operationalized by two sets of questions each. The unit *Familiarity* is operationalized via one set of questions and the unit *Use* via three sets. These sets of questions are referred to in the course of the analysis as building blocks BB1 to BB10 to differentiate them from the conceptual units.

Table 4 provides an overview over the building blocks and the implemented conceptual units, as well as the abbreviations used. An overview over the sub-categories / sets of questions of all building blocks except for BB9 (single metric variable) can be found in Table 8 in the appendix.

Table 4: Abbreviations

Building Block	**Abbreviation**	**Scale**	**Sub-Categories**	**Conceptual unit**	**Abbreviation**
Information Gathering	BB1	Nominal	13	Awareness	CU1
Influencers	BB2	Nominal	8		
Brand Knowledge	BB3	Nominal	8	Familiarity	CU2
Selection Criteria	BB4	Ordinal	11	Consideration	CU3
Material Preferences	BB5	Nominal	6		
Point of Sale	BB6	Nominal	10	Purchase	CU4
Willingness-to-Pay	BB7	Metric	6		
Motives for using underwear	BB8	Metric	10	Use	CU5

Time for Selection	BB9	Ordinal	1
Special Occasions	BB10	Nominal	8

Source: Own Table

Using the notation from Table 4, the „Triple-C-Model“ implemented in this study can be rewritten as seen in Figure 2.

Figure 2: Implemented Version of the Triple-C-Model

Source: Own Figure

Considering the research questions, first, the consistency of the multi-block conceptual units is analyzed. Second, the strength of the links between the conceptual units as motivated by Figure 2 and the „Triple-C-Model“ is estimated (Research Question RQ_1). Finally, the results are used to argue the validity of the „Triple-C-Model“.

Considering that the linear "Triple-C-Approach" to the CJ is not able to capture the complexity of all the different relevant links between all building blocks and conceptual units, a two-dimensional non-linear network structure is proposed as a new alternative perspective on the CJ (Research question RQ_2).

Keeping research question RQ_3 in mind, an artificial neural networks approach is used (e.g. Hastie et al. (2009) and Nunes Silva et al. (2017)) to provide an estimate of the overall importance of the different impact factors with regard to the willingness-to-pay for underwear. The advantage of using Artificial Neural Networks (ANN) in addition to classical statistical methods lies in the fact that they provide good results even in the presence of complex, non-linear relations, potential problems with multi-collinearity or simply a limited sample size and many dependent and independent variables (Hassoun, 2003; Hastie et al., 2009; Whitby, 2003). Tkac and Verner (2016) provide a most comprehensive overview on the use of ANN in a business context. In Patel et al. (2021) ANN have been successfully used to determine the relevance of input factors in a comparable context. The quality of the results was superior to those of a classical regression analysis and due to the better real-time scalability of ANN as compared to a regression analysis regarding data availability ANN provide a practically speaking more relevant tool.

4 Analysis

4.1 Description of the Data Set

A set of 1,050 women, aged 35 to 49 years (roughly representing generation X as defined by Strauss and Howe (1991)), completed a detailed questionnaire on their decision-making and habits when buying and wearing underwear. Considering, this cohort captures women that still have a strong interest in fashion while also having the monetary means to realize these interests. The 1,050 women in the data set are uniformly distributed across the 15 different years of age, with each year of age represented by a minimum of at least 59 women.

99.5% of the women explicitly state their income, and all income categories contain at least 68 women each. Categories 501€ and above contain at least 172 women each. Similarly, the data set contains a relevant number of women for each category of city size. Finally, all types of marital / family statuses are represented in significant quantities as well.

The originally implemented questionnaire consisted of twenty questions of which two were used for screening purposes (gender and age), four for the collection of additional sociodemographic data and personal values and one for the opinion regarding the brand Lascana (the original initiator of the survey). Of the thirteen remaining questions, ten represented the ten building blocks motivated above. A shortened version of the translated questionnaire has been included with the appendix.

4.2 Consistency of the Conceptual units

Conceptual unit CU2 (see Table 4) is the only unit represented by a single building block, and thus is excluded from this preliminary analysis.

Table 5 shows that of the remaining four units, the first CU1 reports a very strong internal coherence as the two building blocks BB1 and BB2 are strongly associated – the test conducted reported a significance level of 0.

Unit CU3 reports a decent, even if not very strong internal coherence, as five out of eleven tests turn out to be significant – even with a significance level of 0. Thus, the internal coherence of this building block is not so much influenced by an inherent instability as by the fact that for some selection criteria the choice of material is rather predetermined. I.e. this becomes particularly obvious with aspects like sexiness and functionality, where there also persists a very strong relation between selection criterion and material preference.

The fourth unit, consisting of the point of sale and the willingness-to-pay, reports only a very low internal coherence. Thus, this unit might summarize two distinctly different aspects motivating a model based on the building blocks rather than on the conceptual units.

Finally, unit CU5 reports a rather strong internal coherence, except for the relation between the motives for buying underwear and special occasions. As with unit CU3, this is not surprising at all considering that between some occasions and motives very strong relations are self-evident whereas for others any type of relation would be rather hard to be explained. I.e. sexiness and attractiveness are very strongly related whereas solemn occasions and feeling well are not related in any which way.

Thus, using the conceptual units as inherently consistent units in the „Triple-C-Model“ is only in partly backed up by the data set. Due to the low consistency of CU3 and CU5 in particular, the first part of the ongoing analysis is based on a more detailed perspective by implementing the building blocks BB1 to BB10 instead of the units CU1 to CU5. Not only will this decision reduce the overall complexity, it will make the results easier to be interpreted by decision makers.

4.3 Testing the Triple-C-Model

Using the abbreviations from Table 4 and the notation introduced in the previous methodological section, Table 5 can be constructed summarizing the results of the quantitative evaluation of the "Triple-C-Model".

Table 5:Strength of the Relations between the Building Blocks

		CU1		CU2	CU3		CU4		CU5		
		BB1	BB2	BB3	BB4	BB5	BB6	BB7	BB8	BB9	BB10
CU1	BB1		**0**								
	BB2	**0**									
CU2	BB3	0.875	0.375								
CU3	BB4	0.261	0.636	0.375		0.455					
	BB5	**0.016**	**0.003**	0.625	0.455						
CU4	BB6	**0**	**0.051**	0.375	0.261	**0.058**		0.104			
	BB7	0.469	0.625	0.375	0.667	1	0.104				
CU5	BB8	0.376	0.487	0.267	0.45	0.6	0.163	0.417		0.7	0.423
	BB9	**0**	**0**	0.25	0.727	**0**	**0.475**	1	0.7		0.714
	BB10	**0**	**0**	0.5	0.727	**0**	**0.019**	0.66	0.423	0.714	

Source: Own Table

Each column or row represents one of the ten building blocks; fat horizontal and vertical lines are used to mark – in accordance with Table 4 – the conceptual units. The relations within the fat outlines should be strongly pronounced as they describe the conceptual units, which are to be inherently homogeneous. The parts below the conceptual units marked by medium-sized outlines describe the relations that are to be assumed if the model depicted in Figure 2 holds. All other relations are not part of the traditional approach to the CJ. As the table is symmetrical, only the lower left part of the table is presented.

Except for the weak link between block BB6 and those in unit CU5, which has a dampening effect on the overall strength of the link between units CU4 and CU5, all other units are consistently links to their corresponding neighbors. Many of the links – medium and dark gray - can be considered to be very strong. The „Triple-C-Model“ does not conflict with the data set and thus is considered valid for the sector of women's underwear, and first positive evidence for research question RQ_1 results.

While a comprehensive CJ can be constructed incorporating all conceptual units, not all building blocks are strongly linked with all building blocks of their predecessor or successor unit. The only weak point in the overall model seems to lie with building block BB6 – the point of sale.

Thus, the „Triple-C-Model“ as introduced can be empirically verified, even though a problem remains insofar as it is not possible to use the data set to establish causal relations between any of the conceptual units or even between any of the building blocks.

4.4 A Multidimensional Approach to the Customer Journey Construct

Considering the potential problem of strong and significant links between building blocks that are not backed by the „Triple-C-Model“ or any linear model of the CJ as introduced in section 2 (the outside fields in Table 5), this section considers the second of the motivated research questions and expands on the linear approach to the CJ. Aside from describing relations between two building blocks that are not part of the „Triple-C-Model“, these significant links give rise to the existence of potential moderating or mediating effects inside the model. Table 5 particularly shows that at least six links of the fields report strong relations between building blocks that are not considered in the “Triple-C-Model” like (BB1-BB9, BB1-BB10, BB2-BB9, BB2-BB10) or (BB5-BB9, BB5-BB10) exist with other omitted relations being of no minor relevance either.

This implies that while the data can be fitted into the „Triple-C-Model“ it might be more suitable to consider an extended model based on the data set and thus move from a theory-driven to a data-driven perspective in analyzing the CJ. Considering that in the discussion above and in the corresponding literature an additional vertical dimension to the traditionally linear CJ has been advocated, the presence of significant interlinkages between the different building blocks would indicate the presence of such a vertical dimension.

To represent the CJ in a two-dimensional more illustrative way the coloring scheme applied in Table 5 is used to assign each a relation a weight; a single digit number representing the strength of the relation (0 – white / 1 – light gray / 2 – medium gray / 3 – dark gray).

The resulting matrix with ten rows and ten columns can be interpreted as a 10x10 adjacency matrix representing a network. An adjacency matrix is a quadratic matrix where each column and row represent a node in a network – (Goodrich & Tamassia, 2015). Here each building block represents one of the nodes in a 10-node-network. An entry in row i and column j of the adjacency matrix describes the strength of the link/edge connecting node i to node j. E.g. the strength of the edge connecting BB4 and BB7 can be found as the element in the fourth row and seventh column in Table 5. This field is medium gray, therefore the strength of the respective line would be 2.

The matrix is symmetric if the network and the relations are undirected, as the relations results from symmetric measures. The edges in the corresponding graph are displayed therefore as two-way arrows, reflecting that effects can occur both ways. The resulting network is illustrated in Figure 3. In the graph, black arrows mark relations between nodes belonging to the same conceptual unit, while medium gray arrows mark relations that are to be expected if the „Triple-C-Model" is considered. Light gray lines describe relations not covered by the Triple-C-Model.

Figure 3 shows that a significant number of very strong relations exist that are not part of the "Triple-C-Model" and the degree of cross-linking also differs in intensity. While this has already been evident from Table 5 the advantage of a network-based approach is that it allows for more intuitive insights into the relevance of the different nodes / building blocks of the CJ thus supporting the study of research question RQ_2. However, while the graph illustrates that a one-dimensional linear model is not sufficient to explain the structure inherent in the data, it does not invalidate the temporal logic of the CJ concept per se.

While a very dense network exists, four of the nodes play a more marginal role – *Point of Sale*, *Motives for using underwear*, *Selection Criteria* and *Brand Knowledge*. Arguments with regard to all four of these blocks have already been given in the previous section.

In addition to the classical linear model of the CJ as illustrated in Figure this approach has the advantage that is can be used as a multidimensional tool for decision makers focusing on different parts of the network. E.g. a social media manager might be particularly interested in the specifics of the 'Influencers' node and its relations to all the other nodes – in strong ones like the one to the material preferences as well as in weak ones like the point of sale.

If the relations illustrated in Figure 2 could – in a succeeding study – be established as causal effects the network model can be used to determine whether a main linear route exists. It additionally would provide insights into whether the other pronounced links simply act as feedbacks, mediators, moderators or whether the needs to be inherently rethought. Such a directed network model can be used to study how 'experience' or 'information' is transmitted in this network.

Additionally, building on these results, a new survey using a simpler operationalization of the building blocks would allow for an estimation in a structural equation model. A model thus extended would then allow for more sophisticated simulations and strategic planning. It thereby could offer decision support on strategies to cope with external shocks as well as on managing the effects of shocks companies decide to introduce on their own e.g. as part of their marketing activities.

4.5 Willingness-to-pay in an artificial neural network approach

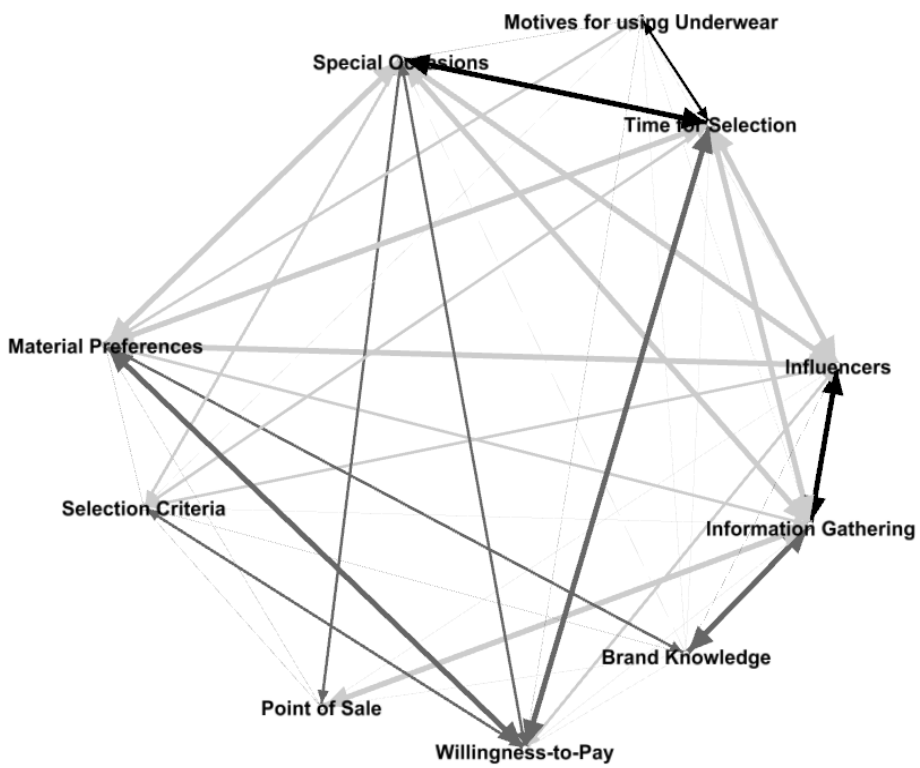


Figure 3: Building blocks of the „Triple-C-Model" in a Network Layout

Source: Own Figure

Figure 3 clearly shows the most important and most central block in the network is the 'Willingness-to-pay'. It also is the most important success factor for retailers and furthermore reflects the 'Purchase' part of the CJ. The empirical results thus far can therefore additionally be used as motivation for research question RQ_3.

While the figure already gives us a first insight into the integration of the willingness-to-pay into the CJ affirming research question RQ_3, it still remains open which of the other building blocks impacts willingness-to-pay in which way and which of them has the overall strongest effect. To tackle this third research question, the succeeding section employs an artificial neural network approach.

Artificial neural networks (ANN) can be used in a broad range of applications due to their prominent features of being very adaptable and offering good results in the absence of big data and linear relations. While Whitby (2003) provides an introduction into the topic, Tedesco (1992) or Woelfel (1992) provide early applications of ANNs to marketing related questions. Kietzmann et al. (2018) present one of the approaches where artificial intelligence in general is applied with regard to the predicting aspects relating to the CJ.

A significant advantage of artificial neural networks is that results can be continuously enhanced by incorporating the inflow of newly available data making them predetermined when working in a big data environment.

While the data aspect is not relevant in the context of this study, the flexibility of the algorithm and its limited requirements with regard to the input data make it the ideal tool in studying research question RQ_3.

For the ongoing analysis, the implementation of the estimation for multilayer perceptrons in SPSS 26 is used, which falls into the category of supervised learning with back propagation. An in-depth introduction into the field of ANN can be found in Hastie et al. (2009).

Following Hastie et al. (2009), an ANN consists of three main parts; the input layer, the hidden layer and the output layer. The hidden layer itself can consist of a number of layers, allowing the modelling of very complex designs. Figure 4 illustrates the typical design of an ANN and compares it with the typical design of a regression model. In the example, the ANN only consists of a single hidden layer which itself only contains a single node. It also shows that an ANN is not limited to a single output variable, which is the standard approach in regression analysis.

While ANNs have the advantage that they generally deliver better results in the presence of non-linearities in the relations, they operate as black box estimators, meaning that it is nearly impossible to get an idea how each of the independent variables actually impacts the dependent variable(s). Only by resulting to sensitivity analysis is it possible to glean at least the relative importance of the different independent variables.

The ANNs estimated are designed as three level networks with a single hidden layer. The stopping criterion in all estimations is the relative change in the training error, with the threshold being set to 0.00001. Due to the stochastic nature of the learning process and thus the estimation of the synaptic weights, 25 consecutive runs each that are averaged generating the reported relative errors. In Table 6 the first values report the averaged relative errors across all 25 runs. The values in brackets report the relative error for the best result with regard to each of the categories. The relative errors are defined as the sum of squares errors for the dependent variable to the sum of squares errors of the model, where the mean value of the dependent variable is used.

In all estimated models, the inputs are the questions for the different sub-categories, as referenced in Table 8 in the appendix. In the results, they are referred to as impact factor as they influence the outcome in each of the building blocks.

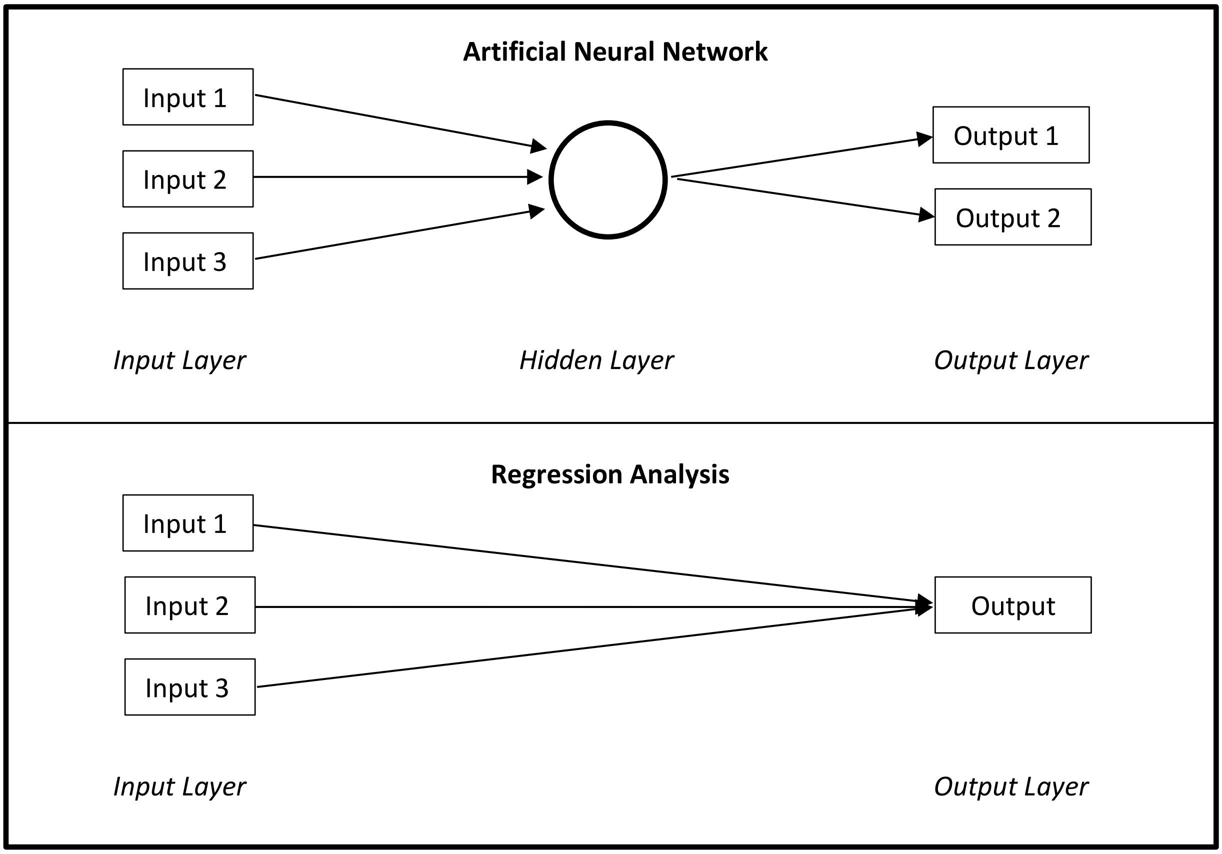


Figure 4: Structure of an Artificial Neural Network

Source: Own Figure

Willingness-to-pay can be split into six sub-categories – the six types of clothing considered here. A list of all sub-categories for all building blocks can be found in Table 8 in the appendix. A single artificial neural network is estimated for all six categories as dependent variables at once. Independent variables are the other nine building blocks or their corresponding sub-categories, respectively. Table 6 and Table 7 summarize the results of the estimation of an artificial neural network for the willingness-to-pay.

The model consists of six dependent variables and aims at explaining behavioral patterns. Thus, an overall relative error of 0.588 shows that the „Triple-C-Model“ offers a suitable framework for studying key aspects of the buying and payment decision. In particular, the WTP, as dependent variable in the respective model, can be explained very well. In addition to the results from Table 6 which summarizes the results of estimations where all observations were used for training the model, the data set can be split into a training and a testing set. The results for the training set will then reflect on the out-of-sample and thus predictive quality of the mode. For the results in Table 6 the relative errors of a corresponding testing set are in each case within a 10% margin of the presented ones. Thus, the model also yields suitable out-of-sample results which, however, would not be suitable for exact forecasting.

Considering the partial results, they illustrate that the willingness-to-pay can be explained for some categories. These categories are also those that are also more frequently bought by the interviewees.

Table 6:Relative Errors - Willingness-to-pay

Willingness-to-pay Category	Relative Error
Bra	0.469 (0.382)
Slip	0.517 (0.418)
Bustier	0.754 (0.677)
Body	0.722 (0.664)
Underwear-set	0.494 (0.398)
Nightwear	0.574 (0.508)
Overall	0.588 (0.522)

Source: Own Table

While Table 6 reports on the quality of the estimates, Table 7 reports on the ten most relevant and the ten least relevant impact factors. The scores result from a sensitivity analysis as it is performed by the neural network implementation of SPSS 26. Since the independent variables can report different scales, a normalization is applied assuring that the impact score lies between 0 and 100. Comparing these results with Figure 3 proves the assumption right that the results displayed are strongly biased by moderator or mediator effects. Aspects of building block BB8 dominate the top 10 of impact factors, whereas Figure 3 reports only a marginal relation between these two building blocks.

On the other hand, the bottom 10 factors show that links with the Point of Sale and the Influencers are only marginally linked to the willingness-to-pay, similarly to the results in Figure 3. Thus, artificial neural networks allow for a more flexible approach to modelling links within the Triple-C-Model.

Table 7:Top 10 and Bottom 10 Impact Factors – Willingness-to-pay

Top 10 – Impact Factors		Bottom 10 – Impact Factors	
Factor	**Normalized Score**	**Factor**	**Normalized Score**
BB8 Shapewear	88.72	BB10 Feeling good	28.66
BB8 Other	85.10	BB6 Department Stores	28.69
BB8 Business	83.51	BB10 Feeling attractive	29.47
BB4 Fit	82.09	BB6 Online Retailer	30.26
BB8 Going out	81.19	BB1 Stores	30.88
BB8 Festivities	80.33	BB1 Mail-order catalogs	32.07
BB8 Sexiness	78.29	BB2 Partner	32.65
BB8 Sport	76.93	BB10 Pure necessity	33.07
BB1 Youtube	76.16	BB10 Body forming	33.17
BB8 Period	74.66	BB6 Affiliate Retailer	33.23

Other Social Media Channels, Radio excluded (less than 5 observations)

Source: Own Table

5 Conclusions, Limitations and Outlook

5.1 Summary of the Results

Providing a comprehensive approach to the concept of the CJ, the multidimensional "Triple-C-Model" concept was developed. The authors consider this model a summary of the three parallel existing scientific and management disciplines "Customer Journey", "Customer Relationship" and "Customer Experience Management". Strictly speaking, all three model groups serve to achieve optimal Customer Centricity Marketing. To test the model's validity it is applied to a representative data set of 1,050 women of generation X, capturing their views on different parts of the CJ when shopping for or wearing underwear.

