Duncker, Christian; Perret, Jens K.

Article

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

Research Journal for Applied Management (RJAM)

Provided in Cooperation with:
International School of Management (ISM), Dortmund

Suggested Citation: Duncker, Christian; Perret, Jens K. (2022) : Beyond Linearity – An Analysis of the Interdependencies across the Customer Journey, Research Journal for Applied Management (RJAM), ISSN 2701-6633, BoD – Books on Demand GmbH, Norderstedt, Vol. 3, Iss. 1, pp. 53-84

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.

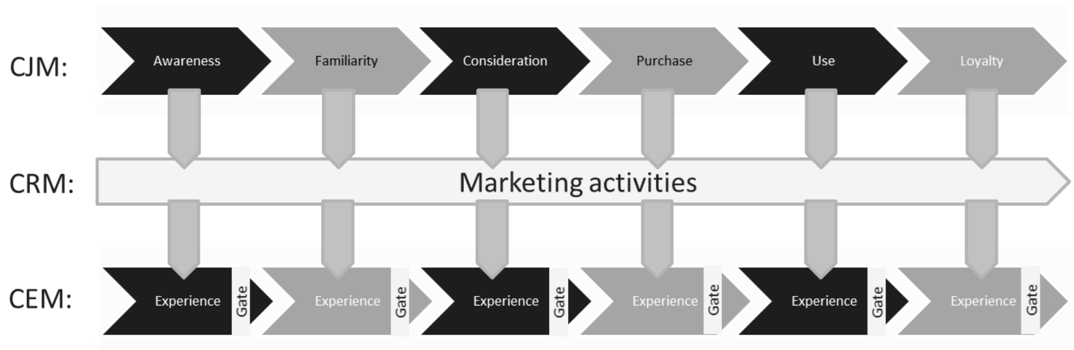

Figure 1 Relationship between CJM, CRM & CEM – the „Triple-C-Model“

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

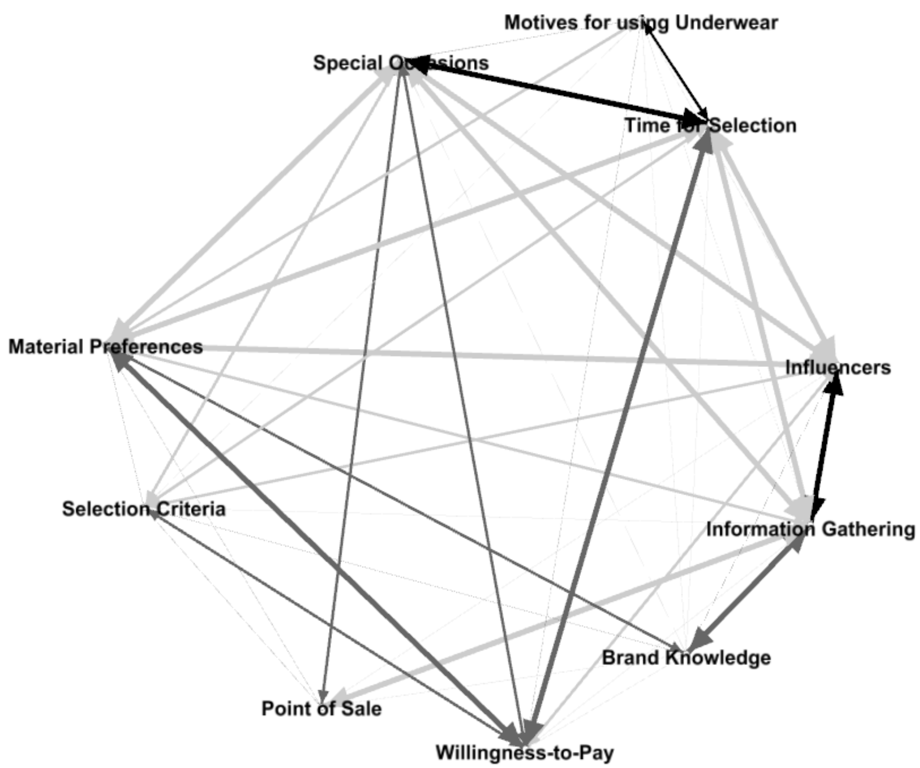

Figure 3: Building blocks of the „Triple-C-Model" in a Network Layout

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.

