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**MASS PERSONALISATION: UNDERSTANDING OF VALUE
PERCEPTION AND PURCHASE INTENTIONS**

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Master Thesis

presented as partial requirement for obtaining a Master's Degree in Data-Driven Marketing

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação

Universidade Nova de Lisboa

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by

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Master Thesis as partial requirement for obtaining the Master's degree in Data-Driven Marketing, with a specialisation in Digital Marketing and Analytics

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism, any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

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ABSTRACT

The industry is facing a high demand for personalised products which can be addressed by mass personalisation (MP). However, MP is still underexplored within the marketing area. This study aims to investigate the impact of MP on consumer purchase intentions, with a particular focus on the mediating role of value perception. Using 3,500 online reviews from Trustpilot for the Care/Of brand, the data were analysed through text mining and Partial Least Squares Structural Equation Modelling (PLS-SEM). The findings reveal that product/service personalisation significantly enhances value perception, which subsequently boosts purchase intentions. Interestingly, the study found that neither price nor shopping channels significantly moderate this relationship. These results suggest that companies should prioritise co-creation with customers to elevate perceived value and drive purchase intentions, irrespective of price sensitivity or the shopping channel used. This research contributes to the marketing literature by highlighting the critical role of personalisation in consumer experience and providing actionable insights for businesses aiming to implement effective mass personalisation strategies.

KEYWORDS

Mass Personalisation; Value Perception; Purchase Intentions; Co-creation

Sustainable Development Goals (SDG):



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LIST OF ABBREVIATIONS AND ACRONYMS

| | |
|----------------|---|
| B2B | Business to Business |
| B2C | Business to Consumer |
| CX | Customer Experience |
| MP | Mass Personalisation |
| O2O | Online to Offline |
| PLS-SEM | Partial Least Squares Structural Equation Modelling |
| UX | User Experience |

1. INTRODUCTION

The manufacturing industry is facing a growing demand for personalised products (Katoozian & Zanjani, 2022). These products are manufactured to provide a purchasing experience to the companies revealing customers' individual tastes and preferences (Büchi et al., 2020), and producers need to satisfy those heterogeneous customer needs through individualisation with impact on scale effects along the value chain (Katoozian & Zanjani, 2022).

In 2015, the results of a study by a renowned consulting firm found that 1 in 5 consumers questioned who expressed an interest in personalised products or services are willing to pay a 20% premium. In some product categories, more than 50% of these consumers expressed interest in purchasing personalised products or services and they were willing to pay more for a customised product or service, and they would like to be actively involved in the process (Deloitte, 2015).

Therefore, it is relevant that companies adopt new forms of personalisation, focusing on customers' demands, where their wishes are the key to success (Y. Wang et al., 2017). Involving the customer in the production and co-creation of personalised products based on customer knowledge guarantees the product's origin, use, and destination and ensures that these products are monitored from the factory to the customer (Büchi et al., 2020).

A new market driver manufacturing paradigm called Mass Personalisation (MP) enables the production of unique personalised products at affordable production costs through the customer's active and individual participation in the design process (Qin et al., 2023). Mass personalisation is a promising strategy that makes "the one-person market" a reality (Zhou et al., 2013). It is lucrative and rapidly approaching (Qin et al., 2023). Consumers and producers will benefit from the value created by this method, as these inputs to design allow for companies to produce personalised products cheaper and in shorter cycles when compared to standardisation and mass production (Y. Wang et al., 2017). Additionally, in the near future, MP could become an established key production method (Turner & Oyekan, 2023).

However, the research on mass personalisation is limited. The few articles found that focus on MP address topics related to: manufacturing and industry 4.0 (Büchi et al., 2020; Castelo-Branco et al., 2023; Katoozian & Zanjani, 2022; Turner & Oyekan, 2023), the difference between MP and mass customisation (Barata et al., 2023; Espinoza Pérez et al., 2022; Y. Wang et al., 2017), MP design (Tseng et al., 2010), affective and cognitive design (Zhou et al., 2013), its production scheduling by designing a reinforcement learning-based approach for job shop scheduling problems (Qin et al., 2023), and its predictive marketing algorithms and shape of consumer knowledge, i.e., a study of algorithmic processes who adjust predictions to unique individuals involving computation of massive datasets and how local preexisting consumer knowledge is critical to the success of predictive marketing (Kotras, 2020).