The analysis of this data set complements the theoretical model. The different stages of the CJ are logically based on each other following the "Triple-C-Model"; nevertheless it detects complex connections in individual decision-making that are not visible through the horizontal orientation of a CJ perspective alone. These 'invisible' connections have been considered in previous studies to the extent of loops or a vertical dimension; a meta-level to the CJ model. The aim of the study was accordingly to extend the pure horizontal perspective on the CJ. To this end, all possible connections - especially those not explicitly covered by the „Triple-C-Model" - between the individual building blocks of the model were considered and modelled as a network structure.

The network shows that many of the links identified (i.e. a number of links not covered by the horizontal dimension of the "Triple-C-Model") are very strong. A linear model is therefore too simplified to adequately capture the complexity of the customer's decision-making process, giving additional credit to studies considering the CJ a multidimensional construct. This applies in particular to modelling the willingness to pay for underwear. These results were reinforced by the application of an artificial neural network to ensure the consistency of the results.

5.2 Insights for Practitioners

This study offers valuable insights for practitioners in three regards. The Triple-C-Model provides practitioners with a holistic view of the customer journey, relating it the CRM and the CEM perspective. It thereby stresses the applicability of tools from CRM and CEM in the context of CJM.

Second, the study, by challenging the linear structure of the CJ shows that the customer decision process at all stages is complex and multi-dimensional. The proposed network structure illustrates in detail relevant impact factors when discussing e.g. the willingness to pay. While there is no doubt that a success-oriented brand must proactively serve all stages, the results show brand management which stages have what value contribution to the success of a brand. As a result, scarce resources can be used even more efficiently in the future. Additionally, this can be achieved across all marketing levers (product, price, sales and communication policy). Combining this with artificial neural network algorithms help marketing experts to exploit available and growing big data pools while gaining valuable insights about the customer’s behavior patterns (Peng et al., 2020).

Third, considering the availability of constantly growing big data pools the implementation of ANNs is self-evident. While in this study ANN have only been used to complement the basic analysis, for practitioners they offer additional advantages. The weights in an artificial neural network are estimated based on a training data set. This, however, means that a starting set can be used to calibrate the synaptic weights (the ANN pendant to the coefficients / parameters of a regression model) in the network and when new data becomes available this data can be fed into the network helping it to continuously learn (adjust the synaptic weights) and become more precise (by reduction of the relative error) (Hastie et al., 2009; Kietzmann et al., 2018). Practitioners thus profit from having a modeling approach that allows for running suitable forecasts on critical indicators like the willingness-to-pay. While the data set with 1,050 participants implemented herein is already well proportioned before usable forecasts to support decision-making are possible a real big data set is required and a more sophisticated custom-made network design and algorithm should be applied.

5.3 Limitations and Outlook

For academics, this new approach in viewing the CJ gives rise to a number of additional research questions; first and foremost among them the existence of causal links within the network. Due to the nature of the implemented data set, no causal links could be established. This aspect can best be approached by aligning comparable data sets from different product and target group areas.

While the data set offers a representative view of women from the set age group, it has the weakness to be only a snapshot of one point in time. The questions used in the survey did not yet consider any dynamics in behavioral patterns. Additionally, the study focused in particular on women by the age of 35 to 49. As this is a rather narrow age group, the question arises whether the results of this study hold as well for women of different age groups or respectively for men.

Considering the sample size of 1,050 women, representativeness of the sample can be assumed. As all participants originate from Germany, the scope of the study and thus its representativeness are however limited by the degree that the CJ for women’s underwear differs across nationalities. Future research must also be extended beyond the segment of women’s underwear to test whether the results remain stable across other segments of the market and different sectors.

References

Accenture. (2015). Improving customer experience is top business priority for companies pursuing digital transformation [Press release]. https://newsroom.accenture.com/news/improving-customer-experience-is-top-business-priority-for-companies-pursuing-digital-transformation-according-to-accenture-study.htm

Anderl, E., Becker, I., Wagenheim, F. von, & Schumann, J. H. (2016). Mapping the customer Journey: lessond learned from graph-based online attribution modeling. International Journal of Marketing Research, 33(3), 457–474.

Barcelo-Valenzuela, M., Hernandez-Rojas, E., Perez-Soltero, A., & Ochoa-Hernández, J. L. (2018). A CRM Strategy for Integrating Customer Knowledge. IUP Journal of Knowledge Management, 16(4), 7–28.

Brakus, J.J., Schmitt, B. H., & Zarantonello, L. (2009). Brand Experience: What is it? How is it measured? Does it affect loyalty? Journal of Marketing, 73(3), 52–68.

Brysch, A. A. (2017). Tourismus 4.0: Digitale Herausforderungen für die Reisebranche. In A. Aebli, U. Bauer, A. A. Brysch, R. Freericks, M. A. Gardini, & B. Grüter (Eds.), Tourismus – E-Tourismus – M-Tourismus: Herausforderungen und Trends der Digitalisierung im Tourismus (pp. 35–42). Erich Schmidt Verlag.

Buttle, F. (2006). Customer Relationship Management: Concept and Tools. Elsevier.

Cambra-Fierroa, J. J., Centenob, E., Olavarriaa, A., & Vazquez-Carrasco, R. (2017). Success factors in a CRM strategy: technology is not all. Journal of Strategic Marketing, 25(4), 316–333.

Court, D., Elzinga, D., Mulder, S., & Vetvik, O. J. (2009). The consumer decision journey. McKinsey Quarterly, 3(3), 96–107.

Davey, N. (2012). Meet the new boss: Is customer experience management the new CRM? http://www. mycustomer.com/topic/customer-experience/meet-new-bosscustomer-experience-management-new-crm/141272

Dierks, A. (2017). Re-Modeling the Brand Purchase Funnel. Springer.

Duncan, T., & Moriarty, S. (2006). How integrated marketing communication's "touchpoints" can operationalize the service-dominant logic. In R. F. Lusch & S. L. Vargo (Eds.), The service-dominant logic of marketing: Dialog, debate, and directions (pp. 236–249). Taylor & Francis.

Edelman, D. C., & Singer, M. (2015). Competing on Customer Journeys: You have to create new value at every step. Harvard Business Review, 93(11), 88–100.

Fitzgibbon, C., & While, L. (2005). The role of attitudinal loyalty in the development of customer relationship management strategy within service firms. Journal of Financial Services Marketing, 9(3), 214–230.

Folstad, A., & Kvale, K. (2018). Customer Journeys: a systematic literature review. Journal of Service Theory and Practice, 28(2), 196–227.

Furnham, A., & Boo, H. (2011). A literature review of the anchoring effect. Journal of Socio-Economics, 40(1), 35–42.

Goodrich, M. T., & Tamassia, R. (2015). Algorithm Design and Applications. Wiley.

Gummesson, E. (2004). Return on relationships (ROR): The value of relationship marketing and CRM in business-to-business contexts. Journal of Business & Industrial Marketing, 19(2), 136–148.

Hamilton, R., Thomson, D., Bone, S., Chaplin, L. N., Griskevicius, V., Goldsmith, K., Hill, R., John, R. D., Mittal, C., O'Guinn, T., Piff, P., Roux, C., Shah A., & Zhu, M. (2019). The effects of scarcity on consumer decision journeys. Journal of the Academy of Marketing Science, 47(3), 523–550.

Hassoun, M. (2003). Fundamentals of Artificial Neural Networks. MIT Press.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). The elements of statistical learning: data mining, inference, and prediction. Springer.

Homburg, C., Jozic, D., & Kuehln, C. (2017). Customer experience management: toward implementing an evolving marketing conception. Journal of Academic Marketing Sciences, 45, 377–401.

Hughes, C., Swaminathan, V., & Brooks, G. (2019). Driving Brand Engagement Through OnlineSocial Influencers: An Empirical Investigation of Sponsored Blogging Campaigns. Journal of Marketing, 83(5), 78–96.

Jackson, T. W. (2005). CRM: From 'art to science'. Database Marketing & Customer Strategy Management, 13(1), 76–92.

Jansen, B., & Schuster, S. (2011). Bidding on the Buying Funnel for Sponsored Search an Keyword Advertising. Journal of Electronic Commerce Research, 12(1), 1–18.

John, W. (2018). Some functionality aspects of Customer Relationship Management: A review of studies. The Marketing Review, 18(2), 181–199. https://doi.org/10.1362/146934718X15333820910174

Kietzmann, J., Paschen, J., & Treen, E. (2018). Artificial Intelligence in Advertising – How Marketers can Leverage Artificial Intelligence Along the Consumer Journey. Journal of Advertising Research, 58(3), 263–267.

Krämer, A., & Schmutz, I. (2020). Mythos Value-Based-Pricing: Der Versuch einer (wertfreien) Einordnung. Marketing Review St. Gallen, 2, 44–53.

Lavidge, R. J., & Steiner, G. A. (1961). A Model for Predictive Measurements of Advertising Effectiveness. Journal of Marketing, 25(6), 59–62.

Lee, G. (2010). Death of 'last click wins': media attribution and the expanding use of media data. Journal of Direct, Data and Digital Marketing Practice, 12(1), 16–26.

Lemon, K. N., & Verhoef, P. C. (2016). Understanding the customer experience throughout the customer journey. Journal of Marketing Research, 80(16), 69–96.

Ling, R., & Yen, D. C. (2001). Customer relationship management: An analysis framework and implementation strategies. Journal of Computer Information Systems, 41(3), 82–98.

Lingqvist, O., Plotkin, C., & Stanley, J. (2015). Do you really understand how your business customers buy? McKinsey Quarterly, 1, 74–85.

Loussaief, L., Ulrich, I., & Damay, C. (2019). How does access to luxury fashion challenge self-identity? Exploring women's practices of joint and non-ownership. Journal of Business Research, 102, 263–272.

Maslow, A. (1987). Motivation and Personality (3.th ed.). Prahat Prakashan.

Meyer, C., & Schwager, A. (2007). Understanding the Customer Experience. Harvard Business Review, 85(2), 116.

Muret, P. (2013). Introducing 'the customer journey to online purchase' – interactive insights on multi-channel marketing. https://analytics.googleblog.com/2013/04/introducing-customer-journey-to-online.html

Nunes Silva, I., Hernane Spatti, D., Andrade Flauzino, R., Liboni, L.H.B., & dos Reis Alves, S. F. (2017). Artifical Neural Networks. Springer.

Opresnik, M. O., & Yilmaz, O. (2016). Die Geheimnisse erfolgreichen YouTube-Marketings: Von YouTubern lernen und Social Media Chancen nutzen. Springer.

Patel, R. K., Perret, J. K., & Samunderu, E. (2021). Unbundling CRM - A RFMC Perspective. Forthcoming.

Payne, A., & Frow, P. (2005). A strategic framework for customer relationship management. Journal of Marketing Research, 69(4), 167–175.

Peng, C.-C., Wang, Y.-Z., & Huang, C.-W. (2020). Artificial-Neural-Network-Based Consumer Behavior Prediction: A Survey (2020 IEEE 2nd Eurasia Conference on Biomedical Engineering, Healthcare and Sustainability (ECBIOS)).

Pham, M. T., & Lee, L. (2019). Introduction to Special Issue: Consumer Emotions in the Marketplace. Journal of the Association for Consumer Research, 4(2), 98–101. https://doi.org/10.1086/702851

Richardson, A. (2010). Using customer journey map to improve customer Experience. Harvard Business Review, 15(1), 2–5.

Rosenbaum, M. S., Otalore, M. L., & Ramírez, G. (2016). How to create a realistic customer journey map. Business Horizons, 60(1), 1342–1350.

Schwarz, T. (2019). Praxistipps Customer Experience. https://www.marketing-boerse.de/whitepaper/download/1910-praxistipps-customer-experience/154739

Skinner, C. (2010). The complete customer journey: Avoiding technology and business barriers to measure the total value of media. Business Strategy Series, 11(4), 223–226.

Sota, S., Chaudhry, H., Chamaria, A., & Chauhan, A. (2018). Customer Relationship Management Research from 2007 to 2016: An Academic Literature Review. Journal of Relationship Marketing, 17(4), 277–291. https://doi.org/10.1080/15332667.2018.1440148

Strauss, W., & Howe, N. (1991). Generations – The History of America's Future 1584 to 2069. Quill.

Tedesco, B. G. (1992). Neural Marketing: Artificial Intelligence Neural Networks in Measuring Consumer Expectations. Grey Associates.

Tkac, M., & Verner, R. (2016). Artificial Neural Networks in Business: Two Decades of Research. Applied Soft Computing, 38, 788–804.

Venturini, W. T., & Benito, O. Z. (2015). CRM software success: a proposed performance measurement scale. Journal of Knowledge Management, 19(4), 856–875.

Verhoef, P. C., Lemon, K. N., Parasuraman, A., Roggeveen, A., Tsiros, M., & Schlesinger, L. A. (2009). Customer Experience reation: determinants, dynamics and management strategies. Journal of Retailing, 85(1), 31–41.

Wansink, B., Kent, R., & Hoch, S. (1998). An anchoring and adjustment model of purchase quantity decisions. Journal of Marketing Research, 35(1), 71–81.

Whitby, B. (2003). A Beginner’s Guide: Artificial Intelligence. Oneworld Publications.

Winer, R. S. (2001). A framework for customer relationship management. California Management Review, 43(4), 89–105.

Woelfel, J. (1992). Artificial Neural Networks for Advertising and Marketing Research: A Current Assessment. University of Buffalo Press.

Zablah, A., Bellenger, D., & Johnston, W. (2004). Customer relationship management implementation gaps. Journal of Personal Selling & Sales Management, 24(4), 279–295.

Appendix:

Comments on the Statistical Methodology and the Notation

To account for the specificity of the building blocks, the survey implemented a questionnaire consisting of different scales. Whenever the association of any two building blocks have been analyzed, not always has it been possible to use an aggregated version where each building block is represented by a single variable. As can be seen from Table 8, most building blocks consist of questions that cannot be summarized since they refer to inherently different brands or clothing types. Thus, relating any two building blocks with each other requires a measure for an m to n relation. To solve this problem three alternatives are possible; averaging the results of all sub-variables, the use of structural equation model or considering all possible m x n relations and summarizing them into a single measure. Since the first two solutions require the a priori establishment of an underlying structure how the questions make up each of the building blocks, this study realized the third alternative and was conducted at different levels of detail and the following notation illustrates how the tables summarizing the results (i.e. Table 5 and Table 6) have to be read. It is noted that the implemented approach has the problem that results might be skewed since it theoretically allows for large number of very weak links to result in a perceived strong overall link between the two building blocks. Thus, the values reported in Table 5 used as proxies for the strength of the relation of two building blocks should not (unless otherwise stated) be interpreted as being comparable to the strength of a statistical measure of association but rather as a share of pairwise relations that are at least significantly related to each other.

To measure this proxy for the strength of the association of any two building blocks, one of four approaches have been implemented. In each approach, the implemented tests have been chosen with regard to the scale level of the variables involved in the tests:

- Two nominal variables / One nominal and one ordinal variable:
  χ^2-contingency tests for stochastic independence by Pearson – (Pearson, 1900)
- Two ordinal variables:
  Spearman correlation coefficient – (Spearman, 1904)
- Two metric variables:
  Pearson correlation coefficient - (Pearson, 1895; Bravais, 1846)
- One nominal and one metric variable:
  T-tests – (Student, 1908) or Variance analyses - (Fisher, 1921)

In each situation, the implementation of the method in SPSS 23 has been used. With regard to the first four methods, Perret (2019) provides the mathematical background.

If a single test has been possible to relate two building blocks (i.e. all combinations of the building blocks 1, 2, 5, 6, 9 and 10 with one another) the significance level of the underlying test defines the strength of the relation. In this case, the following color-coding scheme has been used in addition to reporting the significance level.

Very strong relation	dark gray	Significance level < 0.01
Strong relation	medium gray	Significance level between 0.01 and < 0.05
Weak relation	light gray	Significance level between 0.05 and < 0.1
No relation	white	Significance level ≥ 0.1

Alternatively, for a combination containing any of building blocks 3, 4, 7 and 8 more than a single test is required as their sub-categories cannot be summarized into a single variable. Thus, a set of tests is conducted here. For example, the block BB3 *Brand Knowledge* cannot be summarized into a single variable. Thus, when the relation between the blocks BB2 and BB3 – *Influencers* and *Brand Knowledge* - is analyzed for each brand a separate test is conducted, leading to eight tests in total.

To evaluate the strength of the relation between two building blocks in this context, the share of tests that report a significance level of at least 0.1 (weak significance) is considered. The following four groups of equal width define the strength of the relation. Note, that strength does at this point not refer to the effect size of a relation between two variables, but whether there is an established relation between two building blocks. The quality of the analysis has been assured by performing the analysis with and without a Bonferroni correction – (Dunn, 1958; Dunn, 1961) – leading to comparable results. A Bonferroni correction implies that the required significance level is adjusted by the number of sub-tests involved. For example, with ten subtests the critical significance levels changes from 0.05 to 0.005.

Very strong relation	dark gray	Share ≥ 0.75
Strong relation	medium gray	Share between 0.5 and < 0.75
Weak relation	light gray	Share between 0.25 and < 0.5
No relation	white	Share < 0.25

E.g. if 16 subtests are required and 7 of them report on a significant relation, with a share of 7/16 = 0.4375 it is assumed to be an overall weak relation.

To differentiate between the first and the second type of relations, the first type (significance levels) of relations are printed in bold face.

Additional Table

Table 8:Categories of the different Building Blocks

BB1	BB2	BB3	BB4	BB5	BB6	BB7	BB8	BB9	BB10
Homepages	Partner	Lascana	Quality	Cotton	Affiliate Retailer (Offline)	Bra	Wear-at-Home	-	Necessity
Catalogs	Friends	H&M	Fit	Lace	Affiliate Retailer (Online)	Slip	Sport		Wellbeing
Journals	Retailer	Passionata	Price	Polyester	Specialized Store (Offline)	Bustier	Workaday Life		Acceptance
Newspapers	Advertisements	C&A	Convenience	Silk	Specialized Store (Online)	Body	Sexyness		Body Forming
Stores	Influencer	Trumph	Sexyness	Functional Textiles	Department Store (Offline)	Set	Celebratory		Self Gratification
TV	Celebrities	Hunkemöller	Sustainability	Other	Department Store (Online)	Nightwear	Business		Self Realization
Facebook	Other	Schiesser	Trends/Fashion		Clothing Chain (Offline)		Period		Feeling Attractive
Instagram	Not influenced	Calvin Klein	Functionality		Clothing Chain (Online)		Shapewear		Sonstiges
Youtube			Experience		Online (Offline)		Going-out		
Other SM			Established Brand		Online (Online)		Other		
Radio			Other						
Other									
Not interested									

Source: Own Table

Questionnaire

The following summary represent an English translation of the German original of the questionnaire implemented in this study.

Q1: You are a… ○ man ○ woman

Q2: First of all, we would like to know from you where you mainly buy your laundry? Please name only the three most important shopping sources. Please also differentiate between online and on-site business.

	On-site	Online
Branch of a specific lingerie brand (e.g. Hunkemöller, Victorias Secret)	☐	☐
Lingerie specialty store	☐	☐
Department store (e.g. Galeria Karstadt Kaufhof)	☐	☐
Clothing chain (e.g. H&M, Esprit, C&A)	☐	☐
Online retailers (e.g. Amazon, Zalando)	☐	-

Q3: How much money do you spend on average on the following laundry items? If you generally do not buy one of the laundry items from the list, please indicate this in the corresponding field.

		I generally do not buy this type of laundry
Bra	_______€	☐
Slip	_______€	☐
Bustier	_______€	☐
Body	_______€	☐
Underwear-Set (Bra and Slip)	_______€	☐
Nightwear (e.g. pajamas, nightgown)	_______€	☐

Q4: Which of the following criteria are important to you personally when buying underwear?

	Important	Rather important	Rather unimportant	Unimportant
Quality	○	○	○	○
Shape	○	○	○	○
Price	○	○	○	○
Convenience	○	○	○	○

Sexyness	O	O	O	O
Sustainability	O	O	O	O
Trends/Fashion	O	O	O	O
Functionality	O	O	O	O
Shopping Experience	O	O	O	O
Established Brand	O	O	O	O
Other	O	O	O	O

Q5: Who or what influences you in choosing your underwear? Please name a maximum of three alternatives:

- I am not influenced in this
- Partner
- Friends
- Salesperson
- Ads
- Online Influencer
- Celebrities wearing the brand
- Others: _____________

Q6: What material do you prefer when buying your underwear?

- Cotton
- Lace
- Polyester
- Silk
- Functional Textiles
- Others: _____________

Q7: Now please think about all the underwear you have in your closet. According to which occasions would you categorize them? You can name a maximum of five occasions.

Q8: You can see some possible categories here. If you would sort your laundry drawer at home in your mind: Which proportion would meet the following criteria? Please distribute a total of 100 points - according to their importance for you.

Wear at home
Sport
Daily Wear (Practical)
Sexyness / Seduction
Festive occasions
Business
Period
Shapewear
Going-out (with friends / partner)
Others

Q9: On average, how much time do you take in the morning to choose your underwear?

- 0 – 30 Seconds
- > 30 Seconds – 1 Minute
- > 1 Minute – 3 Minutes
- > 3 Minutes

Q10: Do you inform yourself about lingerie trends? If yes, through which information channels? Please name only the three most important sources.

- I am basically not interested in lingerie trends.
- Homepages of lingerie retailers
- Mail order catalogs
- Journals
- Newpapers
- In stores
- TV
- Facebook
- Instagram
- Youtube
- Other Social Media Channels
- Radio
- Others: ____________________

Q11: Which of the following brands of underwear are you familiar with?

	Familiar with	Do not know
Lascana	○	○
H & M	○	○
Passionata	○	○
C & A	○	○
Triumph	○	○
Hunkemöller	○	○
Schiesser	○	○
Calvin Klein	○	○

Q12: (Showing only those brands selected in Q11) Which brands do you like the most? Assign the value 1 to the brand you like the most and the value 8 to the one you like the least.

	Rank
Lascana	
H & M	
Passionata	
C & A	
Triumph	
Hunkemöller	
Schiesser	
Calvin Klein	

Q13: Which of the following statements about lingerie best apply to you? Please name only the three motifs that are most appropriate for you personally.

- I wear underwear from pure necessity.
- Underwear helps me feel comfortable in my body.
- Underwear helps me to accept myself in my body.
- I use underwear to "shape" my body a bit.
- Buying underwear represents a kind of self-reward for me.
- Underwear helps me to realize myself.
- Underwear helps me feel attractive/ sexy.
- Others: ______________________________

Q14: How big is the town you live in?

- Up to 5,000 inhabitants
- 5,001 – 20,000 inhabitants
- 20,001 – 100,000 inhabitants
- 100,001 – 300,000 inhabitants
- 300,001 – 500,000 inhabitants
- > 500,000 inhabitants

Q15: How do you currently live?

- Stable relationship, living with partner in one household
- Stable relationship, but living in two households
- Living with partner and child/children in one household
- In a stable partnership and with child/children, but living in two households
- Single with child/children
- Single without children

Q16: How much money do you personally earn net per month?

- No personal income
- < 500€
- 501 – 1,000€
- 1,001 – 1,500€
- 1,501 – 2,000€
- > 2,000€

Authors

Prof. Dr. Christian **Duncker** has many years of experience in the fields of fashion, brand management and marketing. After studying sociology, business administration and psychology at the University of Hamburg, he worked in strategic marketing for various companies. This was followed in 2004 by the founding of the Institute for Empirische Markenforschung. In 2011, he was appointed Professor of Marketing at the Brand Academy Hamburg, where he took over as Head of the Department of Management and, in 2012, as Vice President for Teaching and Research. From 2019 to 2021, he was Professor of Marketing and Brand Management at ISM in Munich. He currently works with his institute Empirische Markenforschung for various clients in the field of brand and fashion research in Wiesbaden.