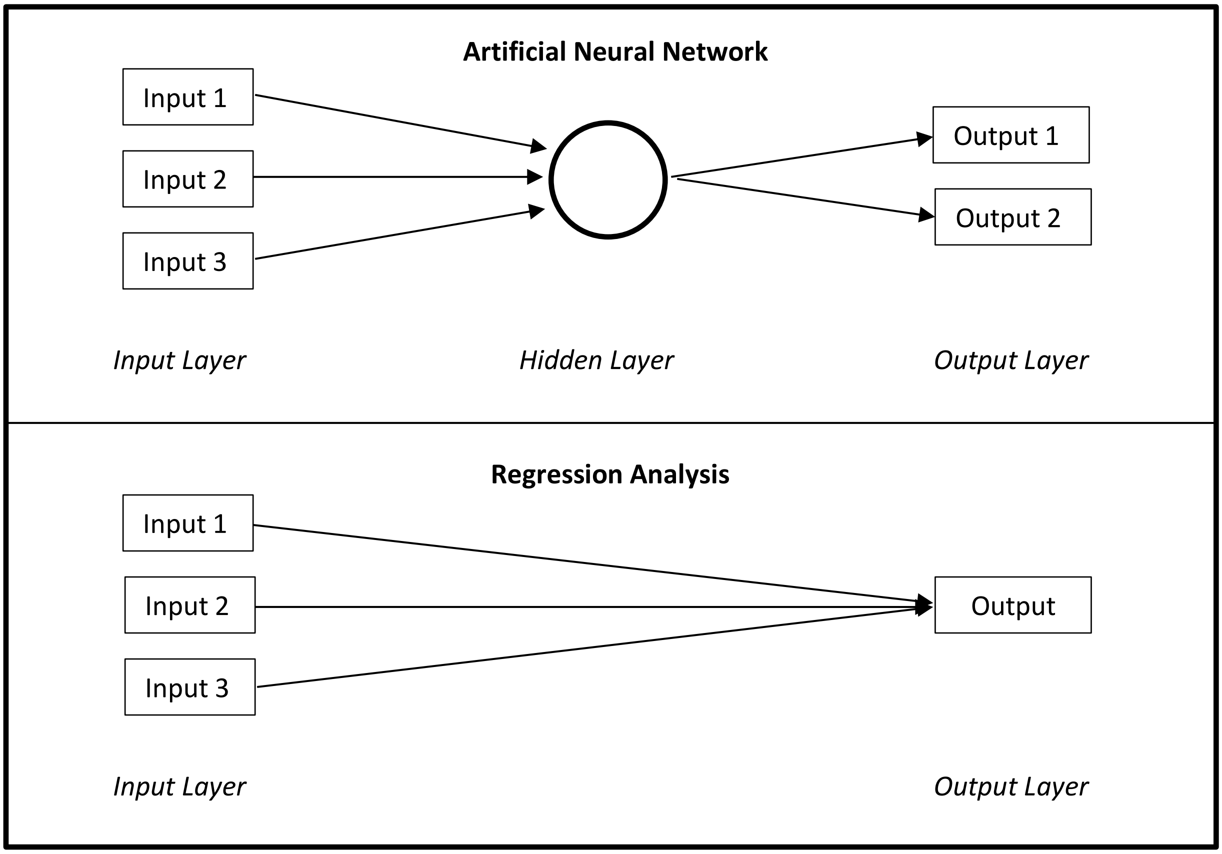

Figure 4: Structure of an Artificial Neural Network

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.