Summarising, while mass personalisation (MP) has been explored in various contexts such as manufacturing, industry 4.0, and the distinction between MP and mass customisation, there is a notable gap in the literature regarding its impact on customer experience (CX) in the marketing area. Existing studies have primarily focused on technical aspects, production scheduling, and predictive marketing algorithms. However, the specific influence of MP on purchase intentions, mediated by value perception, remains underexplored.

To address this gap, the study will explore the following research questions: 1. How does mass personalisation (MP) influence consumer purchase intentions? 2. What role does value perception play in mediating the relationship between MP and purchase intentions? 3. Do price and shopping channels moderate the relationship between value perception and purchase intentions in the context of MP?

This study aims to fill this gap by investigating how MP affects purchase intentions through the lens of value perception, using online reviews from Care/Of's clients that will be collected from Trustpilot and analysed through text mining techniques and Partial Least Square – Structural Equation Modelling (PLS-SEM) to validate the raised hypotheses. This approach not only contributes to the marketing literature but also provides actionable insights for businesses looking to implement effective MP strategies by understanding how mass personalised products impact the value perceived in customer experience and their purchasing intention that comes from that value perception.

2. LITERATURE REVIEW

Mass Personalisation arises from the need to adapt to changes in the market and industry (Barata et al., 2023). There is an actual shifting focus from a value created for the company to the value of customer demand (Y. Wang et al., 2017). Customers aim to establish an experience beyond obtaining a product (Bascur & Rusu, 2020). CX is essential in maintaining a competitive advantage (Bascur & Rusu, 2020). In Contentsquare (2024), customer experience is the number one priority for companies, as 88% of consumers believe that the experience offered by a company has the same importance as its products or services. In the context of retail marketing and management, recognising customer experiences throughout their journey has been identified as a crucial element for the success of retail brands and businesses with positive effects on client loyalty and engagement (Alexander & Kent, 2022). The value of co-creation allows to improve these effects, taking companies and consumers to a win-win situation (Hsiao et al., 2015). Therefore, retail brands enhance customer value and satisfaction by crafting seamless experiences (Alexander & Kent, 2022; Both & Steinmann, 2023), as evidenced by the smooth integration of various channels and touchpoints (Both & Steinmann, 2023) generating purchase intentions (Alexander & Kent, 2022). This study aims to explore the relationship between the personalisation of products or services, value perception and purchase intention through the mediating role of price and shopping channels, in order to understand the impact of MP on value perception and purchase intention, since according to the research carried out, all relationships are part of the customer experience, and the final results will demonstrate the positive, negative or even absent impact on this.

2.1. THE INFLUENCE OF PRODUCT/SERVICE PERSONALISATION IN VALUE PERCEPTION

Because MP aims to satisfy each customer, product differentiation happens for the individual customer (Tseng et al., 2010); is a shift to a higher level of individual marketing vision (Barata et al., 2023), a boost for a stagnant manufacturing market (Qin et al., 2023), and an important business strategy since customer expectations have been increasing with the significant improvements in technology (Ben-Jebara & Modi, 2021).

In a Trend report, Content Square presented ten online customer experience trends for 2024 based on a survey answered by more than 2,700 marketing, user experience (UX), and product role experts in retail, B2B, financial services, telecoms and more. Personalisation appeared in second place among the top 10 trends (Contentsquare, 2024).

Personalisation refers to individualised attention and personalised services for customers (Silva et al., 2023), is a process where a product enhances personal relevance to the client by the definition and change on its appearance, characteristics and/or functionality (Mugge et al., 2009). In this process, customers evaluate the retailer's ability to tailor products and services, and the transactional environment in the different channels (Rahman et al., 2022).

The goal of MP turned into value differentiation, while the role of the consumer turned into design participation (Barata et al., 2023).