Prof. Dr. Jens K. **Perret** studied Business Mathematics and Business Administration at the University of Wuppertal. He finished his doctoral thesis in Economics on the knowledge society in Russia at the University of Wuppertal. Between 2004 and 2016 Mr. Perret worked at the European Institute for International Economic Relations first as a research assistant and later as a scientific researcher. From 2007 till 2016 Mr. Perret has been working as a Research Assistant at the Chair for Macroeconomic Theory and Policy. From 2012 to 2014 he has been a contractual lecturer at the Technical University Kaliningrad. Since September 2016 he holds a full professorship for Economics and Statistics at the International School of Management in Cologne.

Traut, Joshua; Simonov, Alexander; Meitner, Matthias

Quantifying Alpha of Active Managers: A Case Study on Factor-Based Performance Attribution in Fixed-Income

Abstract

This paper contributes to the ongoing debate of whether active investing is still worthwhile in presence of factor investing. It provides a universal framework that selects presumably factor-heavy fixed-income funds. To test the framework, returns of an exemplary fund are neutralized for factor exposures. Roughly 60% of returns are attributed to factors and the remaining 40% are interpreted as the manager's alpha. While these results are only valid for this particular fund, the analysis provides a better understanding of the active/passive discussion in fixed-income and contributes worthy insights to the fund manager selection and performance evaluation literature and practice.

Keywords: *Factors, factor investing, fixed-income, manager selection, performance attribution, performance evaluation, portfolio management, style investing*

1 Introduction

Factor investing has gained a lot of traction among practitioners and academia. The rise of smart beta ETFs initiated a greater trend toward using factor investing in passive portfolios (Blitz 2016; Kenechukwu et al. 2020). This rise has led to a discussion on whether traditional mutual funds are still worth their relatively high costs compared to ETFs. The ongoing discussion has been fueled by various academic findings. For example, that most alpha of mutual funds is just an overweighting of beta (Fung & Hsieh, 2004; Crowell et al., 2012; Ibbotson et al., 2013). Furthermore, funds with a high variation in exposure underperform their peers (Ammann et al., 2020). This shows that active management destroys value rather than creates it.

While most studies in this field focus on equities, research on fixed-income has gained more attention lately. Here, similar concerns about the value of active management are raised (Mattu et al., 2016; Baz et al., 2017). One study even claims that most performance of active fixed-income managers can be attributed to factors (Brooks et al., 2020). Another one shows that the factor exposure of funds is a significant predictor of future returns (Chin & Tang, 2020). These findings indicate that active excess returns are unlikely attributable to managers' market timing and security selection ability but rather to overweighting factors. This strategy could also be implemented in a passive, more cost-efficient way.

To illumine factor use in the mutual fund industry, researchers have recently investigated the fund returns of widely known fund managers (Frazzini et al., 2018; Brooks et al., 2019; Dewey & Brown, 2019). These studies are most closely related to the paper at hand. They measure active managers' exposure to passive factor portfolio benchmarks that they find to be relevant for the return generation of the fund. All of them at least partly support the claim that mutual fund managers do not generate excess returns through their superior asset selection or market timing ability. They do so rather through the implementation of factor strategies.

This paper enhances the discussion on active mutual funds. It pursues the primary purpose to apply the approach of the above-mentioned studies to another exemplarily mutual fund in the area of fixed-income. Research has focused primarily on managers of large mandates who publicly declared following structured long-term strategies and to some extent factors. Given the large size of these funds, it comes at little surprise that they follow systematic investment strategies to some extent because they may not be able to identify enough undervalued assets to invest all liquid funds. This is especially important in fixed-income where investible assets have a fixed nominal amount. To illumine factor use for smaller mandates that may not be exposed to that issue, this paper selects a smaller fund based on a framework that is created to detect funds that likely use factors. This framework is designed to be applicable to other markets and fund types. A factor return attribution is executed on the fund's returns to critically evaluate the manager's alpha generation skill. Following the literature on factor use for large mandates, factor portfolios are built that are used in a regression framework to assess the fund's factor exposure. This attribution analysis can be compared to creating a synthetic ETF that mimics the investment strategy of the active fund manager. The performance of this tailor-made ETF and the active fund is then compared to draw conclusions on the manager's idiosyncratic alpha generation skill. To reduce the risk of overfitting or so-called "p-hacking" factors used in the analysis are justified by insights gathered on the manager's style via an interview.

The results of the analysis suggest that the manager's contribution to returns comprises roughly 40% of the fund's average annual performance. More precisely, a relatively large remainder of 2.11% p.a. (that can be interpreted as the manager's alpha) remains unexplained by the model. However, 75% of the variance in the fund's returns can be explained by the tested factors. This demonstrates that factors play a significant role for the fund's returns.

Though large parts of this paper are dedicated to the exemplary performance attribution of one selected fund, its insights are relevant for literature and practice from a more general perspective. It demonstrates that factors are not only relevant for the largest mutual funds but also play a considerable role for smaller mandates. Consequently, when evaluating performance and selecting fund managers, including factors in the analysis is inevitable to make well-found decisions. This paper provides useful practical tools to evaluate investment opportunities. The comprehensive factor literature collection, which reaches beyond the factors that are used in the exemplary performance attribution, is a good starting point to evaluate fixed-income funds for factor exposure. The general framework of the fund selection process can be used in the manager/fund selection process by investors and can be adapted to any other asset class. Overall, the findings create valuable insights into the ongoing discussion of active vs. passive investments. These insights can be used to make better investment decisions and improve performance evaluations.

This paper is structured into 10 sections. Section 2 outlines a theoretical foundation and provides a comprehensive summary of performance attribution and factor investing in fixed-income. It broadly presents the tools that are available for the analysis and covers those that are actually used in more detail. Section 3 covers the structured fund selection process that intends to objectively select a presumably factor-heavy fund for the analysis. Section 4 identifies the style of the fund's manager. This is done to detect the appropriate factors for the analysis among those that were outlined in the theoretical foundation. Section 5 describes the data used in the empirical analysis. Section 6 provides a detailed explanation of the factor construction and section 7 explains the design of the factor portfolios. These portfolios embody a benchmark of factor investing strategies that were found to be relevant in for the fund in the style analysis. Section 8 then measures the fund's exposure to these portfolios and presents the results of the performance attribution. In other words, it evaluates how much of the fund manager's performance can be attributed to structured factor strategies. Section 9 critically discusses the results of the analysis. Section 10 concludes the paper with a summary of the outcomes, practical implications of the findings, and a future outlook.

2 Literature Review

In the literature, different types of performance attribution are discussed. The two most commonly executed attribution methodologies are the sector-based attribution based on the work of Fama (1972) and Brinson et al. (1986) and the factor-based attribution. At its roots, a fixed-income security can be thought of as a structured investment that promises to pay off cash-flow streams. These payments are either fixed or depend on observable variables. This quasi-formulaic nature of bonds allows expressing their present value as a function of economic variables. Given this rationale, scholars argue that fixed-income performance attribution should follow rather a factor-based than a sector-based approach (Khang & King, 2004; Daul et al., 2010; Fabozzi, 2012, pp. 1670–1710).

Factor investing is an investment style that seeks to deliver long-term returns by creating exposure to specific factor risks to generate a favorable risk-return profile. The foundation of factor investing is built on the capital asset pricing model (CAPM). It takes exposure to market risk as the only driver for returns (Treynor, 1961; Sharpe, 1964; Lintner, 1965; Mossin, 1966) and can be interpreted as the first single-factor model. After the finding that excess returns can be harvested with relatively simple investment strategies, Fama and French (1992) declared that the CAPM is a rather useless tool for explaining the average returns of securities. Ever since then, many schematic investment strategies – so-called factor strategies – have been identified and researched across different asset classes and markets. Even though most factors were primarily developed for equities, they are also relevant for fixed-income, as equities are found to lead corporate bonds regarding firm-specific information (Kwan, 1996; Gebhardt et al., 2005), equity KPIs can be used to predict bond returns (Chordia et al., 2017) and equity factors are proven to generate excess returns in bond markets (Harvey et al., 2002). Regardless, factors that are specifically modified for bond markets work better than unmodified equity factors in fixed-income (Houweling & van Zundert, 2017).

For this paper, the value and defensive factors are most relevant as other return factors are found not to be relevant for the return generation of the selected fund. The selection process of appropriate return factors is further described in section 4. A more detailed literature review will only be provided for the two relevant factors – value and defensive – in the following paragraphs. However, other common return factors in fixed income that were also considered for the analysis are listed below including a very short description of that strategy and a non-exhaustive list of related literature:

- Momentum: Buying (selling) past outperformers (underperformers) generates excess returns

(Jegadeesh & Titman, 1993; Daniel et al., 1998; Hong & Stein, 1999; Khang & King, 2004; Gebhardt et al., 2005; Dimson et al., 2008; L'Hoir & Boulhabel, 2010; Pospisil & Zhang, 2010; Luu & Yu, 2012; Moskowitz et al., 2012; Asness et al., 2013, 2014; Jostova et al., 2013; Duyvesteyn & Martens, 2014; Hambusch et al., 2015; Houweling & van Zundert, 2017; Zaremba & Czapkiewicz, 2017; Brooks, 2017; Israel et al., 2018; Brooks et al., 2018; Zaremba & Kambouris, 2019).

- Carry: Investing (lending) in higher-yielding markets or assets and financing the position by shorting (borrowing) in lower-yielding markets generates excess returns (Asness et al., 2014; Brooks & Moskowitz, 2017; Brooks et al., 2018; Israel et al., 2018; Koijen et al., 2018; Beekhuizen et al., 2019; Bektić et al., 2020; Kothe et al., 2021).

- Volatility: Selling volatility is rewarded with excess returns (Goodman & Ho, 1997; Duarte et al., 2007; Ni, 2008; Simon, 2010; Choi et al., 2017; Israelov et al., 2017).

- Liquidity: Holding less liquid assets is rewarded with excess returns (Amihud & Mendelson, 1991; Warga, 1992; Kamara, 1994; Krishnamurthy, 2002; Longstaff, 2004; L. Chen et al., 2007; Goyenko et al., 2011; Ejsing et al., 2012; Acharya et al., 2013; Ibbotson et al., 2013; Boudoukh et al., 2016).

- Credit: Holding credit risk generates higher returns (Elton et al., 2001; Longstaff et al., 2005, 2011; Kozhemiakin, 2007; Hallerbach & Houweling, 2013; Asvanunt & Richardson, 2017; Dockner et al., 2017; Zaremba & Czapkiewicz, 2017).

- Inflation: Exposure to inflation uncertainty risk yields a premium (Ang & Piazzesi, 2003; Wei et al., 2005; D'Amico & Orphanides, 2008; Wright, 2011; Hördahl & Tristani, 2012; Joslin et al., 2014; Cieslak & Povala, 2015; Brooks & Moskowitz, 2017; Bauer & Hamilton, 2018).

First documented by Basu (1977) in equity markets, the value factor is widely adapted and researched for fixed-income markets. Generally, the value premium refers to the regularity with which assets with low valuation ratios – usually the market price relative to a fundamental measure – tend to outperform. For government bonds, a widely used value measure is the 5-year change of yields in 10-year government bonds. This factor generates significant excess returns (Asness et al., 2013) and is motivated by the finding that a direct link exists between past bond returns and equity value factors (Fama & French, 1996; Gerakos & Linnainmaa, 2018). Another value measure is the real yield of government bonds, which is calculated by subtracting maturity-matched inflation from nominal treasury yields. This factor is used across government bond markets and contributes to the overall alpha of style portfolios (Asness et al., 2014; Brooks & Moskowitz, 2017; Brooks et al., 2018; Kothe et al., 2021). A more comprehensive methodology for the value factor in government bond markets is to define value as the residual of a regression of yield-to-maturity of a bond on its duration and credit score (Zaremba & Czapkiewicz, 2017). For corporate bonds, literature differentiates between publicly traded and private companies when constructing value factors. For public companies, a structural model that is based on the work of Correia et al. (2012) is commonly used. In contrast, for non-public companies, an empirical model motivated by Israel et al. (2018) is employed. The aggregated results of both methodologies are used to build the value factor for public and private corporate bonds, with which significant excess returns in the U.S. government bond sector can be earned (Brooks et al., 2018; Israel et al., 2018). A simpler value factor methodology calculates a theoretical spread based on a regression of the option-adjusted spread on the issuer's rating, time to maturity, and the bond's 3-month spread change. Portfolios built based on the difference between theoretical and actual spread generate significant excess returns in U.S. markets (Houweling & van Zundert, 2017). Similar results are achieved in the U.K. market following the same methodology but here market as well as company-specific factors are considered (L'Hoir & Boulhabel, 2010).

The defensive factor is based on the findings that unlike predicted by the CAPM, risk does not correlate with higher returns (Black et al., 1972; Fama & MacBeth, 1973; Haugen & Heins, 1975; Haugen & Baker, 1991, 1996; Black, 1993; Clarke et al., 2010; Baker et al., 2011). Based on these insights, a "defensive" investment strategy exploits the circumstance that risky assets earn lower risk-adjusted returns than their defensive counterparts. In government bond markets the most promising risk-adjusted returns can be earned by assets with short maturities and high credit ratings (Ilmanen et al., 2004; Pilotte & Sterbenz, 2006). Long-short portfolios for Treasury bills sorted on maturities generate excess returns (Frazzini & Pedersen, 2014). Similarly, effective duration can be used as the measure of government bond risk to create favorable risk-return profiles (Brooks et al., 2018; Kothe et al., 2021). The same applies to modified duration with which significant average excess returns can be earned in developed and emerging markets (Zaremba & Czapkiewicz, 2017). A comparison of 3-month LIBOR rates with bond index yields is also found to create positive excess returns if used as a defensive measure (Duyvesteyn & Martens, 2014). The methodologies used for corporate bonds follow similar approaches. Low-maturity corporate bonds are found to generate outperformance compared to their high-maturity counterparts (Derwall et al., 2009; Frazzini & Pedersen, 2014; Aussenegg et al., 2015). To enhance the robustness and stability of defensive strategies, some scholars suggest extending the methodologies by fundamental measures of risk. The downside of this procedure is that the defensive strategy may overlap with value factors (Asness et al., 2014). This more comprehensive methodology is used in two broad market studies. In addition to low duration, low market leverage and high gross profitability are taken as defensive measures and favorable risk-return ratios can be earned with the resulting portfolios (Brooks et al., 2018; Israel et al., 2018). A more simplified approach uses maturity and rating to define defensive portfolios for the U.S. corporate bond market where significant excess returns can be earned with the strategy (Houweling & van Zundert, 2017).

Multifactor investing can yield various benefits. It is reported in various studies that the low correlation among factors can be used to increase risk-return ratios of portfolios, making the whole more efficient than the sum of its parts (Bender et al., 2010; L'Hoir & Boulhabel, 2010; Asness et al., 2014; Houweling & van Zundert, 2017; Zaremba & Czapkiewicz, 2017; Brooks et al., 2018; Israel et al., 2018; Kothe et al., 2021). Furthermore, Ilmanen and Kizer (2012) prove that a factor portfolio delivers better risk-adjusted returns than a comparable portfolio that is well-diversified across asset classes. When designing factor portfolios, some principal guidelines should be followed. Well-designed factors should not be related to macroeconomic variables to ensure that the factor measures the exposure to the desired characteristic and is not caused by other variables. Most factors that were presented in this literature review are shown to fulfill this characteristic (Brooks & Moskowitz, 2017; Choi et al., 2017; Brooks et al., 2018). Also, different design choices of factors can result in varying factor exposures and performances. For example, L'Hoir and Boulhabel (2010) employ two momentum measures in U.K. bond markets, one measuring cash flow surprise and the other capturing equity price momentum. Even though both factors measure momentum and are short-term oriented, their correlation is negative. As these design choices yield different results, some scholars recommend using multiple measures for a specific factor as this tends to increase the factor's performance and coverage (Israel & Ross, 2017).

3 Fund Selection Process

The fund selection framework is driven by various criteria. The first is a long employment relationship of the head portfolio manager with the fund. It is documented that changes in top management lead to significant differences in fund performance (Khorana, 2001). This phenomenon is likely accompanied by a significant change in the manager's style. So, taking a fund that has experienced multiple changes of management in the past would make concluding the individual style of the manager impossible. Because stricter investment guidelines leave less room for the fund manager to implement his style in the fund, weak investment guidelines are the second criterion in the selection framework. Regarding the fund’s size, as securities in fixed-income have a defined nominal amount and more favorable investments have to be found with increasing fund size, fundamental bottom-up investing might not be beneficial for larger funds. Such larger funds are favored in the fund selection because it is assumed that their managers express their views rather through factors than through security selection. Lastly, successful funds are favored in the selection because it is assumed that such funds follow an effective, market-proven investment strategy that has not been altered in the past making an attribution to factors more implementable. As a result, the four criteria for the selection framework are

1. The manager’s employment relationship duration,
2. The restrictiveness of investment guidelines,
3. The fund’s size,
4. The fund’s success.

Based on the criteria, the M&G Global Macro Bond Fund is chosen for the analysis. Its head fund manager, Jim Leaviss has been the fund manager since 1999 (M&G Investments, 2020a), which is long enough to create statistically significant attribution insights into his investment style. Investment restrictions are found to be relatively low, meaning that Jim Leaviss can express his market views freely (M&G Investments, 2020b). Regarding the fund’s size, as of November 2020, the M&G Global Macro Bond Fund had $1,04 billion assets under management (M&G Investments, 2020a). By the end of 2019, the average worldwide fund size was $448 million assets under management. In the U.K., where the M&G fund is registered (M&G Investments, 2020d, p. 10), funds are larger with an average of $600 million assets under management for all funds and $620 million for bond funds. Given that the M&G fund is roughly 75% larger than the average bond fund in the U.K., it sufficiently fulfills the third criterion of the fund selection. Lastly, the fund can be considered successful as it outperformed its benchmark in 7 of the past 10 years (M&G Investments, 2020c). It won the award of the best developed-market fixed-income fund (Portfolio Adviser, 2019) and received a 4-star Morningstar rating as well as a silver Morningstar Analyst rating (M&G Investments, 2020a). Additionally, Jim Leaviss was awarded to be the fund manager of the year by Morningstar U.K. in 2019 (Morningstar UK, 2019). Overall, the M&G Global Macro Bond fund meets all criteria sufficiently, making it an optimal fund for the exemplary analysis of this paper.

4 Manager's Style

The identification of the manager's style was first approached following literature-proposed criteria and using publicly available data sources. Because this undertaking yielded non-sufficient results the decision was made to gather own data for the analysis following the process proposed by St. John et al. (2014). The additional data was collected via a semi-structured interview with the head portfolio manager of the M&G fund, Jim Leaviss. The choice for an interview was made because it is a good tool to understand the knowledge, values, beliefs, and decision-making processes of the interviewee (Young et al., 2018). An interview guide was created following the recommendations of Young et al. (2018) and Bell et al. (2019), p. 433 ff.[1] The interview was executed on the 25th of September 2020 at 10:00 am CET via the video communication platform Zoom. The main purpose of the interview was to evaluate what return factors that are listed in the literature review in section 2 are relevant for the return generation of the fund. A summary of the key insights is provided in the following paragraph.[2]

The fund was initially set up as a fund of funds in 1999 but after 5 years, the structure changed and the fund was allowed to invest in assets directly. The head portfolio manager's market opinion is properly reflected in the fund and he has been the lead fund manager ever since its inception. He determines the overall strategy and allocation of the fund in a top-down process that can be summarized as follows: First, the allocation in worldwide bond markets is determined. Then, based on the resulting currency outcome, an overlay may be performed to adjust the currency exposure. Lastly, futures and swaps are used to adjust the duration and to hedge in and out of markets. Within that process, the fund's internal risk benchmark, the Bloomberg Barclays Global Aggregate Index, does not influence the asset allocation. Regarding style, the manager claims that his investment approach is more qualitatively driven with a focus on global market trends. When the interview was executed, these trends were demographics, technology, and central bank regimes. Macroeconomic data, general market sentiment, spread levels, and break-even inflation rates are some of the primary data sources to form the manager's opinion on the market. Though the he states not to follow factor strategies, some trends in his asset allocation can be observed. Most of the time, the fund underweights credits and tends to sell off risky assets early in the cycle. Also, though the fund can invest worldwide, it has a home bias and thus has most of its competence in European and American markets. Liquidity is an important criterion for the fund's investments and hence the fund majorly holds liquid government bonds, currencies, credit default swaps, and futures. The latter are mostly used to enter short positions. Currencies deliver an important contribution to the fund's performance and are selected based on the relative cheapness according to their real purchasing power. Also, the fund always has exposure to the Japanese Yen.

[1] The complete interview guide can be made available by the authors on request.

[2] A transcript of the interview can be made available by the authors on request.

Overall, three main style factors were identified to be used by the fund. As price levels as well as relative and absolute valuations are important sources of information for the manager, a value factor is chosen to be incorporated in the performance attribution analysis. Second, as the manager mentioned that usually, he has relatively low credit exposure compared to the market, he should have exposure to defensive factor returns. Also, though not mentioned in the literature review, the fund's unusually high currency exposure calls for a tailor-made currency factor that replicates the currency strategy of the fund. The manager's currency investments seem to be driven by relative valuations so a currency value factor is likely to be closely related to his currency strategy. Evidence for other factor-related strategies that are outlined in section 2 such as the execution of momentum, carry, volatility, liquidity, credit or inflation trades is not seen to be sufficient enough to justify the inclusion of further factors. This relatively restrictive view on the inclusion of factors is intended to avoid so-called "p-hacking". This phenomenon describes the attempt of researchers to use many factors in analyses to increase the chance of receiving significant results with the downside that unjustified factors may have high loadings and distort results (Harvey et al., 2016; Harvey, 2017).

5 Data

The period of the analysis is set between January 2004 and November 2020 because then the manager was not bound by the fund-of-fund structure anymore regarding his investment universe. The analyzed share class of the fund is the Great Britain Pound accumulation share class (ISIN: GB00B78PGS53). Government bond data of 26 different countries (United States, Canada, United Kingdom, Germany, Japan, Italy, France, Netherlands, Switzerland, Sweden, Denmark, Spain, Belgium, Greece, Austria, Portugal, Czech Republic, Hungary, Poland, Australia, New Zealand, China, India, Singapore, South Africa, and Mexico) for bonds with maturities of two and ten years is taken from the Refinitiv Datastream Benchmark Indices. Data for China and India is available after June 2007, for Singapore after December 2008, and for Mexico after June 2010. Corporate data for bonds denominated in the U.S. Dollars, Euros, and Great Britain Pounds is used from Markit IBoxx Corporate Indices. Between January 2012 and January 2014, the Euro index for corporate bonds with a rating of AAA and maturities between one and three years is reported to have an unrealistic duration of zero in the dataset. To have duration data for this timeframe, the index duration in December 2012 is adjusted with the duration change of the Euro index for corporate bonds with a rating of BBB and maturities between seven and ten years. In addition to index data, all constituent data of bonds denominated in the above three currencies of the Bloomberg Barclays Global Aggregate Corporate Index is retrieved from Bloomberg. Though the data was requested back to 2004, only data in the timespan between March 2017 and November 2020 is available. G10 currency rates (U.S. Dollar, Euro, Great Britain Pound, Japanese Yen, Norwegian Crown, Canadian Dollar, Swedish Crown, Swiss Franc, Australian Dollar, and New Zealand Dollar) as well as rates for the Indian Rupee, Chinese Renminbi, Mexican Peso, Brazilian Real, and the Russian Ruble are retrieved from Refinitiv Datastream. The overnight Libor U.S. Dollar rate is taken from the ICE Benchmark Administration. The MSCI World Index and the MSCI Emerging Market Index are taken as benchmarks for global equity and emerging market equity benchmarks. The S&P GSCI Commodity Index is retrieved as a benchmark for commodities. The iBoxx $ Corporates Index, the iBoxx £ Corporates Index, and the iBoxx € Corporates Index are aggregated and represent credit markets. The global bond market is embodied by the Bloomberg Barclays Global Aggregate Index. All of the above data is retrieved monthly at month's end for the analyzed period. Additionally, all price and return data is converted into U.S. Dollars. Though the M&G fund is denominated in Great Britain Pound, this is done because the purchasing power conversion factor for the currency factor converts a country's GDP into international dollars (U.S. Dollars) and an additional conversion into Great Britain Pound was to be avoided. Regarding economic data, purchasing power conversion factors from the Worldbank Databank, GDP deflators from the Federal Reserve Economic Databank, and consumer price indices from Refinitiv Datastream are retrieved for each country/region of the currencies mentioned above.