Value can explain individual consumer behaviour, it's a reference criterion in consumers' cognitive and behavioural processes (Ahn & Lee, 2019). It is a fundamental concept of marketing, since marketing definitions, tasks, and strategies are value oriented. The perceived value is evaluated by customers when they compare the cost and benefit of an offer with other competing products/services/experiences. Consumers increasingly demand personalised experiences (Witek-Krowiak et al., 2024) and tend to prefer products/services/experiences with high perceived value (Saif et al., 2024) like the creation of unique packaging tailored to individual preferences or specific requirements (Witek-Krowiak et al., 2024). Packaging personalisation design enhances the product value by meeting consumer needs (Rodríguez-Parada et al., 2019).

Perceived value has two different approaches in literature: a simple approach where perceived value is based on economic and utility theory, consumer choice behaviour is guided by maximising utility. Based on this theory, perceived value comes from the trade-off between benefit and sacrifice, i.e. the customer evaluates the usefulness of the product according to their perception of what they will receive and what they will give (Hyun & Fairhurst, 2018; Saif et al., 2024). Another approach sees perceived value as a complex concept that contains several dimensions, presenting a structure of different levels (Saif et al., 2024): economic value, functional value, emotional value, social value, and convenient value. These dimensions help to understand the perception of consumer values (Ahn & Lee, 2019), and they going to be used to explain the relationship between the constructs of the conceptual model and the hypotheses in this research.

The functional value refers to the existence of obvious utility, performance, functional or physical attributes of a product/service/experience (Hyun & Fairhurst, 2018). The Social value is related to social acceptance, it has an impact on how consumers want to express themselves socially to other individuals, it is defined according to the motivation for buying or using the product. This motivation depends on what the customer wants to look like or appear like when using the product (Ahn & Lee, 2019). These two dimensions can be implied in the goal of product personalisation which is also a dimension that highlights the "utility-related" and the "appearance-related" when the customers personalise products, improving the product functionality and the look of the product to match their tastes and preferences (Mugge et al., 2009).

The convenience value is the degree of easiness of acquiring products or services, it is related to effort and/or time to acquire or use a product or service. Convenience is achieved if either of these is reduced (Ahn & Lee, 2019). According to this, the convenience value is related to the easiness and simplicity of the personalisation process.

However, the convenience value can also be related to the personalisation method. The vision that the best approach for creating good products by the inclusion of users in the development process emerged in the 2000s, when product development, which had previously been the firm's research and development department responsibility, became dependent on the interactions between the company and its consumers (Zuniga Huertas & Pergentino, 2020). In general, the concept of co-creation stands for a process where companies and customers co-create a product or a service (Hsiao et al., 2015) and has been associated with different application areas like design or product/service development (Ramaswamy & Ozcan, 2018).

From a personalisation perspective, customers can choose service components, service mechanisms, service levels, and service frequency, co-design, co-product, and co-deliver through the product service system. Intense customer-company interactions can motivate customers to get involved in the co-creation process stage. Research can also identify the individual needs of each of these customers (Hsiao et al., 2015).

Going deeper into co-creation, this is a process where there is an interaction among two or more interested parties, including companies' employees, consumers, specialists, partners, product development professionals, or any other stakeholders, in any phase of the activity system which means that may occur in the development of the product or service, in its production, exchange or even when it is being used (Zuniga Huertas & Pergentino, 2020). The customers are value creators, they construct and experience value through the integration of resources/processes/outcomes in their social context (Grönroos & Voima, 2013; Ramaswamy & Ozcan, 2018). MP allowed companies to control time adaptation to required production systems and new production methods. Following the transformation regarding the industry 4.0, manufacturers can now achieve this MP paradigm by using 3D printing, augmented reality, or cloud, for example, to produce unique pieces, which creates new and different ways of interacting with customers (Barata et al., 2023). The interactions between customers and retailers serve as the foundation for the customer experience, which is related to customer reaction to the retailer. When interacting with products, systems, and services (Bascur & Rusu, 2020), its reaction involves the customer's emotions and affective, physical, social, and cognitive responses (Alexander & Kent, 2022) which could also be related to the emotional value, that is the result of the emotions and feelings, for example positive emotions about an enjoyable and fun service experience that consumers have, about a product or service, when they are purchasing or consuming. Accordingly, the following hypothesis is proposed:

H1: Product/Service Personalisation on MP positively influences Value Perception

2.2. RELATIONSHIP BETWEEN VALUE PERCEPTION AND PURCHASE INTENTIONS OF MASS PERSONALISATION PRODUCTS

The need to understand the individual decision-making process has generated several studies on purchase intention. This behaviour is part of consumer behaviour and is influenced by what

other consumers think is right or wrong in a society, consumers' behaviour beliefs, and perception of self-control. These beliefs result in certain choices and behaviours justified by the evaluation of previous experiences, which can influence the perception of the product's characteristics and attributes, make the customers more interested and guide their purchase intention (Costa et al., 2021). The purchase intention is based on client evaluation of how expensive or cheap the product or service is (Antwi, 2021) and what value and quality they perceived (Casidy & Wymer, 2016). Purchase intention is a useful indicator for measuring whether a consumer would have bought a product; conversion is the main indicator of success in traditional retail (Summerlin & Powell, 2022).

Perceived value is highly important in customer decision making (Ahn & Lee, 2019). When clients need to make this decision, they tend to search for product information to assess its value (J. J. Wang et al., 2018). The social dimension of value perception referred above is related to the motivation for purchasing a product or service based on what the client wants to be and express to society (Ahn & Lee, 2019). This concept is related to the previous experiences of consumers within the purchase intention process considering the social and psychological consequences of the previous decision-making (Costa et al., 2021). No studies were found that specifically demonstrated the relationship between the perceived value of mass personalisation products and purchase intention of mass personalised products. However, it is known that consumers are looking for personalised experiences. Companies that provide it generate more revenue, and there is an effort to simplify the process of hyper-personalisation (Contentsquare, 2024). Therefore, the following hypothesis is proposed:

H2: Value Perception of MP products positively affect the Purchase Intentions of MP products

2.3. MEDIATING EFFECT OF PRICE OF MASS PERSONALISATION PRODUCTS

Price is referred as the money that a customer must pay for purchase products or services (Lima et al., 2024). In e-commerce, price can comprise other costs besides the product or service, like the shipping fee, or other additional fees (Antwi, 2021). Nowadays, the market has highly competitive offers for consumers, companies must understand the drivers behind customers' willingness to pay for their preferences (Casidy & Wymer, 2016).

The effect of price between the value perception and purchase intention is relevant for this research since consumers consider economic value when prices or costs are reasonable, or cheaper than what they expected for the utility of products and services (Ahn & Lee, 2019). There is a preference for acceptable, reasonable, and fair prices (Antwi, 2021). The economic value attributed increases or decreases according to the difference between price and utility, and according to the comparison that consumers make with other alternative products or services (Ahn & Lee, 2019; Saif et al., 2024) and the decision to purchase (Antwi, 2021).

The customer satisfaction, behavioural and purchase decision may be affected by the price (Lima et al., 2024). Higher prices reflect higher value and better quality (Casidy & Wymer,

2016). Some customers are willing to pay premium price for specific services when compared with other alternative brands (Casidy & Wymer, 2016), in fact in a study on mass personalisation carried out by a major consulting firm, 1 in 5 consumers who expressed an interest in personalised products or services are willing to pay a 20% premium (Deloitte, 2015). Price plays a relevant role because it can influence, as it can destroy or maintain, the relationship between customers and online retailers and influence on repurchase intention (Antwi, 2021). Despite the existing research into the relationship between price, perceived value and purchase intentions, there is still a lack of research into how they relate to products produced through mass personalisation. Therefore, the following hypothesis is proposed:

H3: Price of MP products moderate the effect of Value Perception of MP products on Purchase Intentions of MP products