6 Factor Construction

Recall from section 4 that three style factors were identified to be relevant for the return generation of the selected fund. Those are a bond value factor, a currency value factor, and a defensive bond factor. Generally, the employed methodology of the factor construction and performance attribution follows the guidelines suggested by Israel and Ross (2017). They emphasize that factors should be as close to the implementation in the examined portfolio as possible and that overly theoretical factors may result in negative alpha.

6.1 Value

In line with the literature on bond value factors, factors for government and corporate bonds are designed separately.

For government bonds, as the manager reported to follow inflation rates closely, 10-year real government bond yields are taken as the measure for value, following academic research (Asness et al., 2014; Brooks & Moskowitz, 2017; Brooks et al., 2018; Kothe et al., 2021). Due to the lack of commonly used 10-year consensus inflation forecasts this paper follows Kothe et al. (2021) who use the fixed leg of 5-year inflation swaps and year-on-year changes in consumer prices, if swap data is not available, to calculate real yields. Though swap data would be a more accurate measure of maturity matched inflation it is not available for every country. To ensure an apples-to-apples comparison between countries in the portfolio construction solely changes in consumer prices are used to calculate real yields of 10-year government bonds.

For corporate bonds, the methodology of selecting the most valuable assets follows Houweling and van Zundert (2017). Unlike other scholars who use different methodologies for publicly traded and private bonds (Brooks et al., 2018; Israel et al., 2018), they apply a uniform approach, which only uses market data that is available for all bonds. Same as for the government bond valuation factor, this uniform methodology is favored for reasons of comparability. Following Houweling and van Zundert (2017), for every bond, a theoretical option-adjusted spread is calculated based on the results of a least square regression of the bond's actual option-adjusted spread on its rating, 3-month absolute spread change, and maturity. Regressions are calculated every month to ensure that changing sensitivities of the depending variables are reflected in the model.

6.2 Currency

As the fund manager declared that he selects currencies based on purchasing power parities, the currency factor is built by comparing currency spot rates relative to the purchasing power conversion factor of the respective country/region. Currencies for which the resulting ratio is relatively high are favored by the factor as it is assumed that currencies move back to an equilibrium, where the international value of currencies compared to GDP and therefore purchasing power are equal across countries. This strategy can be evaluated as a value factor for currencies as market data (spot rate) is compared to a fundamental anchor (purchasing power conversion factor). This currency value factor is already used in a performance attribution by Brooks et al. (2019). This paper follows their factor and covers the G10 currencies, the Indian Rupee, the Chinese Renminbi, the Brazilian Real, the Mexican Peso, and the Russian Ruble. The emerging market currencies are chosen as they represent the largest economies in terms of GDP from South America and Asia. African currencies are excluded from the analysis because as the fund manager never mentioned Africa in the interview, it is assumed that the fund has little to no exposure to that continent. The analysis of the currency factor is carried out separately for G10 and emerging market currencies. This is done because when adjusted with purchasing power conversion factors, emerging market currencies generally have higher spot rate to conversion factor ratios. The difference is so pronounced that emerging market currencies would always be favored by the currency factor. The resulting portfolio would be a bet that emerging market currencies outperform G10 currencies which is not what this factor intends to measure.

Generally, the currency factor suffers from the obsolescence of data, as the purchasing power conversion factor is published only once a year in June. To overcome this shortfall the conversion factor can be adjusted with inflation data throughout the year. Quarterly published GDP inflation rates help to partly overcome the problem and the remaining gaps between quarters can be adjusted with changes in consumer price indices, which are published monthly. As economic data is typically published a few weeks after the period it covers ended, it is assumed that the most recent economic data is available with a lag of one month. The currency conversion factor for each month is calculated based on a methodology that favors the most representative and up-to-date adjustment for each month, resulting in a hierarchy that favors adjustments with GDP inflation data over adjustments with consumer price index changes. At each month, the methodology checks what values are available and performs the adjustment following the hierarchy. The adjustment process for one year is demonstrated in the figure below. The arrows demonstrate what values are adjusted with what measure and the numbers represent the adjustments made in the months after the latest release of the purchasing power parity factor. For example, in October, the latest purchasing power parity factor is adjusted with GDP inflation data. That process is represented by the number "3" in the figure below.

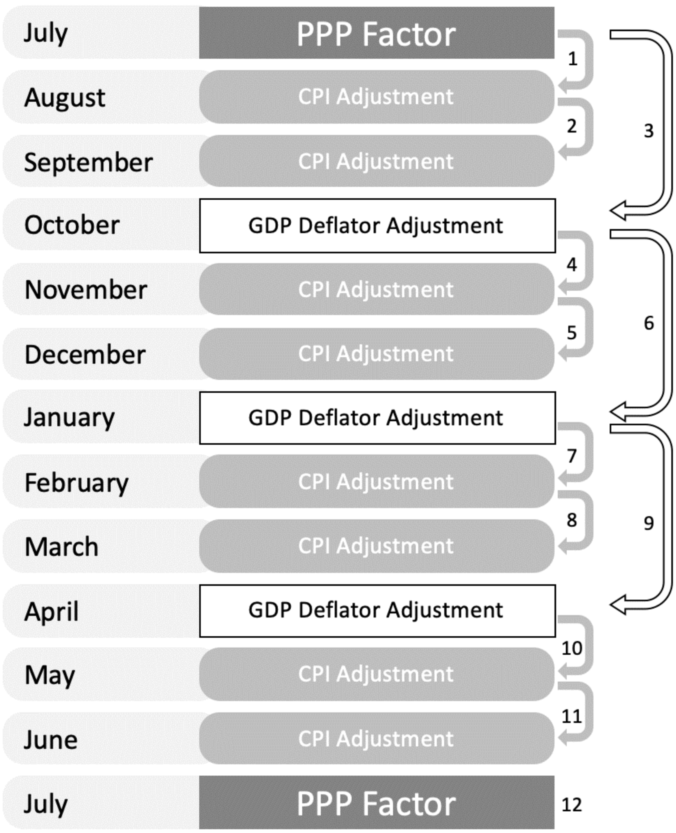


Figure 1: *Conversion Factor Adjustments*
Source: *Own illustration*

6.3 Defensive

The defensive factor is constructed for government and corporate bonds separately, which is commonly done in academic literature. As in two other studies (Brooks et al., 2018; Kothe et al., 2021), the defensive factor for government bonds is a pure maturity bet across all countries that enters a long position on the short end of the yield curve and a short position on the long end.

For corporate bonds, the factor construction is similarly simple. This is done because an extensive coverage of fundamental ratios can increase correlation with the value factor and most fundamental ratios can solely be calculated for publicly traded companies, which decreases the potential investment universe. The defensive factor for corporate bonds follows the methodology of Houweling and van Zundert (2017) who differentiate defensive corporate bonds from their offensive counterparts based on their maturity and rating. While defensive assets are characterized by a high rating and a low maturity, offensive ones are distinguishable from them due to their low rating and high maturity. This rating-maturity bet is executed for corporate bonds denominated in U.S. Dollars, Euros, and Great Britain Pounds. Due to the fund's home bias, the factor focuses solely on those three currencies as it is assumed that corporate bonds denominated in other currencies are not bought by the fund.

7 Portfolio Construction

To construct a passive factor benchmark that can be compared to the M&G fund, individual factor portfolios have to be built that can then be aggregated. To be able to do so, factor portfolios are built as investment-neutral long-short portfolios. This has the advantage that factor portfolio returns can be stacked without introducing leverage to the aggregated portfolio. Because such long-short portfolios are generally designed to be market neutral, a general market factor – the returns of the Bloomberg Barclays Global Aggregate Index – is also included in the passive benchmark so general market moves are also represented in the aggregated factor portfolio.

Based on the methodologies described in the previous section, factor portfolios are built for every factor that are rebalanced monthly. As the value and the currency factor distinguish favorable from unfavorable assets, both follow a similar portfolio construction approach and are covered in a conjoint chapter hereafter. In contrast, the defensive factor portfolio construction is explained in a separate chapter because it places a maturity (and rating) bet across government (corporate) bond markets.

7.1 Value & Currency

When building portfolios, literature either splits assets into buckets or uses z-scores to assess position sizes. Generally, z-scores measure the desired factor more accurately because each factor derivation can be expressed in a trade but the downside of their limited practical implementation and replication make them a rather useless methodology for this paper. Hence, the breakdown of assets into favorable and unfavorable buckets is chosen as a compromise between academic accuracy and practical feasibility.

Following this approach, for the value government factor, all countries are ranked according to their real yields. In accordance with Asness et al. (2014), they are grouped into tercile buckets and the final factor portfolio buys the most favorable bucket and shorts the least favorable one. The positions of the portfolio are 10-year government bonds of the respective countries, which are scaled to have the average duration of all countries' 10-year bonds each month. Even though target durations differ each month, the decision to follow this methodology is made to keep duration adjustments as low as possible. Within the outer buckets, assets are equally weighted, resulting in a duration-neutral long-short portfolio. Starting in 2004, the least and most favorable buckets comprise seven countries and from July 2007 on, with the inclusion of China and India, they are built out of eight countries.

For the value corporate factor, favorable assets are chosen similarly but following literature, quintile buckets are used. Corporate bonds are ranked according to their absolute difference between the theoretical and actual spread. The bonds, whose theoretical spread exceeds the actual spread by the greatest absolute value are least favored by the selection process. The average bucket size equals roughly 2,000 equally weighted bonds and the final portfolio is a long-short portfolio constructed out of the most and least favorable quintile bucket. The final portfolio is constructed over the period between June 2017 and October 2020 because of the limited data availability.

Following a similar approach, tercile buckets are built for the currency factor. Currencies are ranked according to their spot rate to purchasing power conversion factor ratio and are allocated into tercile buckets. Within each bucket, currencies are equally weighted and the final portfolio buys the most favorable and sells the least favorable bucket each month. As outlined in the factor construction chapter, separate factor portfolios for G10 and emerging market currencies are built. These portfolios comprise three currencies in the upper and lower bucket for the G10-portfolio, and one currency for the emerging market currency portfolio. Though intuitive and reasonable, the decision to adjust the seemingly outdated conversion factor in the factor construction of the currency factor is abandoned. A comparison of a portfolio following the above-explained adjustment methodology and a portfolio taking unadjusted conversion factors reveals that the selection of currencies is alike for most months. In cases when the methodologies build differing currency portfolios the methodology executing ongoing adjustments makes worse selections compared to the methodology with constant conversion factors.[3]

[3] The results of this additional analysis can be made available by the authors on request.

Overall, the value and currency factor portfolios are characterized by their self-financing ability, meaning that assets contained in the short and long legs of the portfolio are equally weighted. For all factors, weights of assets are chosen to sum up to one on each side for the return calculation.

7.2 Defensive

To avoid the influence of yield curve shifts on the maturity bet implemented by the defensive factor, long-short portfolios with the same duration on the short and long end of the maturity curve are built. For government bonds, portfolios are constructed for each country that enter a long position of government bonds with a 2-year maturity and a duration equivalent position of 10-year government bonds. Similarly, the defensive corporate factor buys AAA-rated corporate bonds with a maturity between one and three years and shorts a duration equivalent position of BBB-rated bonds with maturities between seven and ten years. Strong evidence exists that investment-grade and high-yield markets are treated as two separate asset classes by market participants and that this segmentation ultimately affects bond prices (Ambastha et al., 2010; Z. Chen et al., 2014). Hence, BBB-rated bonds are used as bonds with the least favorable rating to enhance the comparability of assets because BBB is the last rating that falls into investment grade.

To ensure a duration-neutral portfolio, the long and short legs have to be levered/de-levered to a certain target duration. This introduces the problem that the costs of levering/de-levering can have an impact on the performance of the portfolio. As the fund manager said that he does not use leverage, a portfolio that invests all available funds in the duration-neutral maturity bet without any liquidity gaps or cash leftovers is found to be a good factor to replicate his investment style. With the requirement of duration neutrality and the requirement that all liquid funds I have to be spent, for government bonds the weight of the 2-year maturity bonds in a duration-neutral portfolio that uses all funds efficiently can be calculated as follows for every month:

$$w_2 = \frac{I}{\left(1 - \frac{d_2}{d_{10}}\right)}$$

Here, **d** represents the respective durations and **w** the respective weight or the monetary amount that is to be invested. With the weight of the 2-year maturity long leg, the weight of the 10-year maturity short leg can be calculated following the requirement for duration neutrality.

To make the defensive portfolios more comparable to their value and currency counterparts, the defensive portfolio could also be created as a self-financing investment neutral portfolio, meaning that the purchases of 2-year maturity bonds in excess of available funds would have to be financed with external capital. Put simply, in our example, the initial investment amount **I** would have to be borrowed at the duration-neutral risk-free rate. The performance of the efficient portfolio that invests all funds available and a portfolio that borrows required funds from capital markets is illustrated in the following graph. The performance is calculated based on an investment amount of $100 to make portfolios comparable.

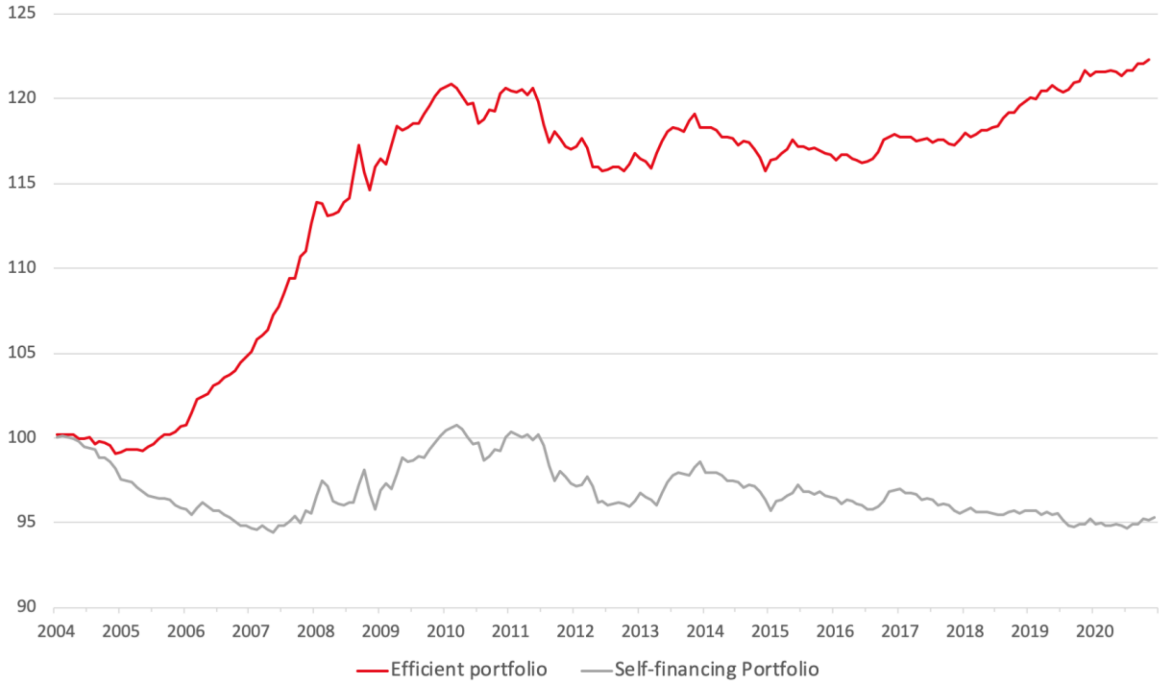


Figure 2: Defensive Portfolio Comparison Self-Financing & Efficient
Source: Own illustration

While both portfolio methodologies have their raison d'être, the approach that has liquid funds available to implement the portfolio is chosen for this paper. Even though the self-financing characteristic would make factor portfolios more comparable and be better suited for the aggregation/stacking of the final benchmark portfolio, the above graph illustrates that this implementation is dominated by the financing costs. The portfolio including leverage does not behave as one would expect from a defensive factor – that it generates profits in times of economic shocks. The other portfolio demonstrates that behavior, especially during the financial crisis of 2008 and the global pandemic in 2020. Additionally, it is assumed that portfolio managers would not create self-financing portfolios with borrowed funds when they want to implement a defensive trade. Using leverage for its implementation would be contrary to the desire of having a defensive position. The decision in favor of the methodology that is non-self-financing was made because it is presumable more representative of what is done in practice, behaves more in line with what is expected from defensive strategies and in literature such defensive portfolios also do not include financing costs to make portfolios self-financing (see e.g. Asness et al., 2014; Frazzini & Pedersen, 2014).

Overall, the portfolios within each country/currency for the defensive government/corporate factor are calculated following the methodology of the example above. As performance is measured on a relative scale, the nominal investment amount I is of relevance for the performance calculation. All defensive portfolios are aggregated and the defensive government bond factor portfolio is an equally-weighted portfolio of the maturity bets in each country. The final corporate defensive factor portfolio is an equal-weighted portfolio of the rating-maturity bet in each of the three currency markets. Similar to the long and short legs of the value and the currency factor, weights attributed to each asset sum up to one.

7.3 Factor Evaluation

The performance of the constructed factors is illustrated by the following graph that shows the accumulated returns of each factor portfolio. Factors of the same factor category are illustrated in the same tone of color.

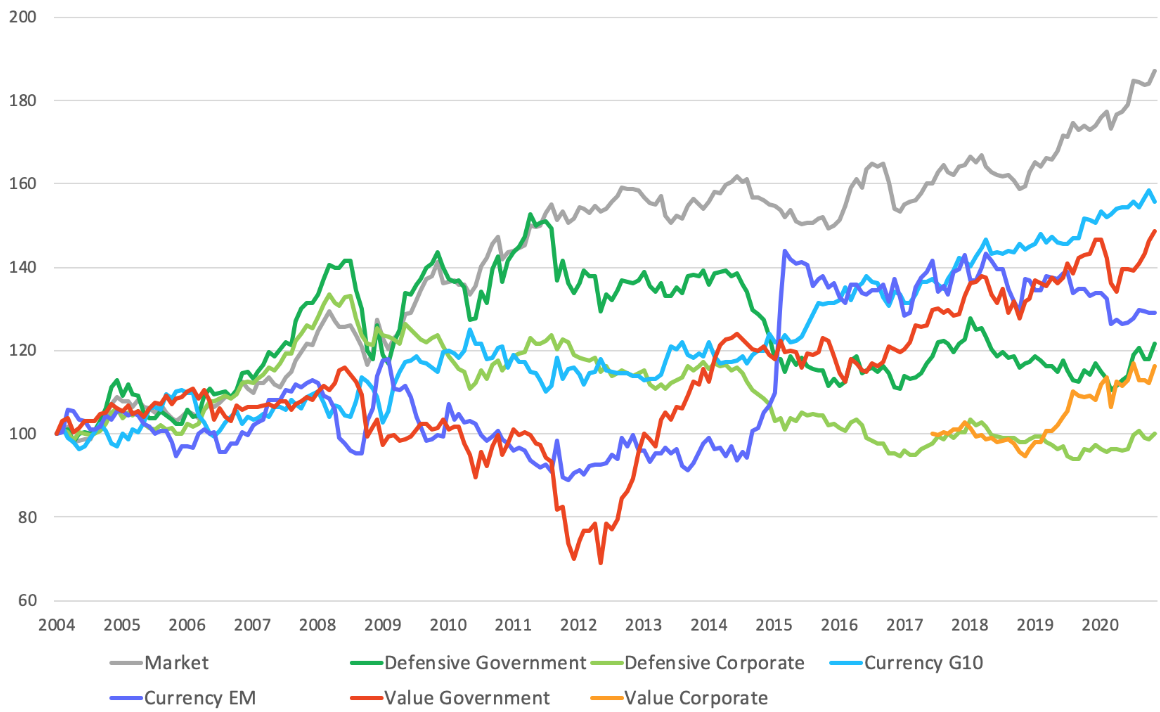


Figure 3: *Cumulated Factor Portfolio Returns*
Source: *Own illustration*

Overall, all factors earned positive returns over the analyzed period, which means that all strategies can potentially be used to boost returns.

A correlation analysis of all factors including market portfolios representing global equities, emerging market equities, commodities, global credits, and global bonds is performed to evaluate the independence of the factors. Two correlation matrices are constructed – one covering the period between January 2004 and November 2020 but excluding the value corporate factor and the other covering June 2017 to October 2020 including the value corporate factor:

Table 1: Factor Correlation Matrices

	Equities	*Equities EM*	*Commodities*	*Credit*	*Bonds*	*Defensive Government*	*Defensive Corporate*	*Currency G10*	*Currency EM*	*Value Government*
Equities	1									
Equities EM	0.85**	1								
Commodities	0.54**	0.55**	1							
Credit	0.06	0.03	-0.02	1						
Bonds	0.38**	0.47**	0.23**	0.10	1					
Defensive Government	0.64**	0.71**	0.52**	0.10	0.74**	1				
Defensive Corporate	0.37**	0.40**	0.40**	0.10	0.57**	0.83**	1			
Currencies G10	-0.18**	-0.20**	-0.16**	-0.15**	-0.29**	-0.36**	-0.34**	1		
Currencies EM	-0.08	-0.11	-0.17*	0.01	-0.07	-0.14**	-0.07	0.01	1	
Value Government	0.53**	0.52**	0.35**	0.00	0.29**	0.57**	0.36**	-0.18*	-0.07	1

	Equities	*Equities EM*	*Commodities*	*Credit*	*Bonds*	*Defensive Government*	*Defensive Corporate*	*Currency G10*	*Currency EM*	*Value Government*	*Value Corporate*
Equities	1										
Equities EM	0.84**	1									
Commodities	0.69**	0.63**	1								
Credit	0.74**	0.82**	0.53**	1							
Bonds	0.36**	0.52**	0.19	0.81**	1						
Defensive Government	0.61**	0.79**	0.47**	0.73**	0.61**	1					
Defensive Corporate	0.37**	0.51**	0.23	0.51**	0.40**	0.84**	1				
Currencies G10	-0.15	-0.15	-0.11	0.03	-0.13	-0.17	0.07	1			
Currencies EM	0.21	0.28	0.13	0.14	0.05	0.03	-0.17	0.02	1		
Value Government	0.46**	0.57**	0.50**	0.34*	0.14	0.50**	0.23	-0.08	0.32*	1	
Value Corporate	0.40**	0.41**	0.17	0.71**	0.74**	0.16	-0.06	-0.04	0.19	0.04	1

Significance levels are indicated as follows: 5% level is indicated with "*", 1% level is indicated with "**"

Source: Own table

The tables show that the factors imitating the manager's investment style have relatively low or negative correlations with each other. In line with the literature review, defensive and value factors are somewhat correlated due to their interrelations. For example, ratings are used as a criterion for the construction of the value corporate and the defensive corporate factor. In contrast to the highly correlated defensive government and currency factor, the different currency and value factors are not related. Hence, the decision to follow academia and create separate factor portfolios for different asset classes within one factor category can be evaluated as reasonable. With regards to other markets, the currency factors are negatively correlated to any other factor and market. The value factors have low to medium positive correlation to equity and commodity markets and show relatively similar correlations to other assets except for bond markets. Here, in contrast to the value government factor, the value corporate factor shows high significant correlation. Out of all constructed factors, the defensive factors exhibit the highest co-movement to other markets. An explanation may be that, unlike the other factors, this factor is not designed to be self-financing and has some directional market exposure.