2.4. MEDIATING EFFECT OF SHOPPING CHANNELS FOR MASS PERSONALISATION PRODUCTS

The purchase journey and customer experience are influenced by the customer interactions with shopping channels. It could be an online or offline channel (Van Nguyen et al., 2024) which represents a challenge for retailers due to variety of channels and consumers' cross-channel purchase behaviour, turning complex the process of purchase decision. Clients switch channels to better understand and gather information about the product, evaluate alternative solutions and make decisions. They're not limited to a single shopping channel (J. Wang & Wang, 2024) and are open to omnichannel shopping, requiring personalised experiences from retailers (Silva et al., 2023) which design personalised journeys and switch experiences to address customers' dynamic needs (Van Nguyen et al., 2024). In turn, consumers have an associative psychology when faced with multiple channels (J. Wang & Wang, 2024). Shopping channels have been created as an alternative to physical stores, offering detailed information and, even more efficient communication (Nagy et al., 2024).

The effect of shopping channel between the value perception and purchase intention is relevant for this research because previous studies considered that consumers evaluated products in their judgement process considering product attributes (J. Wang & Wang, 2024), related to the functional value perception mentioned above. However, recent studies consider that with the emergence and development of online to offline (O2O) commerce, consumers have come to consider channel attributes rather than product attributes when looking for information and make purchasing decisions based on the evaluation of critical channel attributes (J. Wang & Wang, 2024). Social media and O2O commerce made possible for consumers to rely on online information sources as part of their pre-purchase search by providing promotional information such as product prices, discounts, brands, shopper reviews, after-sales service, generating buying insights. Reviews affect purchase intention (J. Wang & Wang, 2024).

It's important to understand motivations behind customer's behaviour for retailers to position channels in a competitive environment (Zielke & Komor, 2025). In a study conducted by (J. Wang & Wang, 2024) shoppers emphasize in the offline channel the product experience and in the online channel product comments and product price, concluding that these results reflect the main motivation behind consumer behaviour: high cost-effectiveness.

Additionally, previous research analysed different motives for choose and switch channels during the customer journey. The motives are related to value perception dimensions like, convenience, price, availability and delivery, shopping enjoyment, and social interaction (Zielke & Komor, 2025). A study with the same approach on the influence of perceived value on the use of omnichannel revealed that although previous research in the context of omnichannel does not specifically examine the link between perceived value and shopping habits in predicting customer behaviours, empirical evidence from previous studies demonstrates a strong relationship between them. However, the strength of that relationship varies on the level of shopping habit (Sharma & Fatima, 2024). Nevertheless, has the shopping channel moderate the relationship between value perception and purchase intention of mass personalised products? No study specifically related with mass personalised products were found.

H4: Shopping Channels of MP products moderate the effect of Value Perception of MP products on Purchase Intentions of MP products

Figure 1 represents the conceptual model of this study.