Overall, the factors can be evaluated to be suitable for the desired undertaking. Even though some interrelations exist among factors and markets, the factor portfolios are expected to embody their respective exposure well because most correlations are relatively low. The low correlations between factors of the same factor category (except for the defensive factors) make an attribution analysis to all factors more reasonable than an attribution to factors that are aggregated within one factor category.

8 Attribution Analysis

Following the literature on alpha assessment of fund managers (Israel & Ross, 2017; Frazzini et al., 2018; Brooks et al., 2019; Dewey & Brown, 2019), the attribution analysis for the selected fund is executed with an ordinary least squares regression. The analysis regresses the fund's returns on the returns of the factor portfolios. The intercept that cannot be explained by the regressors is interpreted as the manager's alpha. In the same manner as the correlation analysis, the regression is executed two times – once over the long-time sample period without the value corporate factor and once for the shorter period including all factors:

Table 2: Regression Results

	Market	Defensive Government	Defensive Corporate	Currency G10	Currency EM	Value Government	Monthly Alpha	R^2
Coefficient	0.65**	0.22**	0.10	-0.08	-0.02	0.06*	0.18%**	75.36%
Std. Error	0.07	0.08	0.09	0.04	0.02	0.03	0.07%	
t-stat	9.37	2.78	1.19	-1.87	-1.00	2.01	2.45	

	Market	Defensive Government	Defensive Corporate	Currency G10	Currency EM	Value Government	Value Corporates	Monthly Alpha	R^2
Coefficient	0.40*	0.16	0.31	0.06	-0.04	-0.04	0.12	0.19%	79.79%
Std. Error	0.19	0.19	0.20	0.10	0.05	0.07	0.09	0.12%	
t-stat	2.14	0.87	1.54	0.58	-0.82	-0.63	1.44	1.65	

Significance levels are indicated as follows: 5% level is indicated with "*", 1% level is indicated with "**"

Source: Own table

The regression over the long term shows that the fund loads significantly on some factors and that 75.36% of the variance in the fund's returns can be explained by them. The coefficients of all factors sum up to 0.93, which can be interpreted as a stacked portfolio that is almost fully invested. A factor is evaluated to be significant when it crosses the 95% significance level. The most significant factor in the long-term analysis is the market factor, which has a positive loading of 0.65. Other statistically significant factors are the value government factor and the defensive government factor. The defensive corporate factor has a small positive loading but is not significant for the return determination of the fund. This can be explained by the strong correlation between the defensive government and the corporate factor. Due to their overlapping, it is likely that if the fund returns load heavily on one factor, the small individual portion of the other factor is not enough to make it significant. Support for this hypothesis can be found when the defensive government factor is excluded from the regression. Then, the defensive corporate factor becomes highly significant.[4] The currency factors both have negative coefficients in the results. While the currency emerging markets factor is of relevance for the return generation of the fund, with a t-stat far from any significant boundaries, the factor for G10 currencies is significant. The result for the currency emerging markets factor can be explained by the speculation that though the manager invests in currencies, he does not express his views in emerging market currencies. The outcome that the currency G10 factor has a negative loading above the 90% significance level, indicates that the manager acts contrary to the factor. Lastly, the value corporate factor appears to be relevant for the return generation of the fund even though it does not reach the 5% significance level as the short period of the regression (41 months) impedes factors from reaching statistical significance. This claim is supported by the decreasing t-stats of all other factors in the short-term regression that are highly significant in the long-term regression. Overall, when comparing the results of the long-term regression with those of its short-term counterpart, the outcomes are relatively consistent for most factors. The value government and the currency G10 factor show results with flipped signs but those of the long-term regressions are found to be more representative as levels of significance are above or close to the 95% boundary while those from the short-term results are not significant.

With its almost significant negative loading, the currency G10 factor is the only one that delivers unexpected results and was hence analyzed in further detail. The manager reported that his fund is always exposed to the Japanese Yen. The negative coefficient of the currency G10 factor could result from the factor portfolio being short in the Japanese Yen more often than being long in that currency. A deeper analysis shows that the Japanese Yen is bought 39 times more often than it is sold in the factor portfolio over the sample period. Nevertheless, to further investigate whether exposure to the Japanese Yen causes the negative coefficient, the attribution analysis is repeated with a new currency G10 factor that follows the same methodology as the old factor but always includes the Japanese Yen as part of the long leg of the portfolio. The new currency G10 factor has a negative loading of -0.15 at a highly significant t-stat of -3.31.[5] To further check these counterintuitive results, the currency G10 factor is replaced by a long position in the Japanese Yen and another regression over the long sample period is executed. The results of the regression (coefficient: -0.00, t-stat: -0.02) show that a long position in the Japanese Yen cannot uncover the source of returns for the fund.[6] As a result, the manager appears to act contrary to the currency G10 factor though it is constructed according to his statements in the interview.

[4] The results of this additional analysis can be made available by the authors on request.

[5] The full results of this additional analysis can be made available by the authors on request.

[6] The full results of this additional analysis can be made available by the authors on request.

The following illustration shows the yearly return contributions of all factors that are found to be significant in the analysis. Same as before, two separate graphs for the different time horizons due to the limited availability of the value corporate factor are created.

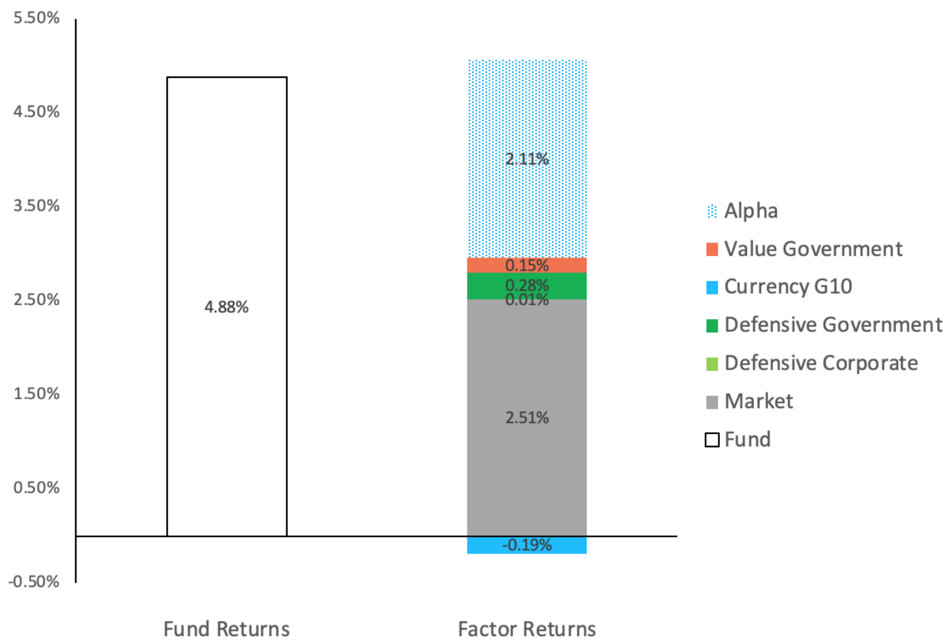


Figure 4: *Performance Attribution January 2004 - November 2020*
Source: *Own illustration.*

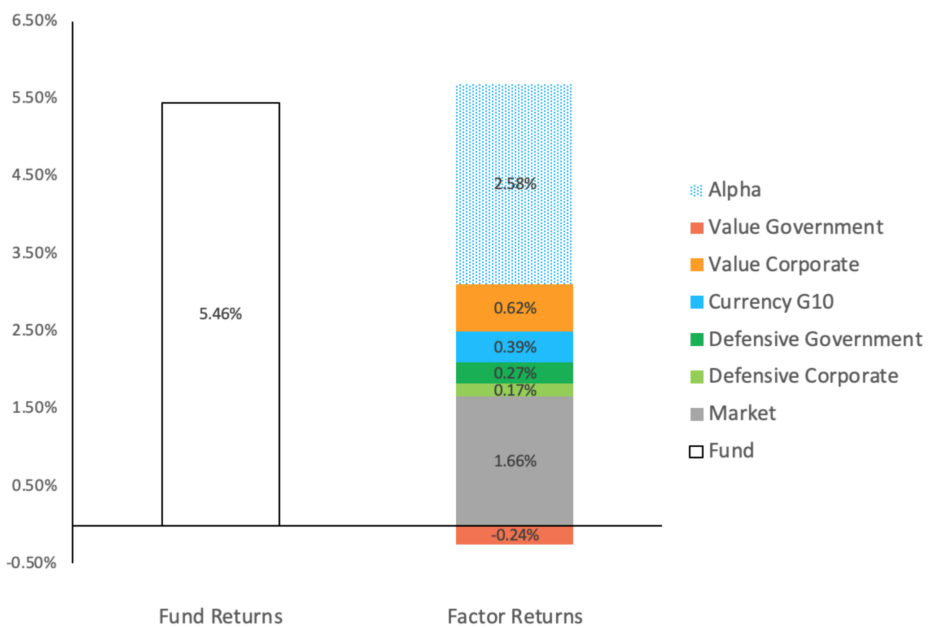


Figure 5: *Performance Attribution June 2017 - October 2020*
Source: *Own illustration*

Both graphs demonstrate that exposure to market risk explains the largest portion of returns. In both time horizons, a portion between 6% and 8% of the fund's returns can be attributed to defensive factors. As discussed before, the long-term results for the currency G10 and the value government factor are assessed to be more representative. In comparison to the other factors, the value corporate factor has a high contribution to the fund's returns of 0.62% p.a. An unexplained remainder of 2.11% is left in the long-term analysis, which increases to 2.58% in the short term that can be evaluated as the manager's alpha. Its t-stat from the long-term regression analysis shows, that this alpha is statistically significant.

9 Discussion of Results

The discussion section of this paper critically reflects the methodology and results of the exemplary performance attribution. More general remarks and implications can be found in the conclusion.

The results, that roughly half of the fund's returns can be attributed to factors and 75% of the returns' variance can be explained by the attribution analysis demonstrate that factors are an important source of returns for the selected fund. However, the unexplained remainder of 2.11% that can be interpreted as the manager's alpha seems relatively high but is thought to be plausible. Mr. Leaviss talks about macroeconomic trends the most in the interview when he refers to his investment style. Though presumably important for the return generation, a factor for macroeconomic trends was not included in the analysis because such trends are impossible to capture with factor portfolios – especially because they change over time. Another reason why the manager's alpha is relatively high could be that as a consequence of avoiding p-hacking not enough factors were included in the analysis. In other words, the remainder of the performance attribution could still comprise factor returns and the true alpha of the manager is smaller. This could also be caused by an inadequate construction of the factor portfolios. As outlined at the end of the literature review in section 2, various ways of building exposure to factor returns exist. If the fund manager implemented styles in his fund that are not captured by the here constructed factor portfolios, these style returns would wrongfully be attributed to his alpha contribution. Another reason why the true alpha of the manager may be smaller is that the analysis mostly relied on the statements made by the fund manager in the interview. Such interviews are imprecise by nature so relevant factors may have been overlooked. Also, the manager has adverse incentives not to share very profitable systematic trading strategies which may also cause imperfections in the analysis. For example, it is questionable why he has negative exposure to a currency factor that was built according to how he claims to invest. Moreover, it can be questioned whether the whole unexplained part of the model can fully be interpreted as the manager's alpha. Such models always contain random components that can alter the results of the analysis. However, as the residual of the analysis across two different time horizons is relatively similar in size and statistically significant for the longer period, it is unlikely that the large residual is caused solely by chance.

Though the methodology of this paper follows a strict literature-based approach, it has some shortcomings that must be addressed to see the results in the right light. First, correlations among factors have to be kept in mind when evaluating the results of the performance attribution. The resulting interchangeability of factors may alter and distort the results. This is especially relevant for the defensive factors and the government value factor. However, as most factors are loosely correlated, the decision to construct separate factors for government and corporate bonds is defensible. Also, further regressions with different settings that exclude one or more correlated factors were carried out to investigate this issue. The results of that analysis show that though some factors overlap, the overall results of the analysis remain largely unaffected by the cross correlations of factors.[7] Second, the limited availability of data caused compromises in the construction of both value factors. Though more data would have made factors more robust, the compromises should not influence the general factor performance. Third, the reliability of the corporate defensive factor has to be questioned as the data it is based on had to be adjusted because some values were unrealistic. The adjustments are thought not to alter the factor too much because they had to be made for 2 out of 16 years – so almost 90% of the data used for this factor is unadjusted. Fourth, the neglection of transaction costs, market frictions, and other generalizations is unrealistic from a practical standpoint. Despite their shortcomings, the neglections are made as they make the portfolio construction simpler. Also, as the performance is evaluated with regards to the fund's loading on the factors, the inclusion of costs should not have a strong influence on the results of the analysis. Fifth, the fact that the value and currency factors are constructed to be self-financing portfolios while the defensive factors comprise directional market exposure, makes a comparison of factors difficult and ambiguous. However, if the defensive portfolios were implemented as self-financing portfolios, the portfolio would be less realistic from a practicability standpoint.

Having these limitations in mind, the whole outcome of this paper can be evaluated more critically. Some factors in the analysis are somewhat close to being statistically significant and/or are argued to play a role based on additional breakdowns. Following Harvey et al. (2016) who advocate higher boundaries for statistical significance when it comes to evaluating factors, the results of the attribution analysis could have been evaluated more strictly. This means that with the shortcomings of the factors in mind, the criteria to assess significance of a factor could have been increased to avoid the wrong classification of factors that are not relevant for the return contribution. However, the deficits of the analysis can be well-justified and should only cause minor distortions in the results. As the performance attribution is only executed exemplarily, the fundamental insights of the analysis are more important than its granular errors.

[7] The full results of this additional analysis can be made available by the authors on request.

10 Conclusion

Before concluding, let us return to Jim Leaviss, the fund manager of the exemplarily selected fund. Even if his performance can be explained in some parts by factors, this does not weaken his accomplishments as a portfolio manager. His ability to successfully stick to his strategies over a time horizon of more than 20 years is impressive. This research is meant to contribute to the growing discussion on factors in fixed-income and the literature on measuring alpha. It is not meant to disparage Jim Leaviss' skill as an investor or person.

Overall, the paper demonstrates that a factor decomposition of mutual fund returns can not only be executed for publicly well-known managers but can also be implemented following a structured fund-selection approach for the analysis. The returns of the chosen fund are found to be partly attributable to general market exposure as well as defensive and value investments. After deducting exposure to systematic investment strategies, the performance attribution leaves a statistically significant remainder of 2.11% p.a. that can be interpreted as the manager's alpha. This shows that while factors are relevant for the return generation of the fund, the manager still contributes a significant idiosyncratic share to the performance. However, given that the analysis is largely based on an interview with the fund manager and some of the results are contrary to his statements, the results have to be interpreted with caution.

For future research, considering solely the results of the exemplary performance attribution, more research should be undertaken to ensure that all relevant factors of the manager's investment style are covered and correctly implemented in the analysis. In the bigger picture, this paper delivers further evidence that exposure to factors should be granted more attention by investors and scholars alike. Similar to other papers in this field of research, it demonstrates that factors are an important driver of returns. Furthermore, the tools and insights developed in this paper can be used by practitioners to improve asset allocations, performance measurement, and manager selection. But, given the limitations of the qualitative interview-based methodology of this paper, follow-up works may also consider a more quantitative approach to verify the results from a different angle.

Overall, future research and developments have to be awaited to address the influence of factors on return generation with certainty. So far, enough evidence exists to suggest that factors should at least not be neglected when evaluating managers or investments. However, no matter whether outperformance comes from alpha or exposure to factors, investors today face low expected returns across traditional asset classes. Given these obstacles, any additional sources of returns should be valued and appreciated. While historically the main way to outperform was via alpha or simply taking more risk, investors now have access to a variety of styles and return premia. This potentially allows for a larger differentiation of investment styles across managers and multiple paths to long-term success for investors. Consequently, investors should revise performance measurement schemes and ensure that those still comply with the current investment environment.

References

Acharya, V. V., Amihud, Y., & Bharath, S. T. (2013). Liquidity risk of corporate bond returns: Conditional approach. Journal of Financial Economics, 110(2), 358–386.

Ambastha, M., Dor, A. Ben, Dynkin, L., Hyman, J., & Konstantinovsky, V. (2010). Empirical Duration of Corporate Bonds and Credit Market Segmentation. The Journal of Fixed Income, 20(1), 5–27.

Amihud, Y., & Mendelson, H. (1991). Liquidity, Maturity, and the Yields on U.S. Treasury Securities. The Journal of Finance, 46(4), 1411–1425.

Ammann, M., Fischer, S., & Weigert, F. (2020). Factor Exposure Variation and Mutual Fund Performance. Financial Analysts Journal, 76(4).

Ang, A., & Piazzesi, M. (2003). A no-arbitrage vector autoregression of term structure dynamics with macroeconomic and latent variables. Journal of Monetary Economics, 50, 756–787.

Asness, C. S., Ilmanen, A., Israel, R., & Moskowitz, T. J. (2014). Investing With Style. Journal of Investment Management, 13(1), 27–63.

Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and Momentum Everywhere. The Journal of Finance, 68(3), 929–985.

Asvanunt, A., & Richardson, S. (2017). The Credit Risk Premium. The Journal of Fixed Income, 26(3), 6–24.

Aussenegg, W., Götz, L., & Jelic, R. M. (2015). Common Factors in the Performance of European Corporate Bonds – Evidence Before and after Financial Crisis. European Financial Management, 21(2), 265–308.

Baker, M., Bradley, B., & Wurgler, J. (2011). Benchmarks as Limits to Arbitrage: Understanding the Low Volatility Anomaly. Financial Analysts Journal, 67(1), 40–54.

Basu, S. (1977). Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratios : A Test of the Efficient Market Hypothesis. The Journal of Finance, 32(3), 663–682.

Bauer, M. D., & Hamilton, J. D. (2018). Robust bond risk premia. Review of Financial Studies, 31(2), 399–448.

Baz, J., Mattu, R., Moore, J., & Guo, H. (2017). Bonds Are Different: Active Versus Passive Management in 12 Points. PIMCO Quantitative Research.

Beekhuizen, P., Duyvesteyn, J., Zomerdijk, C., & Martens, M. (2019). Carry Investing on the Yield Curve. Financial Analysts Journal, 75(4), 51–63.

Bektić, D., Hachenberg, B., & Schiereck, D. (2020). Factor-based investing in government bond markets: a survey of the current state of research. Journal of Asset Management, 21(2), 94–105.

Bell, E., Bryman, A., & Harley, B. (2019). Business Research Methods (5th ed.). Oxford University Press.

Bender, J., Briand, R., Nielsen, F., & Stefek, D. (2010). Portfolio of Risk Premia: A New Approach to Diversification. The Journal of Portfolio Management, 36(2), 17–25.

Black, F. (1993). Beta and Return: Announcements of the ‘Death of Beta’ seem Premature. The Journal of Portfolio Management, 20(1), 8–18.

Black, F., Jensen, M., & Scholes, M. (1972). The Capital Asset Pricing Model: Some Empirical Tests. In M. Jensen (Ed.), Studies in the Theory of Capital Markets (pp. 79–121). Praeger.

Blitz, D. (2016). Factor Investing with Smart Beta Indices. The Journal of Index Investing, 7(3), 43–48.

Boudoukh, J., Brooks, J., Richardson, M., & Xu, Z. (2016). The complexity of liquidity: The extraordinary case of sovereign bonds. NBER Working Paper Series, Article 22576.

Brinson, G. P., Hood, L. R., & Beebower, G. L. (1986). Determinants of Portfolio Performance. Financial Analysts Journal, 42(4), 39–44.

Brooks, J. (2017). A Half Century of Macro Momentum. Alternative Investment Analyst Review.

Brooks, J., Gould, T., & Richardson, S. (2020). Active fixed income illusions. Journal of Fixed Income, 29(4), 5–19.

Brooks, J., & Moskowitz, T. J. (2017). Yield Curve Premia. SSRN Electronic Journal.

Brooks, J., Palhares, D., & Richardson, S. (2018). Style investing in fixed income. The Journal of Portfolio Management, 44(4), 127–139.

Brooks, J., Tsuji, S., & Villalon, D. (2019). Superstar Investors. The Journal of Investing, 28(1), 124–135.

Chen, L., Lesmond, D. A., & Wei, J. (2007). Corporate Yield Spreads and Bond Liquidity. The Journal of Finance, 62(1), 119–149.

Chen, Z., Lookman, A. A., Schürhoff, N., & Seppi, D. J. (2014). Rating-Based Investment Practices and Bond Market Segmentation. The Review of Asset Pricing Studies, 4(2), 162–205.

Chin, A., & Tang, W. (2020). Factor Timing in Fixed Income Strategies. The Journal of Fixed Income, 30(2), 62–75.

Choi, H., Mueller, P., & Vedolin, A. (2017). Bond Variance Risk Premiums. Review of Finance, 21(3), 987–1022.

Chordia, T., Goyal, A., Nozawa, Y., Subrahmanyam, A., & Tong, Q. (2017). Are Capital Market Anomalies Common to Equity and Corporate Bond Markets? An Empirical Investigation. Journal of Financial and Quantitative Analysis, 52(4), 1301–1342.

Cieslak, A., & Povala, P. (2015). Expected Returns in Treasury Bonds. Review of Financial Studies, 28(10), 2859–2901.

Clarke, R., de Silva, H., & Thorley, S. (2010). Know Your VMS Exposure. The Journal of Portfolio Management, 36(2), 52–59.

Correia, M., Richardson, S. A., & Tuna, I. (2012). Value investing in credit markets. Review of Accounting Studies, 17(3), 572–609.

Crowell, B., Israel, R., Kabiller, D. G., & Berger, A. (2012). Is Alpha Just Beta Waiting To Be Discovered?: What Hedge Fund Beta Means for Investors. AQR Capital Management Whitepaper Series.

D'Amico, S., & Orphanides, A. (2008). Uncertainty and disagreement in economic forecasting. Finance and Economics Discussion Series, Article 56.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor Psychology and Security Market under- and Overreactions. The Journal of Finance, 53(6), 1839–1885.

Daul, S., Sharp, N., & Sørensen, L. Q. (2010). Fixed Income Performance Attribution. SSRN Electronic Journal.

Derwall, J., Huij, J., & de Zwart, G. J. (2009). The Short-Term Corporate Bond Anomaly. SSRN Electronic Journal.

Dewey, R., & Brown, A. (2019). Bill Gross' Alpha: The King Versus the Oracle. Journal of Investment Management, 17(3), 65–81.

Dimson, E., Marsh, P., & Staunton, M. (2008). 108 Years of Momentum Profits. SSRN Electronic Journal.

Dockner, E. J., Mayer, M., & Zechner, J. (2017). Sovereign Bond Risk Premiums. Austrian Central Bank Working Paper Series, Article 217.

Duarte, J., Longstaff, F. A., & Yu, F. (2007). Risk and Return in Fixed-Income Arbitrage: Nickels in Front of a Steamroller? Review of Financial Studies, 20(3), 769–811.

Duyvesteyn, J., & Martens, M. (2014). Emerging government bond market timing. The Journal of Fixed Income, 23(3), 36–49.

Ejsing, J., Grothe, M., & Grothe, O. (2012). Liquidity and credit risk premia in government bond yields. ECB Working Paper Series, Article 1440.

Elton, E. J., Gruber, M. J., Agrawal, D., & Mann, C. (2001). Explaining the rate spread on corporate bonds. The Journal of Finance, 56(11), 247–277.