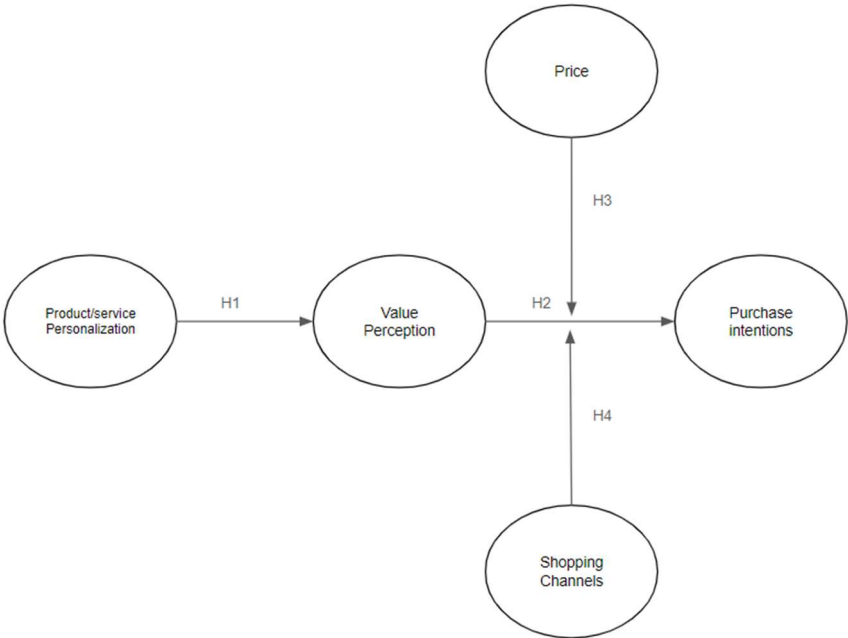


Figure 1 - Conceptual Model

3. METHODOLOGY

This research used data manipulated by two techniques for data analysis, text mining and partial least squares structural equation modelling (PLS-SEM). Instead of using primary data such as questionnaires, only secondary data were analysed to capture freely shared consumer perceptions through online reviews from Trustpilot. Online reviews are a way for customers to share their opinion with others, describing their experience and perception of the product, generating a lot of interesting data for marketing departments allowing them to evaluate, measure and interpret consumer behaviour (Lima et al., 2024). Trustpilot is a popular third-party (ul Hasan et al., 2023) consumer review website (Littlechild, 2021).

3.1. SAMPLE AND PROCEDURES

For this study, 3,500 individual customer reviews made between 21 February 2019 and 5 March 2024 were analysed. The data were collected from Trustpilot, a platform that gives consumers the opportunity to publish their opinions online and delivers rich and valuable insights to understand them (Lima et al., 2024). Online review analysis is a great tool to perceive valuable insights as these are frequently used to understand customers' perspectives of experience (Ramos et al., 2023). The consumer reviews analysed are addressed to the Care/of brand. This brand was chosen to address the topic under study, *mass personalisation*, *value perception* and *purchase intention*, as it offers customers a personalised product made in co-creation between the brand and the consumer through a quiz. Care/Of is a vitamin brand whose goal is to help its customers find their path to personal health by selling a personalised daily plan with vitamins, proteins, and collagen, based on customers' answers to a quiz about their personal characteristics, eating habits, values, goals, and lifestyle. It's customers' reviews on Trustpilot relate to their purchase experiences with the brand, the product, and the service.

These reviews were taken through web scraping, a procedure to extract structured data from text on a website in an automatic way using software (Khder, 2021). In this case, "Browse AI", a platform whose mission is to make possible for anyone to have access to information on the internet (Browse AI, s.d.) was selected. Browse AI allows its users to easily extract data from any website by entering the URL and identify the fields from which they want to extract. The platform offers various ways of automatically extracting the data. The data extracted was: i. client name, ii. Review publication date, iii. review title, iv. review body, and v. order status, exported and organised in an Excel format by columns, allowing the reviews to be analysed later. All the reviews were considered relevant to the analysis.

After collecting these large volume of non-structured data (Lima et al., 2024), an automated approach (text mining) (Moro & Rita, 2022) was used to structure it, allowing to discover patterns in unstructured data and determine the knowledge to be extracted (Moro et al., 2023) in order to organise, later, the words according to the constructs identified in the

literature review (Figure 1). The processing of data was made through R software, a coding-based tool (Lima et al., 2024). The “tm” package was used to tokenisation, divide the text into words and sentences, to filter and eliminate stop words (word non-significant, e.g. “and”, “a”, “the”), and to transform data into lowercase to avoid being case-sensitive. The words were organised and counted according to their frequency in the reviews.

Considering what was found in the literature review, a structured dictionary was created with the constructs and its related items (Lima et al., 2024). The terms found previously were arranged according to the items and constructs related to that specific topic. To validate the dictionary and minimise its subjectivity (Lima et al., 2024; Ribeiro et al., 2024), three independent experts (an E-commerce Director, an E-commerce CX Manager and a Senior Program Manager- Fulfilment) analysed, discussed, reallocated and eliminated the dictionary contents. Table 1 presents a sample of the dictionary with the constructs, items and terms.