Fabozzi, F. (2012). The Handbook of Fixed Income Securities (8th ed.). McGraw-Hill Education.

Fama, E. F. (1972). Components of Investment Performance. The Journal of Finance, 27(3), 551–567.

Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. The Journal of Finance, 47(2), 427–465.

Fama, E. F., & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. The Journal of Finance, 51(1), 55–84.

Fama, E. F., & MacBeth, J. (1973). Risk, Return and Equilibrium: Empirical Tests. Journal of Political Economy, 81(3), 697–637.

Frazzini, A., Kabiller, D., & Pedersen, L. H. (2018). Buffett's Alpha. Financial Analysts Journal, 74(4), 35–55.

Frazzini, A., & Pedersen, L. H. (2014). Betting Against Beta. Journal of Financial Economics, 111(1), 1–25.

Fung, W., & Hsieh, D. A. (2004). Hedge fund benchmarks: A risk-based approach. Financial Analysts Journal, 60(5), 65–80.

Gebhardt, W. R., Hvidkjaer, S., & Swaminathan, B. (2005). Stock and bond market interaction: Does momentum spill over? Journal of Financial Economics, 75(3), 651–690.

Gerakos, J., & Linnainmaa, J. (2018). Decomposing value. Review of Financial Studies, 31(5), 1825–1854.

Goodman, L., & Ho, J. (1997). Are Investors Rewarded for Shorting Volatility? The Journal of Fixed Income, 7(1), 38–42.

Goyenko, R., Subrahmanyam, A., & Ukhov, A. (2011). The term structure of bond market liquidity and its implications for expected bond returns. Journal of Financial and Quantitative Analysis, 46(1), 111–139.

Hallerbach, W. G., & Houweling, P. (2013). Ibbotson's Default Premium: Risky Data. The Journal of Investing, 22(2), 95–105.

Hambusch, G., Hong, K. J., & Webster, E. (2015). Enhancing Risk-Adjusted Return Using Time Series Momentum in Sovereign Bonds. The Journal of Fixed Income, 25(1), 96–111.

Harvey, C. R. (2017). Presidential Address: The Scientific Outlook in Financial Economics. The Journal of Finance, 72(4), 1399–1440.

Harvey, C. R., Liu, Y., & Zhu, H. (2016). ... and the Cross-Section of Expected Returns. Review of Financial Studies, 29(1), 5–68.

Harvey, C. R., Solnik, B., & Zhou, G. (2002). What Determines Expected International Asset Returns. Annals of Economics and Finance, 3, 249–298.

Haugen, R. A., & Baker, N. L. (1991). The Efficient Market Inefficiency of Capitalization-Weighted Stock Portfolios. The Journal of Portfolio Management, 17(3), 35–40.

Haugen, R. A., & Baker, N. L. (1996). Commonality in the Determinants of Expected Stock Returns. Journal of Financial Economics, 41(3), 401–439.

Haugen, R. A., & Heins, A. . J. (1975). Risk and the Rate of Return on Financial Assets : Some Old Wine in New Bottles. The Journal of Financial and Quantitative Analysis, 10(5), 775–784.

Hong, H., & Stein, J. C. (1999). A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets. The Journal of Finance, 54(6), 2143–2184.

Hördahl, P., & Tristani, O. (2012). Inflation Risk Premia in the Term Structure of Interest Rates. Journal of the European Economic Association, 10(3), 634–657.

Houweling, P., & van Zundert, J. (2017). Factor Investing in the Corporate Bond Market. Financial Analysts Journal, 73(2), 100–115.

Ibbotson, R. G., Chen, Z., & Hu, W. Y. (2013). Liquidity as an Investment Style. Financial Analysts Journal, 69(3), 1–34.

Ilmanen, A., Byrne, R., Gunasekera, H., & Minikin, R. (2004). Which Risks have Been Best Rewarded? The Journal of Portfolio Management, 30(2), 53–57.

Ilmanen, A., & Kizer, J. (2012). The Death of Diversification Has Been Greatly Exaggerated. The Journal of Portfolio Management, 38(3), 15–27.

Israel, R., Palhares, D., & Richardson, S. A. (2018). Common Factors in Corporate Bond Returns. Journal of Investment Management, 16(2), 17–46.

Israel, R., & Ross, A. (2017). Measuring factor exposures: Uses and Abuses. The Journal of Alternative Investments, 20(1), 10–25.

Israelov, R., Nielsen, L. N., & Villalon, D. (2017). Embracing Downside Risk. The Journal of Alternative Investments, 19(3), 59–67.

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. The Journal of Finance, 48(1), 65–91.

Joslin, S., Priebsch, M., & Singleton, K. J. (2014). Risk Premiums in Dynamic Term Structure Models with Unspanned Macro Risks. The Journal of Finance, 69(3), 1197–1233.

Jostova, G., Nikolova, S., Philipov, A., & Stahel, C. W. (2013). Momentum in corporate bond returns. Review of Financial Studies, 26(7), 1649–1693.

Kamara, A. (1994). Liquidity, taxes, and short-term treasury yields. Journal of Financial and Quantitative Analysis, 29(3), 403–416.

Kenechukwu, A., Kruttli, M., McCabe, P., & Osambela, E. (2020). The Shift from Active to Passive Investing: Risks to Financial Stability? Financial Analysts Journal, 76(4), 23–39.

Khang, K., & King, T. H. D. (2004). Return reversals in the bond market: Evidence and causes. Journal of Banking and Finance, 28(3), 569–593.

Khorana, A. (2001). Performance Changes Following Top Management Turnover: Evidence from Open-End Mutual Funds. The Journal of Financial and Quantitative Analysis, 36(3), 371–393.

Koijen, R. S. J., Moskowitz, T. J., Pedersen, L. H., & Vrugt, E. B. (2018). Carry. Journal of Financial Economics, 127(2), 197–225.

Kothe, J., Lohre, H., & Rother, C. (2021). Rates Factors and Global Asset Allocation. The Journal of Fixed Income, 30(3), 6–25.

Kozhemiakin, A. (2007). The risk premium of corporate bonds. The Journal of Portfolio Management, 33(2), 101–109.

Krishnamurthy, A. (2002). The bond/old-bond spread. Journal of Financial Economics, 66(2–3), 463–506.

Kwan, S. H. (1996). Firm-specific information and the correlation between individual stocks and bonds. Journal of Financial Economics, 40(1), 63–80.

L'Hoir, M., & Boulhabel, M. (2010). A bond-picking model for corporate bond allocation. The Journal of Portfolio Management, 36(3), 131–139.

Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. The Review of Economics and Statistics, 47(1), 13–37.

Longstaff, F. A. (2004). The Flight-to-Liquidity Premium in U. S. Treasury Bond Prices. The Journal of Business, 77(3), 511–526.

Longstaff, F. A., Mithal, S., & Neis, E. (2005). Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit Default Swap Market. The Journal of Finance, 60(5), 2213–2253.

Longstaff, F. A., Pan, J., Pedersen, L. H., & Singleton, K. J. (2011). How sovereign is sovereign credit risk? American Economic Journal: Macroeconomics, 3(2), 75–103.

Luu, B. Van, & Yu, P. (2012). Momentum in Government-Bond Markets. The Journal of Fixed Income, 22(2), 72–79.

M&G Investments. (2020a). M&G (Lux) Global Macro Bond Fund Euro Class A – Fund Fact Sheet.

M&G Investments. (2020b). M&G Global Macro Bond Fund – Fund Profile.

M&G Investments. (2020c). M&G Global Macro Bond Fund – Key investor Information.

M&G Investments. (2020d). M&G Global Macro Bond Fund – Prospectus.

Mattu, R. K., Devarajan, M., Sapra, S., & Nikalaichyk, D. (2016). Fixed Income Manager Selection: Beware of Biases. PIMCO Quantitative Research Series.

Morningstar UK. (2019). Morningstar Announces Winners for 2019 Fund Manager of the Year Awards. https://newsroom.morningstar.com/newsroom/news-archive/press-release-details/2019/Morningstar-Announces-Winners-for-2019-Fund-Manager-of-the-Year-Awards/default.aspx

Moskowitz, T. J., Ooi, Y. H., & Pedersen, L. H. (2012). Time series momentum. Journal of Financial Economics, 104(2), 228–250.

Mossin, J. (1966). Equilibrium in a Capital Asset Market. Econometrica, 34(4), 768–783.

Ni, S. X. (2008). Stock option returns: A puzzle. SSRN Electronic Journal.

Pilotte, E. A., & Sterbenz, F. P. (2006). Sharpe and Treynor Ratios on Treasury Bonds. The Journal of Business, 79(1), 149–180.

Portfolio Adviser. (2019). Portfolio Adviser Fund Awards winners revealed. https://portfolio-adviser.com/pa-fund-awards-winners-revealed/

Pospisil, L., & Zhang, J. (2010). Momentum and Reversal Effects in Corporate Bond Prices and Credit Cycles. The Journal of Fixed Income, 20(2), 101–115.

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. The Journal of Finance, 19(3), 425–442.

Simon, D. P. (2010). Examination of Long-Term Bond iShare Option Selling Strategies. Journal of Futures Markets, 30(5), 465–489.

St. John, F. A. V., Keane, A. M., Jones, J. P. G., & Milner-Gulland, E. J. (2014). Robust study design is as important on the social as it is on the ecological side of applied ecological research. Journal of Applied Ecology, 51(6), 1479–1485.

Treynor, J. L. (1961). Market Value, Time, and Risk. Unpublished Manuscript.

Warga, A. (1992). Bond Returns, Liquidity, and Missing Data. Journal of Financial and Quantitative Analysis, 27(4), 605–617.

Wei, M., D'Amico, S., & Kim, D. H. (2005). TIPS: Taking Inflation Premium Seriously. Computing in Economics and Finance, Article 363.

Wright, J. H. (2011). Term Premia and Inflation Uncertainty : Empirical Evidence from an International Panel. American Economic Review, 101(4), 1514–1534.

Young, J. C., Rose, D. C., Mumby, H. S., Benitez-Capistros, F., Derrick, C. J., Finch, T., Garcia, C., Home, C., Marwaha, E., Morgans, C., Parkinson, S., Shah, J., Wilson, K. A., & Mukherjee, N. (2018). A methodological guide to using and reporting on interviews in conservation science research. Methods in Ecology and Evolution, 9(1), 10–19.

Zaremba, A., & Czapkiewicz, A. (2017). The cross section of international government bond returns. Economic Modelling, 66, 171–183.

Zaremba, A., & Kambouris, G. (2019). The sources of momentum in international government bond returns. Applied Economics, 51(8), 848–857.

Authors

Joshua **Traut** is a Ph.D. candidate and research assistant at the University of St. Gallen's Swiss Institute of Banking and Finance. His main research interests lie in empirical asset pricing, financial markets, and international finance. Previously, he worked in the field of portfolio and investment management at banks and insurance companies. Also, he was a lecturer at the International School of Management in Munich. He holds a M.Sc. in Finance, a M.Sc. in Administrative Studies, and a B.Sc. in Business Administration.

Alexander **Simonov**, CFA received the B.Sc. Degree in Business Administration from University of Mannheim in 2010, the M.A. Degree in Banking and Finance from University of St. Gallen in 2015. He is CFA Charterholder since 2017. He is a lecturer at International School of Management (ISM), Munich, in the fields of Derivative Instruments, Financial Risk Management, and Credit Rating Agencies since 2017.Between 2013 and 2016 Alexander worked in Account Management covering Financial Institutions at PIMCO, Munich. Thereafter, he became Partner of Eufomex, a boutique consulting firm in Munich. At Eufomex Alexander specializes in advising Asset Managers with regards to Performance Attribution at the intersection of IT and finance.

Prof. Dr. Matthias **Meitner** worked for more than 10 years at Allianz SE and Allianz Global Investors as an equity portfolio manager. Since 2015, Matthias serves as a Partner of the valuation-focussed consulting company VALUESQUE and has been holding a chair of Finance at International School of Management (ISM) in Munich/Germany. He has a doctoral degree from the University of Erlangen-Nuernberg/Germany, is CFA-Charterholder, member of the Supervisory Board of the German CFA Society Germany, Head of the Advocacy Committee of the German CFA Society, member of the EU-related EFRAG User Panel and member of the Capital Market Advisory Committee (CMAC) of the IFRS Foundation.

Rommel, Kai; Sagebiel, Julian

Analysis of consumer preferences in Germany for attributes of fast moving consumer goods with a discrete choice experiment

Abstract

The markets for Fast Moving Consumer Goods (FMCG) in Germany are determined by demographic change, the COVID-19 pandemic and new developments in mobility demand. The current state of research on consumer preferences indicates heterogeneous preference structures in the attributes for FMCG. While the perceived product quality and transaction costs strongly determine the willingness to pay for FMCG, it is important to examine the impact of other attributes such as production type and place of purchase on the willingness to pay. The main aim of this study is to estimate the willingness to pay for individual attributes of FMCG using a discrete choice experiment. The results confirm strong effects of product quality and transaction costs on willingness to pay. Sociodemographic factors such as age and housing situation also have a significant impact. The results contribute to insights in the literature and provide recommendations for retailers to adapt product portfolios to changing market conditions. The paper helps to specify the preference structures of consumer groups and to show the impact of socioeconomic variables on the willingness to pay for FMCG. This also enables a more precise assessment of inflationary effects.

Keywords: consumer behaviour, fast moving consumer goods, choice experiment, willingness to pay

1 Introduction

The International Standard Industrial Classification (ISIC) defines Fast Moving Consumer Goods (FMCG) (United Nations, 2008) and divides them into the food and near-food segments. The food segment includes non-alcoholic and alcoholic beverages and tobacco products. Products such as toiletries, cosmetics, detergents, cleaning agents, other hygiene products and pet supplies belong to the near-food segment (Kenton, 2021). Convenience products in the food sector are understood here to mean ready-made products and meals such as preserves, frozen food, complete meals for the microwave, baking mixes, instant pudding and pouch soups. These products are ready to eat and only need to be thawed or heated depending on their condition.

Markets for FMCG are consumer packaged goods mainly for daily consumption that are bought at low prices and with a high inventory turnover (Kenton 2021). FMCG's food segment in Germany generates annual sales of over 200 billion euros, accounting for around 14% of total private consumer spending. Food products characterize the market for FMCG. The four largest groups Aldi, Schwartz, Rewe and Edeka account for around 70% of the market share, tendency towards further market concentration, reinforced by low margins (Henrich, 2019). In addition, there are two developments that are permanently changing the market for FMCG in the food sector. First, the importance of online consumption is growing in this market segment, although it underperforms compared to other economies (Henrich, 2019). However, the annual nominal growth rate of the entire FMCG market in the food sector is around 1.2% in 2021, well below the average value of the five previous years and shows growth potential (Statista, 2021a: 4). FMCGs have low profit margins but account for more than half of all consumer spending (Kenton, 2021). Second, organic food and regionally produced products are growing slowly but steadily. The market share of organic food doubled between 2006 and 2016 (Federal Environment Agency, 2019) and has continued to grow since 2019 (Global Organic Trade Guide, 2019). Between 2015 and 2019, the annual growth rate was 8.3% (Market Research Reports, 2021). At around 7.8%, the market share of organic FMCG is still far behind that of the conventional FMCG food segment. In particular, the vegetable and fruit segment is attractive to consumers with a total turnover of around €3.25 billion, which corresponds to 27.4% of the total market value (Market Research Reports, 2021). The market share for organic products in Germany is the largest in Europe at 11.4% of global organic sales, followed by France at 7.3% (Wunsch, 2020). Due to the increased importance of organic and vegetarian/vegan products as well as products without allergenic ingredients, it can be assumed that the importance of these market segments will continue to increase FMCG's market shares in the future. These factors, e-commerce and increased consumer quality demands may lead to further changes in market share and influence the relative importance of FMCG attributes in the food sector (Bogomolova et al., 2019). In addition, the sophistication of FMCG markets can influence purchasing behaviour, brand loyalty and perception of marketing measures (Sundstroem, Hjelm-Lidholm, 2019; Buckinx, van den Poel, 2005; Zarantonello et al., 2013).

The markets for FMCG in Germany are traditionally characterized by a dynamic and highly competitive market environment as well as a fast turnover of goods and are bought and consumed at short intervals (Henrich, 2019). The purchase is processed without any special information effort and at low transaction costs. The restrictions imposed by the COVID-19 pandemic are challenging the FMCG market. Across the German FMCG industry, sales increased between 2019 and 2020. At the beginning of the COVID-19 pandemic, private labels benefited first. Their share of sales increased from 74 to 77.5% during this period (Statista, 2022). FMCG sales in non-food retail in Germany have fallen significantly since 2018. Only online trade in this area has increased significantly since 2019, from 22.4 to 38.6 billion euros in 2021 (Statista, 2022). The use of FMCG is associated with a high consumption of resources due to the short sequence and regular purchasing activities in the entire value chain. Extensive distribution costs are incurred for food and beverages in particular, which are associated with negative external environmental and climate impacts. In addition, there are changes in consumer preferences caused by restricted mobility in an aging society, digitization and increasing online shopping opportunities (Ulbricht, Chervyakov 2015).

The market for FMCG in Germany is with dynamic changes in the framework conditions, such as high market concentration and strong price pressure. However, the share of small consumer markets in demand coverage increased steadily since 2015 (Nielsen, 2018: 14). In 2019, rental of small shops in Germany has grown by 4.2 % (Boersenblatt, 2020). Since March 2021 revenues from retailers in Germany are mainly above the same month of the previous year (Destatis 2022a). Particularly, the food sector has slightly decreased between January 2021 and 2022 (Destatis 2022b). The market share of drug stores has slightly increased since 2018 except 2020 with a decrease of 0.5 % compared to 2019. Discounter show a decrease of market share from 44 % in 2019 to 42.2 % in 2021, whereas market shares of full-range provider increased during the same period (Lebensmittel Zeitung 2022).

Manufacturing and production types influence product characteristics such as regionality and supply chains due to the growing awareness of sustainability. Both attributes have an increasing impact on purchasing decisions (Angelez-Martinez et al., 2018). This development on the FMCG markets illustrates the increasing competitive pressure. Solutions to address these problems require a better understanding of consumer behavior. The aim of this study is to examine the effects of the various market changes for FMCG on the consumer preference structures for the properties of FMCG. To achieve this goal, we approach the method of discrete choice experiments (DCE) to examine the willingness to pay (WTP) for certain product properties. In addition, this approach enables the classification of social and economic effects of purchasing behavior. A deeper knowledge of individual preference structures for these goods is crucial for the design of appropriate policies by local government and for the provision of better infrastructure. Further knowledge of consumer preferences enables companies in the supply chain to more efficiently absorb the WTP of selected target groups for individual attributes of FMCG and convert these financial resources into investments in marketing and innovation.

In this paper we first, discuss the relevant literature on FMCG markets and derive the attributes of FMCG for the empirical analysis in section 2. To determine the individual preference structure, we explain in Section 3 the DCE and the experimental design for determining the marginal WTP for changes in selected product properties of convenience products. In addition, the influences of socio-economic determinants such as consumer behavior and demographic data on the WTP are analyzed. In Section 4 we discuss the results of a conditional logit model and a mixed logit model including the WTP estimates. Finally, various implications, recommendations, limitations and conclusions are part of Section 5.

2 Markets and preferences for FMCG

Changes in market shares from different sales locations, such as discounters, drugstores, hypermarkets and supermarkets, can have an impact on consumer behaviour if the shopping environment influences buying behaviour (Nierobisch et al., 2017). In addition, there are increasing expectations from consumers about sustainable value chains and food compatibility (Siegfried, Zhang, 2021). Regionally sourced FMCG can thus become a purchasing-relevant feature that influences the cost structure of manufacturers and retailers (Angelez-Martinez et al., 2018). Younger generations may have a higher WTP for organic food and less packaging waste (Kamenidou et al., 2020). Moreover, Krystallis and Chryssohoidis (2005) point out different correlations between income and preferences for organic food.

Various factors drive consumer behaviour in FMCG markets such as frequency, novelty and sustainability of purchases, gender, brand value, social environment and customer loyalty. Bogomolova et al. (2019) note that there is little opportunity to increase consumer inventories and point to the need for ongoing marketing activities to increase the proportion of first-time buyers in the FMCG market segment, which accounts for around 5% of the items in the shopping cart. The individual perception of the shopping atmosphere and socio-demographic variables such as age, gender and income have a significant influence on purchasing behaviour (Nierobisch et al. 2017). Consumers react differently to price changes. This determines the development of FMCG's market shares. Bogetic et al. (2016) analysed shoppers' preferences for store size and found that affordable prices and close proximity ranked highest among several other attributes. In addition to the distance the consumer travels to the store, the distance the food has travelled also determines FMCG purchasing behaviour. Grebitus et al. (2013) found a decreasing WTP with distance travelled. This indicates a preference for local food production. The variables brand loyalty, brand association and perceived quality have a significant impact on brand value (Mohan, Sequeira, 2015). The authors point to empirical evidence for the multidimensionality of brand equity in the FMCG markets for body wash, dry linen and packaged tea in India. The place of purchase is thus a determinant of consumer behaviour and WTP for FMCG. In addition, the brand experience in the flagship store has a strong influence on brand loyalty. The attributes of price, trust, brand name and perceived quality have a positive impact on FMCG purchases (Omoregbe and Ogbeide 2013). Klein and Schmitz (2016) analyse the cross-format shopping behaviour of consumers in FMCG shopping. Their results illustrate the perceived status of the attributes of price, product and service quality, and store proximity, which differ between consumers' cross-format shopping patterns. In addition, price sensitivity dominates in cross-format shopping patterns. Improving existing business models with data on consumer expectations of certain product properties requires suitable empirical models.

The results of empirical research on FMCG illustrate different determinants of preferences for the attributes product quality, regional or organic production, place of purchase, distance and price. In addition, some sociodemographic determinants such as age and household income appear to have strong influences on individual WTP for FMCG. For our study design, it can be stated that the influences of the product attributes quality, regionality, sustainability, place of purchase and purchasing costs in the form of distance and price, which have been examined in previous research, have significant influences on the preference structure and purchasing behaviour. This data on the stated preferences for individual features of FMCG is useful for marketing measures to convert these preferences into company revenues. For further investigation, we formulate the following research questions on the interactions between individual characteristics, sociodemographic variables and the WTP based on literature findings:

1. How much are consumers willing to pay for individual attributes of FMCG such as product quality, type of store, regionality and distance to the point of purchase?

2. What are the correlations between socio-demographic variables and the WTP for individual attributes of the FMCG examined?
3. Does the perceived importance of local and organic products correspond to an additional WTP for local and environmentally friendly FMCG?

Socio-demographic parameters, market conditions and physical conditions are major factors influencing purchasing decisions. The current market size and the relatively low growth rates indicate further expansion potential. The main goals of this work are to estimate the WTP for certain attributes of selected FMCG and to identify the sociodemographic determinants of the preference structure. To test our hypothesis, we empirically examine the role of the attributes product quality, production type, accessibility, distance and price changes on the consumer purchasing process in FMCG markets using findings from the literature. The insights are needed to estimate the WTP for individual attributes and to support the transformation of revealed preferences for individual attributes into efficiencies in marketing.

3 Research model developments

DCEs are a widely used method to determine individual preferences for individual attributes. This method can be used to estimate the WTP for individual attributes of the product or service under study in hypothetical market situations. In addition, sociodemographic determinants of these values can be estimated. The main feature of DCEs is the breakdown of a product into individual attributes such as quality, types of ingredients, factors used in the production process, etc. To estimate marginal WTP, a monetary attribute such as cost or price is needed for individual attributes. Each attribute is specified at two or more different levels.

3.1 DCE Design

To create a hypothetical market situation, the DCE consists of two options that the respondent can select. Each option presents the product's attributes with randomly selected layers. In addition, a non-purchase option, also called an opt-out, can be used to account for non-purchase behaviour in hypothetical markets (Hensher et al. 2005, Campbell, Erdem, 2019). The profile of the attributes and levels results from the given conditions, e.g., the availability of purchase location and quality standards. We presented respondents with the attributes and levels using a predefined number of choice cards. Each choice card represents two or more product variations with the same attributes and with different variations of the corresponding level. In an iterative process, the respondents selected the preferred alternative from given object configurations. The DCE is embedded in a standardized online questionnaire on attitudes towards FMCG and socio-demographic issues. The online survey was conducted in 2015 with respondents living in Germany. The respondents were specifically recruited by the market research institute *konkret*.

3.2 Attribute Selection

Each of the 407 respondents selected ten consecutive situations with a total of 4,070 choices. Using a DCE creates a hypothetical market for FMCG. This allows the estimation of the marginal WTP for individual attributes based on the different choices related to the corresponding prices of each option. The defined attributes presented in Table 1 reflect the results of the literature review in Section 2 and are considered relevant for consumer decisions. The first attribute, Product Quality, takes into account the perceived product quality based on the items used by Dodds et al. (1991) and the results of Bogomolova (2019) and Mohan and Sequeira (2015) and is confirmed by our own results of the questionnaire. Price and quality of durable goods play a major role for 45 to 55% of consumers. The proportion of consumers who care most about quality has increased over the years to 55% in 2019 (GfK 2019). The results of Dodds et al. (1991) indicate a strong correlation between price and quality. Therefore, in our study, we chose price and quality as two separate attributes. In addition, the type of provider determines the perceived quality; private labels and manufacturer brands are evaluated differently in Germany (HDE 2020). The quality attribute has the levels: premium, high-grade, standard, convenience and no-name product. Premium represents the highest quality level and no-name products the lowest level. No-name brands are not associated with high or average quality. The three levels in between represent gradations between the highest and the lowest level.

The second attribute, “Regional vs. organic production”, is dichotomous and clarifies the assumption that this attribute leads to a perceived increase in utility (Angelez-Martinez et al., 2018, Bogomolova et al., 2019). Retailers see regionality and organic food as the most important trends in the FMCG markets (Lebensmittelzeitung 2020). We have therefore combined these two attributes in order not to overload the choice cards as the DCE's focus is on FMCG quality and delivery. For the third attribute, accessibility options, we used the results of a previous online survey of purchase frequency across different types of vendors: home delivery, available in retail stores, parcel collection stations, mobile shops, and malls. Attribute number four defines the "distance from store to home". The willingness to drive to the place of purchase differs in relation to the driving distance. Around 34% of consumers prefer distances to the place of purchase of 10 km or less (Statista 2021b). To examine this distance more closely for heterogeneity, we use the following levels: very small (about 0 kilometres), 0.5 kilometres, less than 3 kilometres and 3 or more kilometres. This classification is based on findings in the literature such as Bogetić et al. (2016) and Grebitus et al. (2013) assumes a negative correlation between benefit and distance from business to place of residence. The level 0 kilometres means a very short distance between the consumer's destination and the point of purchase, for example in multi-family houses with shopping facilities. The final attribute, Price Increase Percentage, has levels of plus 30%, plus 20%, plus 10%, 0%, and minus 10%. The price attribute is standard in DCE and is required for calculating the marginal WTP for individual attributes in relation to a predefined standard product design. Other studies, such as You and Choi (2022) and Vecchi et al. (2022) use price differentiations in the range of plus and minus 25% (You, Chen, 2022) or in multiple intervals of 5%.

Table 1: Attributes and levels

Attribute	Levels
Product Quality (Pqual)	Premium, High Grade, Standard, Convenient, Original Brands/No-Name
Regional or Ecological Production (Prod)	Yes, No
Access Options (Acop)	Home delivery, Available in store (super market, to-go store), Package pick-up station, Mobile store (grocery cart on wheels), Shopping centre
Distance from Store to Home (Dist)	0 km, 0.5 km, < 3 km, > 3 km
Price Increase in % (including delivery) (Pinc)	+ 30%, + 20%, +10%, 0%, -10%

A choice card consists of two generic alternatives and a no-purchase option. The generic alternatives were described with the help of attributes and differ in the characteristics of their attributes (Table 2).

Table 2: Choice Example

Attribute	Product A	Product B	No purchase
Product Quality	High Grade	Standard	
Regional or Ecological Production	Yes	No	
Access Options	Shopping centre	Available in store (supermarket)	
Distance from Store to Home	0 km	< 3 km	
Price Increase in % (including delivery)	10 %	10 %	
I choose	○	○	○

The statistical design of the DCE, i.e., the arrangement of the attributes and expressions in the respective alternatives, was created with the software package NGene (ChoiceMetrics, 2012). For this purpose, we have chosen a so-called efficient design that minimizes the standard errors of the parameters to be estimated for a multinational logit model (d-efficiency criterion) (Rose and Bliemer, 2008). The weightings of the individual feature levels used here were derived from the results of our own online survey as well as from the literature analysis and the available statistics. The priors[8] were selected based on the results of a preliminary study conducted in September 2014 with 100 respondents. We excluded implausible combinations and dominant alternatives. Table 2 shows an example of a choice situation. The levels in the Product A and B columns were randomly selected from the defined attributes.

3.3 Model Description

The respondents are assumed to maximize utility, and each alternative i can be represented in a utility functionU_i[9].

8 A Prior is the expected value of a parameter. These values are necessary in non-linear models to calculate the variance-covariance matrix and to minimize diagonal elements.

9 In economic theory, a utility function is a function that assigns numerical values to different bundles of goods. Utility functions merely order different bundles of good by its attractiveness. The utility function can

$$\mathrm{U_i} = \mathrm{A_i}\beta + \epsilon_\mathrm{i} = \mathrm{V_i} + \epsilon_\mathrm{i} \tag{1}$$

where $\mathrm{A_i}$ is a vector with the attribute levels in alternative i $(a_{1i}, a_{2i} \dots)$, and β is a vector of associated parameters, interpreted as utility weights. The term ϵ_i is a random component that captures all effects on utility that cannot be described by observed variables. The observed part of utility $A_i\beta$ is denoted as V_i. In the random utility model, the respondent chooses the alternative with highest utility. The assumption that the ϵ_i are identically and independently distributed (iid) and follow an extreme value Type I distribution leads to the conditional logit model (McFadden, 1974).

$$Prob(j) = \frac{\exp V_j}{\sum_{\mathrm{i}=1}^{n} \exp V_i} \tag{2}$$

Equation 2 shows the probability to choose alternative j, conditional on $\mathrm{A_i}\beta$. This non-linear expression of probabilities has two main alternatives: firstly, the probability is always between zero and one. Secondly, marginal effects of attribute changes on the choice probability are not constant, providing a more realistic shape of consumer behaviour. Using the maximum likelihood method (Train, 2008), the parameters β can be estimated. The maximum likelihood values are those where the estimated probabilities are closest to the actual choices.

In our theoretical model of choice, we assume that total utility from a FMCG is the sum of the utilities from each attribute plus a constant utility. For example, the utility for a FMCG can be written as:

$$U_{FMCG} = \beta_n + \beta_1 Pqual + \beta_2 Prod + \beta_3 Acop + \beta_4 Dist + \beta_5 Pinc + \epsilon_i \tag{3}$$

where U_{FMCG} represents utility a respondent receives from this specific configuration of the FMCG, β_n represents the utility increase or decrease of a FMCG in its base configuration compared to no consumption, and the remaining β parameters represent the utility derived from the corresponding attributes. For each option presented in the choice set, the respondent chooses the option that provides the highest level of utility. To increase the number of observations, each respondent was asked to make this choice ten times with different values of the attributes.

take various functional forms, but the most commonly used one is a linear-in-attributes specification (Train, 2008: 200).

Discrete choice regression models can be used to analyze the data (McFadden, 1974). The choice made by respondents serves as the dependent variable and the attribute levels are the independent variables used to explain the choice. The logit model is used to model choice probabilities, which in its simplest formulation as a conditional logit model provides the following formulation.

$$Prob(choose\ FMCG) = exp(U_{FMCG})/\sum(\exp\ (U_i) \qquad (4)$$

where $\mathrm{i} = (1,2,0)$ is an index for the different options A (1), B (2) and no option (0).

The β parameters can be estimated using the maximum likelihood method. The estimated parameters can then be transformed into WTP values by dividing the parameters for the non-cost attributes and vehicle type by the cost attribute parameter. The WTP is the marginal rate of substitution between the attributes and the additional costs, and reflects the maximum amount a respondent is willing to pay for a one-unit increase in an attribute. Since different people are expected to have different preferences (the assumption in the conditional logit model are homogeneous preferences), we extend the model to a mixed logit model, which allows us to study preference heterogeneity.[10]

4 Results

This section presents the results of the descriptive part of the questionnaire on the one hand and the results of the model estimation and the WTP calculation on the other. Based on the results of the literature review in Section 2, we included the relevant socioeconomic determinants in the analysis.

4.1 Personal data

Almost 80% of those surveyed stated that they separate waste very often or often, and over 62% avoid waste. At around 72%, consumers visit discounters most frequently to buy FMCG. Around 57% buy FMCG in large supermarkets and 48% buy very often or often in small supermarkets. Smaller grocery stores and weekly markets are visited very often or often much less frequently at around 14% or 23%, whereas more than 36% shop very often or often in specialist shops. Table 3 illustrates the descriptive results of the interviews.

[10] For the sake of brevity, the authors will not explain the statistical model and estimation procedure in detail. Instead, the authors refer the reader to Hensher et al. (2014) for a general explanation of DCEs and estimation.

Table 3: Personal data

Variable	Mean	S. D.
Household member	2.2	1.2
Female = 46.2%, male = 53.8%		
Age	46.2	85.5
Available net income per month: < 1,000€ = 11.2%, 1,000 – < 2,000€ = 24.6%, 2,000 - < 3,000€ = 28.6%, 3,000 - < 4,000€ = 18.7%, 4,000 - < 5,000€ = 9.0%, ≥ 5,000€ = 8.1%		
Expenditure basic needs: < 750€ = 34.2%, 750 – < 1,500€ = 31.8%, 1,500 - < 2,500€ = 5.8%, 2,500 - < 3,500€ = 1.1%, ≥ 3,500€ = 0.6%		

The characteristic of fresh food is the most important, with around 87.5% indicating a high or very high preference, followed by the characteristic of food quality with around 81.5% (Table 4). In addition, regional products are important or very important for the majority (around 57%). A low price is important for around 62%. 49.5% have a high preference for fair trade FMCG and around 36% indicated a high importance for organic food.

Table 4: Attitudes towards features of FMCG

Feature	Frequency
Freshness	87.8 %
Quality	81.5 %
Regionality	56.9 %
Low price	62.2 %
Fair trade	49.5 %
Organic food	36.4 %

Feature	Frequency
Premium quality	26.2 %
Wide range of products	77.0 %
Time flexibility	68.3 %
Frequency of in-store purchases: at least once a week	94.3 %
Frequency of permanent online purchase	33.0 %

Consumers rate premium quality as low at 26.2%. 77% of those surveyed indicated a high preference for a wide range of products and good accessibility. Temporal flexibility is important for 68.3%. More than 94% of respondents buy FMCG at least once a week. 33% of respondents buy FMCG online sometimes, often or very often. The share of online shopping in Germany in total sales rose from 8.0% in 2017 to around 11.2% in 2021 (Online Monitor 2018, 2022). Other features of the questionnaire are: fair trade, free from additives, convenience and longevity. The reported importance for these attributes is between 36 and around 58%.

4.2 Model results

We estimated the models using the statistical software Stata and the user-written command mixlogit (Hole, 2007a). In order to model the observed preference heterogeneity, interaction terms with the sociodemographic variables and the constant were formed. The constant measures the impact of the "Don't Buy" option and reflects the attractiveness of the alternatives compared to the option of not buying either product. The total share of the non-call option is 33.2%. The interactions then provide information about the extent to which the sociodemographic variables have an influence on attractiveness. The two attributes product quality and access options were dummy-coded, i.e., a new variable was created for each attribute that takes the value 1 if the attribute is named in the alternative and otherwise has the value zero. One category serves as a reference, the parameter values of the other categories are to be interpreted in relation to the reference. A positive parameter value means that the benefit of the product with this characteristic is higher than the benefit of the reference category, ceteris paribus. The characteristic curve that achieves the lowest benefit was selected as a reference. Thus, the parameters estimated in the model for the other terms are positive, i.e., they represent improvements that make interpretation easier. The regional/organic dichotomous variable takes on the value 1 if the product is regional/organic. A positive parameter value then implies a positive effect of a regional/organic product on the utility value. Since none of the expressions are relevant for the non-purchase alternative, the values here were coded as -1. Thus, the constant can be estimated without distortion. The attributes of distance and price premium were included linearly in the utility function. In this case, a negative parameter means that greater distances and price premiums have a negative impact on the utility. Since not all decision-relevant variables can often be queried in surveys, models that depict unobserved preference heterogeneity via correlation structures of the confounding variables are often used to evaluate DCE (Sagebiel, 2011; Train, 2008).

Since the existence of unobserved preference heterogeneity cannot be ruled out in this study either, we estimated several models that explicitly model preference heterogeneity. With the mixed logit model, we assume that the parameters of the attributes are normally distributed. That is, we assume that preferences within our sample are normally distributed. The estimated parameters are the mean and standard deviation of this normal distribution. A high significant standard deviation implies the presence of unobserved preference heterogeneity. Table 4 shows the results of the conditional logit model (without unobserved preference heterogeneity) and the mixed logit model with parametric preference heterogeneity. In both the conditional logit model (column 2 in Table 4) and the mixed logit model (columns 3 and 4 in Table 5), all coefficients are significant at least at the 10% level. The constant has a positive sign in both models, which means that the respondents would tend not to buy either product. However, the value of the constant depends on the coding of the attributes and is therefore not interpretable per se.

Table 5: Results of the Conditional Logit and the Mixed Logit model

	Conditional Logit	**Mixed Logit**	
		Mean	Standard Dev.
Interactions			
Constants	4.220***	4.300***	
	(8.65)	(7.45)	
Gender (1= Male)	-0.350***	-0.554**	
	(-4.94)	(-2.39)	
Age	0.0117***	0.0169**	
	(5.95)	(2.57)	
Rent	-0.433***	-0.670***	
	(-5.68)	(-2.66)	
Income	-0.0315***	-0.0563*	
	(-3.06)	(-1.73)	
Product Quality (Reference: Convenient)			
Premium	0.375***	0.463***	0.435***

	(4.55)	(4.44)	(3.18)
High Grade	0.558***	0.705***	0.490***
	(6.55)	(6.62)	(4.02)
Standard	0.271***	0.346***	0.109
	(3.18)	(3.49)	(0.49)
Original Brand	0.377***	0.426***	0.384***
	(4.71)	(4.35)	(2.84)
Access Options (Reference: Pick-up Station)			
Home Delivery	0.508***	0.513***	0.630***
	(5.03)	(4.06)	(4.03)
Available in store/Supermarket	0.743***	0.969***	0.556***
	(9.65)	(9.82)	(6.13)
Mobile Store	0.271***	0.216**	0.628***
	(3.77)	(2.33)	(6.42)
Shopping Centre	0.485***	0.523***	0.774***
	(6.26)	(5.11)	(7.94)
Regional/Ecological	0.337***	0.360***	0.706***
	(6.83)	(5.09)	(9.54)
Distance	-0.0675***	-0.113***	0.143***
	(-3.26)	(-4.26)	(2.58)
Price Increase	-0.415***	-0.554***	
	(-20.90)	(-20.37)	
Respondents	407	407	
χ^2	685.4	862.5	
Log Likelihood (Null)	-4471.4	-4128.6	
Log Likelihood	-4128.6	-3697.4	

Values in Brackets, * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Chi Square value: $p < 0.01$

A positive sign means that respondents would not buy either of the two products if both products tend to have negative characteristic values. This (non-purchase) effect is weaker for male participants, who are younger, rent their homes and have higher incomes. The dummy coded attribute Product Quality has the phrase Convenient as a reference. The positive signs of the other attributes indicate that convenience products are the least useful. The attribute quality (β=0.558) offers the highest benefit, followed by Private Label (β=0.377) and Premium (β=0.375) and finally Standard (β=0.271). All standard deviations of the terms other than Standard were significant and similar to the mean, indicating high preference heterogeneity.

The attribute Access Option had the expression Time-independent Packing Station as a reference category. The positive coefficients mean that the other terms give more utility than the reference. Respondents were most likely to shop at a grocery store or supermarket (β=0.743). Next best options are home delivery (β=0.508) and mall (β=0.485), followed by mobile delivery (β=0.271). A time-independent packing station is the least preferred option. For this attribute, too, the high and significant standard deviations indicate preference heterogeneity, partly to the effect that the sign of the coefficient is reversed for some respondents. The standard deviations are above the mean for the attributes shopping center and mobile supply in particular; Some respondents would prefer a packing station that is not dependent on time to a mobile supply and shopping center. The coefficient of the attribute Regional/Organic is significant and positive. The corresponding standard deviation is also significant and relatively high. Therefore, the majority of respondents prefer to buy those products, but this is not the case for all. The distance also plays a role. Respondents prefer shorter distances, but the significant but rather low standard deviation suggests that distance is not relevant for some respondents.

As expected, the price premium is significant and negative. Therefore, respondents prefer to buy products at a lower price, all things being equal (Bogetić et al., 2016). Overall, the results indicate that high product quality generates the highest benefit and convenience products the lowest benefit. The respondents prefer to shop in grocery stores or supermarkets and most respondents prefer to buy regional or ecological products. To answer our first research question, it makes sense to calculate the WTP values for each attribute. This is the marginal rate of substitution between an attribute and its price. In other words, it is the monetary value for an improvement in a quality that the respondent is willing to pay without being made worse off or better off. We calculate the WTP by dividing the attribute coefficient by the price coefficient. In this DCE, the price is the percentage increase (decrease) of the current price. Therefore, we interpret the WTP values as percentage values. Table 6 shows the WTP values and confidence intervals for all attributes and characteristics.

The confidence intervals were calculated using the method of Krinsky and Robb (1986, 1991), whose non-parametric approach to calculating the WTP has advantages over the more commonly used delta method (Hole, 2007b). The attributes that seem to have the biggest impact on WTP are access options and product quality. Respondents are willing to pay 13 % more for a high-quality product than for a convenience product. For deli standard and private label products, the additional WTP is between 6 and 8 % compared to a convenience product. In addition, those surveyed are willing to pay almost 18 % more when shopping in a supermarket than when buying at a packing station that is independent of the time. The WTP is about 9 % higher for home deliveries and malls. Those surveyed would pay almost 4 % more for mobile supply. The additional WTP for regional/organic products is 6.5 %. A distance of more than three kilometers results in a negative WTP of 8.2 %, i.e., respondents would pay this premium if they could purchase the product in their immediate vicinity. If one compares a non-regional/organic convenience product that can be bought at a pick-up station more than three kilometers from home with a regional/organic (6.5 %) high-quality product (12.7 %) in a shop or supermarket (17.5 %) in close proximity (8.2 %), the additional WTP is approximately 44.7 %.
A retailer can therefore charge up to 45 % more for products with these characteristics. Price, product quality and easy availability are the strongest drivers for FMCG purchases, what corresponds with several studies such as Bogetić et al. (2016), Mahalingam (2012), Klein, Schmitz (2016) and Pallavi, Shashidhar (2015). The non-buying effect shown in Table 5 indicates that younger, higher-income male renters tend to buy more FMCG. For this specific constellation, we can confirm that some socio-demographic variables determine the overall WTP for FMCG. In addition, high estimates for the coefficient of the attribute Regional/Organic indicate strong influences of this attribute on the WTP. The high importance of regional origin (approx. 67 %) underlines this status. Consumers reported an additional WTP for local and eco-friendly FMCG of 6.5 %. Compared to the WTP for all other attributes except mobile store, this value is relatively low.

Table 6: Willingness to Pay and confidence intervals

	WTP (%)	Confidence Interval	
		lower limit	Upper limit
Product Quality (Reference: Convenient*)*			
Premium	8.4	4.6	12.1
High Grade	12.7	9.0	16.6
Standard	6.3	2.9	9.6
Original Brand	7.7	4.3	11.3
Access Options (Reference: Pick-up Station)			
Home Delivery	9.3	4.8	14.3
Available in store/Supermarket	17.5	14.2	21.3
Mobile Store	3.9	0.8	7.3
Shopping Centre	9.4	6.0	12.9
Regional/Ecological	6.5	4.2	9.0
Distance (from 0 to over 3km)	-8.2	-12.0	-4.2
Confidence Interval calculated with the Krinsky & Robb Method			

5 Discussion and conclusion

The conditional logit model and the mixed logit model show price awareness. In supermarkets and shopping centers, the preferences for availability are particularly high. Consumers are willing to pay extra for mobile shops, but at a relatively low level. The influences of sociodemographic variables are limited, but income, gender, and housing situation significantly affect FMCG consumption behavior, as shown in Table 4. Furthermore, attitudes towards the importance of regional and environmentally friendly products correspond to additional WTP for regional and environmentally friendly consumer goods, but at a relatively low level. With the start of the COVID-19 pandemic and restrictions in Germany and other countries since March 2020, preferences for the properties examined have changed due to legal restrictions and fear of contagion. The purchase frequency in supermarkets and shops is still relatively high as long as food and beverages are exempt from access restrictions. Additionally, the direct and indirect macroeconomic impacts of the COVID-19 pandemic have increased the pressure on retailers in FMCG markets to make structural changes.

First, the federal government has put together an extensive financial aid package to avoid mass unemployment and mass bankruptcies due to the restrictions imposed by the COVID-19 pandemic. In order to finance these investments, the government must increase the public debt. Combined with rising energy prices since 2020, this led to a rise in the consumer price index (CPI) of more than 5% in 2022 (inflation.de 2022), compared to less than 0.5% before 2019. Second, global production and supply chains have has changed significantly for a variety of reasons, including rising resource prices due to scarcity and political instability in some regions. These changes result in additional costs and price volatility (ET Brand Equity 2022). These impacts at the micro and macro levels, caused directly and indirectly by the COVID-19 pandemic, have not changed the conditions in the FMCG markets but have reduced the opportunities for traders to innovate. Although the survey began ahead of the COVID-19 pandemic, the results show that retailers are able to respond to additional market pressures in the form of fluctuating commodity prices and restricted market access. The intense growth of food and beverage delivery services since 2017, and especially since the COVID-19 pandemic, indicates a major shift in FMCG consumption patterns. As early as June 2020, around 40 % of consumers in Germany had reduced their purchases in stores and shopping centers. Around 22 % used online delivery services and more than 80 % will continue this behavior after the pandemic is over (PWC 2020). Around 88 % are satisfied with online consumption of food and beverages, leading to an increase in online retail market share from 0.8 % in 2015 to 1.4 % in 2020. The forecast for online groceries is around 10% by 2024.

The results of our models, first show a strong preference for higher product quality over a convenient reference and for access options other than a pickup station. Second, the key demographic group of young male participants with higher incomes and higher rents is more likely to purchase FMCG with higher product quality and availability in supermarkets. This supports the results of Bogomolova et al. (2019) who point to the need to target younger and educated consumers. In addition, men with children are a target group for discounters (Mintel 2021). Applying the results of our study to the specific situation of FMCG during the COVID-19 pandemic shows that mobile stores are of comparatively little importance. This makes it difficult to implement the necessary restrictions during pandemics, as many consumers prefer to buy in-store. Furthermore, high price sensitivity (Table 3) combined with a relatively strong preference for proximity to purchase location (Table 4) may be enough to drive growth rates of online food and beverage delivery services. Obviously the COVID-19 pandemic will be a multiplier for this effect.

Here, too, the price segment of FMCG is decisive. Only in higher price segments does demand have high price elasticity and thus demand falls relatively sharply as a result of a price increase. The FMCG examined in this study are in the lower price segment with low price elasticity of demand (Huang et al. 2017). The inflation rate in Germany has been over 7 % since April 2022, and the consumer price index (CPI) has risen by around 10% since the beginning of the year (Destatis 2022a). Household inflation expectations for the next twelve months point to an inflationary trend. Expected values of just over 8 % (Beckmann, Schmidt 2022) show that private households have high expectations. From an economic point of view, the expectation of rising inflation alone leads to an increasing demand for money with a corresponding inflationary effect. Losses from high inflation have a greater impact on the expected inflation rate than gains from inflationary effects. This applies in particular to consumer durables (Vogel et al. 2009). Inflation effects on FMCG buying behavior have implications for strategic marketing. In the following section, we discuss appropriate combinations of attribute levels with the highest WTP.

5.1 Strategic implications

The results of the choice experiment show several significant effects of the attribute features compared to the fixed reference. This heterogeneity, combined with the socio-economic characteristics of age and rent, reveals strategic potential for FMCG companies to optimize product design and access options. Certain combinations of attribute levels and socioeconomic variables significantly determine the WTP. Together with the results of related studies such as Bogomolova et al. (2019) several strategic implications for FMCG offerings are highlighted here. At 12.7 %, the WTP for the second highest level of the product quality attribute (high quality) is almost twice as high as the WTP for the next level (standard). These results are consistent with Sundstroem and Hjelm-Lidholm (2019). They recommend HR management to identify customer motivations and preferences for product attributes. Macroeconomic conditions, especially inflation, reduce the remaining WTP for additional attributes such as higher quality and regional or organic production. This limited pricing flexibility requires constant study of consumer preferences and expectations to maximize the conversion of WTP to revenue. The additional WTP for organic or regional products is comparatively low at around 6.5 %, but with potential for marketing measures. Growing share of local businesses and products supported by the impact of the COVID-19 pandemic; 23 % of consumers in Germany have been using local shops since the beginning of 2020 and only 61 % of consumers are satisfied with the labeling of origin on products (Mintel 2021).

In agreement with the results of Angelez-Martinez et al. (2018), FMCG providers should market this attribute in combination with other highly preferred attributes. Some retailers in the FMCG market invest large sums annually, for example in TV advertising. In the group of retailers with the highest annual investments, only a few companies, such as Ferrero and Henkel, increased their investments between 2019 and 2021 (xadspoteffects 2019, 2021). This contrasts with the results of our study, which indicate potential for higher investment. When combining the attributes and levels described in Chapter 4, high-quality FMCG that are regionally or organically produced and available in close proximity add up to almost 45 % additional WTP. Although there is some overlap in economic evaluation when each WTP value is accumulated, this additional sales per unit can be used to fund targeted marketing to increase customer retention, product placement and frequency of purchase. Such financial measures are necessary to take advantage of the limited opportunities to expand the customer base (Bogomolova et al., 2019) and to create customer loyalty that is strongly determined by the attributes of price, perceived quality, trust and brand name. Around 71 % of companies invest 2 % of total sales in investments to increase customer loyalty. Customer attitudes towards brand loyalty have changed. In addition, the impact of the COVID-19 pandemic and the rising CPI increase the need for additional investments in customer and brand loyalty (Oszi 2021). In order to translate the results and findings into coherent measures, the following recommendations can be derived from the findings:

1. Discounters and other retailers should intensify targeted marketing tools to increase brand loyalty and awareness of quality branded and organic food. Despite the increasing share of the respective market segments in Germany in recent years, the results show an additional WTP for these brands.
2. Targeted investments in supermarket locations in urban centers with a high proportion of young, high-income tenants are successful in large cities. In medium-sized cities and rural areas, retailers should take more risks when investing in these target groups outside of large cities. However, the continued rise in CPI and related consumer expectations, discussed here, are worsening the investment climate.

5.2 Limitations

Our study shows a strong heterogeneity between the characteristics of selected FMCG in Germany. However, the results are subject to some limitations. First, although the study examined FMCG in general, the authors cannot rule out heterogeneity within the FMCG group. Therefore, our results show the preference structure for FMCG in general, without distinguishing between FMCG groups such as food, drink, and durable goods. Further research should examine whether preference structures differ between FMCG groups. Second, additional socioeconomic parameters should be included in the choice experiment to test whether characteristics such as household size, living space structure, and diet style determine the WTP for selected attributes of FMCG. Third, the design of the choice experiment used in the study reflects specific buying situations. However, further applications of choice cards should include other attributes such as different labels for organic and regional production and distribution as well as travel costs to the point of sale. Furthermore, the study of consumer behavior in FMCG markets is driven by more than the maximum number of attributes and levels covered by choice experiments.

This limitation requires interdisciplinary approaches to identify psychological and institutional determinants of consumer behavior in FMCG markets. Finally, the model results represent consumer preferences in the study period 2015 and 2016. The results of our study underscore the increased vulnerability of the FMCG markets due to the COVID-19 pandemic and can be broadly compared to more recent studies as presented in Sections 4 and 5.1. However, recent developments in the COVID-19 pandemic are associated with fundamental changes in consumer mobility, market access and the financial strength of retailers. This requires a detailed study of the impact of these new conditions on the structure and persistence of consumer preferences for FMCG.

Subjects

The study meets the ISM rules approved by the German Research Foundation (DFG) to ensure good scientific practice. Before participating in the study, each test person was informed about the anonymous use of the data.

References

Angelez-Martinez, L., Theodoropoulos, C., Lopez-Quiroga, E., Fryer, P.J., Bakalis, S. (2018). The Honeycomb model: A platform for systematic analysis of different manufacturing scenarios for fast-moving consumer goods. Journal of Cleaner Production, 193, 315–326.

Beckmann, E., Schmidt, T. (2022). Technical Paper. Bundesbank online pilot survey on consumer expectations. 01/2020. Deutsche Bundesbank.

Boersenblatt. (2020). Kleine Läden besonders gefragt. https://www.boersenblatt.net/ archiv/ 1801052.html. Accessed February 26, 2021.

Bogetić, Z., Stojković, D., Milošević, S. (2016). Shopper Marketing Strategy in Food Retailing. Eco-nomics of Agriculture, 1, 189-204. DOI: 10.5937/ekoPolj1601189B.

Bogomolova, S., Anesbury, Z., Lockshin, L., Kapulski, N., Bogomolov, T. (2019). Exploring the inci-dence and antecedents of buying an FMCG brand and UPC for the first time. Journal of Retail-ing and Consumer Services, 46, 121-129.

Buckinx, W., van den Poel, D. (2005). Customer base analysis: partial defection of behaviourally loyal clients in a non-contractual FMCG retail setting. European Journal of Operational Re-search, 164, 252–268.

Campbell, D., Erdem, S. (2019). Including Opt-Out Options in Discrete Choice Experiments: Issues to Consider. The Patient: Patient-Centered Outcomes Research, 12, 513-526.

ChoiceMetrics. (2012). NGene 1.1.1 User Manual & Reference Guide. Choicemetrics Pty Ltd. http://www.choice-metrics.com/documentation.html. Accessed June 12, 2020.

Destatis (2022a). Inflation rate at +10.0% in September 2022. https://www.destatis.de/ EN/Press/2022/10/PE22_438_611.html

Destatis (2022b). Monthly development of revenues in the retail sector in Germany between Ja-nuary 2021 and January 2022.

Destatis (2022c). Monthly development of different sectors in the retail sector in Germany between January 2021 and January 2022.

Dodds, W. B., Monroe, K. B., & Grewal, D. (1991). Effects of price, brand, and store information on buyers' product evaluation. Journal of Marketing Research, 28 (August), 307–319.

Dominique-Ferreira, S., Vasconcelos, H., Proenca, J.F. (2016). Determinants of customer price sen-si-tivity: an empirical analysis. Journal of Services Marketing, 30, p. 329.

ET Brand Equity (The Economic Times) (2022). FMCG makers to go for around 10% price hike to mitigate inflationary pressures. https://brandequity.economictimes.indiatimes.com/ news/business-of-brands/fmcg-makers-to-go-for-around-10-price-hike-to-mitigate-inflationary-pressures/90344196.

GfK (2019). Consumer Index. Consumer Panels, p. 2.

Global Organic Trade Guide. (2019). https://globalorganictrade.com/country/germany. Accessed March 26, 2021.

Grebitus, C., Lusk, J.L., Nayga, R.M. (2013). Effect of distance of transportation on willingness to pay for food. Ecological Economics, 88, 67–75.

HDE (2022). Online-Monitor 2022. Anteil der Branchen am Gesamtvolumen in Prozent und Branchen-Online Volumen 2021, p. 14.

HDE (2020). Handelsreport Lebensmittel. Corona Update 2020. FMCG Industry Information of HDE and IFH for the retail trade.

HDE (2018). Online-Monitor 2022. Anteil der Branchen am Offline- und Onlinevolumen in Prozent, p. 12.

Henrich, P. (2019). Statistiken zu FMCG. Statista, https://de.statista.com/themen/ 574/fmcg/. Accessed February 26, 2021. Accessed January 29, 2021.

Hensher, D.A., Truong, T.P. (2014). Linking discrete choice to continuous demand in a spatial computable general equilibrium model. Journal of Choice Modeling, 12, 21-46.

Hensher, D.A., Rose, J.M., Green, W.H. (2005). Applied Choice Analysis. A Primer. Cambridge Uni-versity.

Hole, A.R. (2007a). Fitting mixed logit models by using maximum simulated likelihood. Stata Journal, 7, 388–401.

Hole, A.R. (2007b). A comparison of approaches to estimating confidence intervals for willingness to pay measures. Health Economics, 16, 827–840.

Huang, A., Lockshin, L., Dawes, J., Greenacre, L. (2017). Consumer Response to Price Changes in Higher-Priced Brands. Journal of Retailing and Consumer Services, 39, 1-10.

Inflation.de (2022): https://www.inflation.eu/en/inflation-rates/germany/historic-inflation/cpi-inflation-germany-2021.aspx. Accessed March 29, 2022.

Kamenidou, I., Stavrianea, A., Bara, E. (2020). Generational Differences toward Organic Food Behavior: Insights from Five Generational Cohorts. Sustainability, 12, 2299, doi:10.3390/su12062299.

Kenton, W. (2021). Fast-Moving Consumer Goods (FMCG). https://www.investopedia.com/terms/f/fastmoving-consumer-goods-fmcg.asp. Accessed November 7, 2022.

Klein, A., Schmitz, G. (2016). Main-format Dominance in Consumers' FMCG Cross-format Shopping Patterns. Journal of Retailing and Consumer Services, 30, 105-115. DOI: 10.1016/j.jretconser.2015.11.011.

Krinsky, I., Robb, A.L. (1986). On Approximating the Statistical Properties of Elasticities. The Review of Economics and Statistics, 68, 715–719.

Krinsky, I., Robb, A.L. (1991). Three methods for calculating the statistical properties of elasticities: A comparison. Empirical Economics, 16, 199–209.

Krystallis, A., Chryssohoidis, G. (2005). Consumers' willingness to pay for organic food: Factors that affect it and variation per organic product type. British Food Journal, 107, 320–343.

Lebensmittel Zeitung, Nr. 4, 28.01.2022, p. 60.

Mahalingam, S., Kumar, P.N. (2012). A study on consumer behaviour towards selected fast moving consumer goods in Coimbatore city. Indian Journal of Education and Information Management, 1(11), 500-507.

Market Research Reports (2021). https://www.marketresearchreports.com/marketline/ organic-food-germany. Accessed March 26, 2021.

McFadden D. (1974). Conditional Logit Analysis of Qualitative Choice Behavior. In: Zarembka P, edi-tor. Frontiers in econometrics, Academic Press, 105–142.

Mintel (2021): Food and Non-Food Discounters - Germany - 2021. mintel.com.

Mohan, B.C., Sequeira, A.H. (2015). The impact of customer-based brand equity on the operational performance of FMCG companies in India. IIMB Management Review, 28, 13-19.

Niedermeier, A., Emberger-Klein, A., Menrad, K. (2021). Which factors distinguish the different consumer segments of green fast-moving consumer goods in Germany? Business Strategy and the Environment, 30, 1,823-1,838.

Nielsen. (2019). FMCG growth in Europe bounces back in the second quarter of 2019. https://www.fortuneindia.com/macro/rural-fmcg-growth-bounces-back-nielsen-report/101922. Accessed March 26, 2021.

Nielsen. (2018). Nielsen - Handel Verbraucher Werbung Deutschland 2018, 14.

Nierobisch, T., Toporowski, W., Dannewald, T., Jahn, S. (2017). Flagship stores for FMCG national brands: Do they improve brand cognitions and create favorable consumer reactions? Journal of Retailing and Consumer Services, 34, 117-137.

Omoregbe, O., Ogbeide, D.O. (2013). Modelling Brand Loyalty of Fast Moving Consumer Goods. Benin Journal of Social Sciences, 21(2), 44-54.

Oszi, T. (2021). How to Create Customer Loyalty Programs: a Definitive Guide. https://antavo.com/blog/customer-loyalty-programs/. Accessed March 30, 2022.

Pabst, E., Corsi, A.M., Vecchio, R., Annunziata, A. (2021). Consumers' reactions to nutrition and ingredient labelling for wine – a cross-country discrete choice experiment. Appetite, 156, 104843, https://doi.org/10.1016/j.appet.2020.104843.

Pallavi, G.S., Shashidhar, S. (2015). A Study on Consumer Behavior towards Selected FMCG. International Journal of Engineering and Management Research, 5(2), 303-320.

Pradhan, J, Misra, D.P. (2014). Rural Brand Awareness and Preferences for FMCGs: An Empirical Study on Keonjhar District of Odisha, India. Journal of Business and Management, 16(9), 17-29.

PWC. (2020). Global Consumer Insights. COVID-19 Pulse Survey. https://www.pwc.de/ COVID-Konsumentenumfrage#download. Accessed January 29, 2021.

Rose, J. M., Bliemer, M.C. (2008). Stated preference experimental design strategies. Handbook of Transport Modelling, Elsevier, Oxford, 151–180.

Sagebiel, J. (2011). Comparing the latent class model with the random parameters logit: A choice experiment analysis of highly heterogeneous electricity consumers in Hyderabad, India. Paper presented at the International Choice Modelling Conference, 4-6 July 2011, Leeds, UK.

Siegfried, P., Zhang, J.J. (2021). Developing a Sustainable Concept for Urban Last-Mile Delivery. Open Journal of Business and Management, 9, 268-287. https://doi.org/ 10.4236/ojbm.2021.91015.

Statista (2022). Corona und der FMCG-Markt (Nonfood) in Deutschland.

Statista (2021a). FMCG-Markt Deutschland. Accessed March 30, 2022.

Statista (2021b). Bevölkerung in Deutschland nach Fahrbereitschaft zum Einkaufszentrum von 2017 bis 2020. Accessed November 16, 2022.

Stockworld. (2020). Umsatz der Online-Lebensmittel-Lieferdienste wächst jährlich um 9,8 % http://www.stock-world.de/analysen/nc12303944. Accessed January 29, 2021.

Sundstroem, M., Hjelm-Lidholm, S. (2019). Re-positioning customer loyalty in a fast moving consu-mer goods market. Australasian Marketing Journal, https://doi.org/10.1016/ j.ausmj.2019.09.004.

Train K.E. (2008). Discrete choice methods with simulation. repr. Cambridge: Cambridge Univ. Press.

Ulbricht, D., Chervyakov, D. (2015). Population Ageing and Its Effects on the German Economy. DIW Roundup 78.

United Nations. (2008). International Standard Industrial Classification of All Economic Activities. Department of Economic and Social AffairsStatistics Division, Statistical papers Series M No. 4/Rev.4, New York.

Vecchi, M., Jaenicke, E.C., Schmidt, C. (2022). Local food in times of crisis: The impact of COVID-19 and two reinforcing primes. Agribusiness, 1-24.

Wunsch, N.G. (2020). Organic food market in Europe - Statistics and Facts. Statista: https://www.statista.com/topics/3446/organic-food-market-in-europe/. Downloaded on March 26, 2021.Xadspoteffects.com (2021). Ranking of firms in the FMCG-Sector with the highest investments in TV-advertising in Germany, 4th Quarter 2021, Statista.

Xadspoteffects.com (2019). Ranking of firms (without E-Commerce) with the highest investments in TV-Advertising in Germany, first six month 2019, Statista.

You, J.E., Choi, J.W. (2021). An analysis of food culture and technology acceptance for youth: Using a choice experiment and a latent class model. Managerial Decision Economics 2022, 43, p. 514f.

Zarantonello, L. Jedidi, K., Schmitt, B.H. (2013). Functional and experiential routes to persuasion: An analysis of advertising in emerging versus developed markets. International Journal of Re-search in Marketing, 30, 46-56.

Author/s

Prof. Dr. Kai Rommel received his doctorate in agricultural economics at the Faculty of Agriculture and Horticulture of the Humboldt University of Berlin. Between 2000 and 2007 he habilitated at the Chair of Economics, in particular Environmental Economics at the Brandenburg University of Technology Cottbus in Economics, Energy Economics and Environmental Economics. He then worked as a strategist for energy economics at Energie Baden-Württemberg AG. Since March 2010 he has been Professor and since 2014 Vice President for Research at the International School of Management in Dortmund. He manages third-party funded projects in the field of municipal finance and regularly publishes in peer-reviewed journals.

Dr. Julian Sagebiel is an environmental and agricultural economist, working as a PostDoc at the German Centre for Integrative Biodiversity Research (iDiv) Halle-Jena-Leipzig. There he works on valuation of natural capital using choice experiments and other revealed and stated preferences methods. From 2009 to 2013, he worked as a research assistant at the Department of Cooperative Science at the Humboldt-Universität zu Berlin. After working at Technische Universität Berlin and IÖW Berlin, he spent 1.5 years at the Department of Economics at the Swedish University of Agricultural Sciences in Uppsala, Sweden.

CALL FOR PAPERS - RESEARCH JOURNAL FOR APPLIED MANAGEMENT 2022

Das Research Journal for Applied Management (RJAM) ist eine Fachzeitschrift für neue Trends und Strömungen in den praxis-relevanten Managementbereichen Internationalisierung der Wirtschaft, ressourcenökonomische Forschung, Tourismusforschung, Logistik- und Informationsforschung, Finanz- und Bankenforschung, Marketing- und Kommunikationsforschung, Immobilienforschung, Leadership- und Motivationsforschung und Organisations- und Personalforschung. Das Research Journal for Applied Management versteht sich als eine praxisrelevante und transdisziplinäre Fachzeitschrift für Fragen und kritische Analysen von wirtschaftlichen, sozialen und politischen Veränderungen, insbesondere von Systemen, aber auch von interorganisationalen Prozessen.

Ziel des **Research Journal for Applied Management** ist es, die jeweils aktuellen Entwicklungen und Ergebnisse der Forschung zu den Fragen der praxisrelevanten Managementbereiche aufzuzeigen und fortzuentwickeln. Das Research Journal for Applied Management steht für alle Wissenschaftlerinnen und Wissenschaftler offen, die Management als Funktion, Institution oder Praktik untersuchen. Im Focus der Artikel soll die Erarbeitung neuer Perspektiven oder die Erschließung innovativer Problemstellungen stehen. Willkommen sind sowohl empirische Studien, konzeptionelle Analysen als auch anwendungsorientierte Studien. Weitere Informationen zum Research Journal for Applied Management sind hier verfügbar: https://www.ism.de/forschung/forschungsaktivitaeten.

Die Einreichung von Beiträgen ist jederzeit möglich. Im Beitrag sind die verwendeten Zitate (direkte, indirekte) mit Seitenzahl anzugeben. Zur Begutachtung angenommene Beiträge durchlaufen ein Double Blind Peer Review Begutachtungsverfahren nach internationalen Standards – mit mindestens zwei Fachgutachterinnen bzw. Fachgutachtern. Die Publikationssprachen sind Deutsch und Englisch. Zur Erleichterung unserer Disposition bitten wir darum, geplante Beiträge möglichst frühzeitig einzureichen. Die maximale Länge des gesamten Beitrags liegt bei ca. 20 Seiten einschließlich eines Abstracts im Umfang von max. 250 Wörtern. Einreichungen können als Word-Dokument per E-Mail an robinson.nittke@ism.de geschickt werden.

Bitte erstellen Sie zusätzlich Ihre Abbildungen in Microsoft PowerPoint und reichen die entsprechende Datei separat ein. Über eine Eignung des Beitrags entscheidet das Editorial Board zeitnah. Bitte beachten Sie unbedingt den Guide mit Formatvorlage https://www.ism.de/images/downloads/style-sheet-deutsch.pdf. Die Beiträge sollen grundsätzlich das generische Maskulinum verwenden. Abweichende Geschlechterformulierungen müssen den Anforderungen an die deutsche Rechtschreibung gemäß Duden entsprechen und konsistent angewendet werden. Die Literatur sollte als Projekt (Citavi oder ähnliches) zur Verfügung gestellt werden, um den redaktionellen Prozess zu erleichtern.

Artikel zu Themen aller Managementbereiche sind willkommen.

Kontakt

International School of Management (ISM)
Prof. Dr. Kai Rommel (Vizepräsident für Forschung)
Robinson Nittke (Wissenschaftlicher Mitarbeiter/Forschungsreferent)
Otto-Hahn-Straße 19 · 44227 Dortmund
Tel.: 0231.97 51 39-775 · Fax: 0231.97 51 39-39
E-Mail: kai.rommel@ism.de, robinson.nittke@ism.de
https://www.ism.de/
https://www.ism.de/forschung/forschungsaktivitaeten

CALL FOR PAPERS - RESEARCH JOURNAL FOR APPLIED MANAGEMENT 2022

The Research Journal for Applied Management (RJAM) is a specialized journal for new trends and directions in practice-relevant management topics focusing on the internationalization of the economy, resource economics, tourism, logistics and information sciences, finance and banking research, marketing and communication research, real estate, leadership and motivational research and organization, and human resource research. The RJAM itself is a practice-oriented and trans-disciplinary journal for questions and critical analyses addressing economic, social and political change, in particular regarding systems, but also for intercorporate processes.

The RJAM aims to show trends and developments in current studies and further elaborate on questions which arise regarding practice-oriented management fields. The RJAM serves as a platform for all scientists, who intend to publish research in the field of management. Articles published in the RJAM assess management in terms of its function, its methodologies and examine the institutions behind it.

Articles should be focused on elaborating upon new perspectives or an innovative presentation of a problem. Empirical studies, conceptual analysis and application oriented studies are always welcome. More information on the Research Journal for Applied Management are available here: https://en.ism.de/research/research-activities.

It is generally possible to submit articles at any point of time. The article can be submitted in English or German to robinson.nittke@ism.de. The article has to be submitted according to the provided guidelines and style sheet (https://www.ism.de/images/downloads/style-sheet-research-journal.pdf). The maximum size of submitted papers is around 20 pages including an abstract with not more than 250 words. Submissions should use the non-gender specific pronouns e.g. 'they" or 'it'. Any alternative form of gender formulation must be used consistently and according to English grammar Please note, authors are strongly requested to create their figures in Microsoft PowerPoint and to submit the corresponding file separately. Regarding quotes used in the article (direct and indirect ones) page numbers have to be specified. Articles accepted for review will undergo a double blind peer review process in accordance with international standards – the peer review will be conducted by at least two referees.

In addition to the article and abstract itself, authors are asked to submit their references in form of a Citavi project (other reference management programs can be accepted after consultation with the editors).
The editors adhere to decide upon qualification in a timely manner.

Articles concerning all types of management fields are welcome.

Contact:
International School of Management (ISM)
Prof. Dr. Kai Rommel (Vice President Research)
Robinson Nittke (Research Assistant)
Otto-Hahn-Str. 19 · 44227 Dortmund
Tel.: 0231.97 51 39-775 · Fax: 0231.97 51 39-39
email: kai.rommel@ism.de, robinson.nittke@ism.de
https://en.ism.de/
https://en.ism.de/research/research-activitie