Table 1 - Dictionary Sample

| Construct | Items | Sample of terms |
|---------------------------------|--------------------------|--|
| Product/Service Personalisation | Personalisation | personalize, personalization, customizable |
| | Product Offer | magnesium, calcium, chocolate |
| | Product Characteristics | recyclable, sustainable, eco-friendly |
| | Packaging | box, packing, pre-package |
| Value Perception | Satisfaction | love, great, good |
| | Convenience | convenience, convenient |
| | Targeted Health Benefits | healthy, wellness, nutritional |
| Price | Price | price, money, affordable |
| Shopping Channels | Shopping Channels | app, store, website |
| Purchase Intention | Purchase Intention | want, subscription, add |

The reviews were individually analysed to measure the word frequency of each concept. A word frequency matrix was a result from the reviews matched with the dictionary. In this matrix, a row represents a review and a column a term. One cell in the matrix represents the number of times that term was mentioned in a review. It simulates individual survey question responses related to literature review concepts and based on various measurement scales that had been factor-tested for each construct, on a case-by-case basis. Items mentioned frequently were considered important for the reviewer. This approach captures the differences in attitudes and perceptions in a precisely way when compared to a Likert Scale. It enables a more in-depth examination of customers' emotions regarding specific elements of their experience (Ribeiro et al., 2024).

The word frequency matrix was subsequently used as the input for the model’s path estimation using the PLS-SEM method to evaluate the relationship between the collected data and the model's theoretical constructs. The methodological approach scheme is presented in Figure 2.

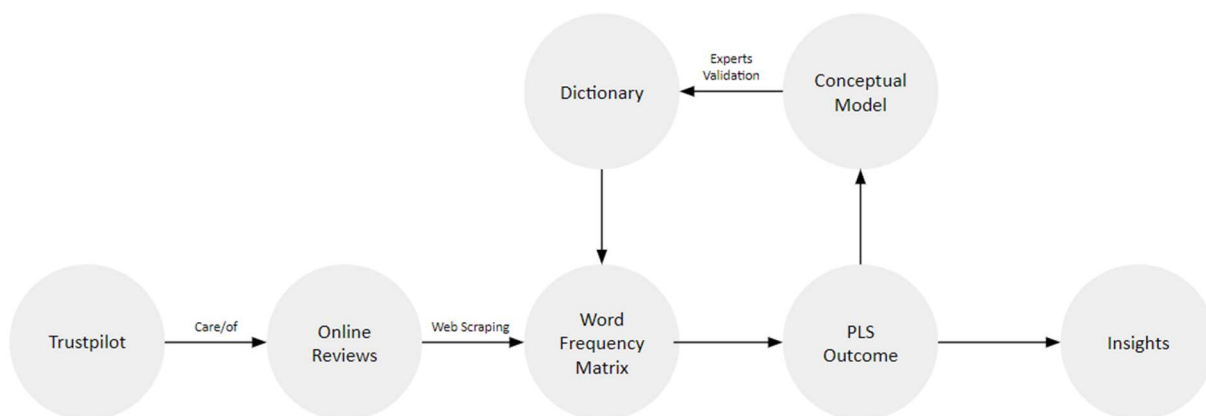


Figure 2 - Methodology Approach Scheme

3.2. DATA ANALYSIS

PLS-SEM is an alternative method to analyse data using SEM. Compared to other methods, PLS-SEM is helpful to use when the sample is smaller, additionally it's useful when the objective of the structure model is predicting and explaining the target outcomes through the sample metrics (J. Hair & Alamer, 2022). PLS is considered suitable for theory development research when analysing secondary data, especially if it is metric or quasi-metric, allowing the free use of single-item and formative measures. PLS-SEM data analysis was done through Smart PLS 4, a programme that enable users to estimate complex models with this method (Ramos et al., 2023).

A formative measurement model was used as the constructs derived from the term frequency of the contents in the dictionary. A formative model was considered over reflective model, because this approach permits individual indicators to be neither conceptually interchangeable nor correlated, as they represent linear combinations of a set of indicators that shape the construct (Lima et al., 2024). All items derived from the conceptual model in the literature were measured through the formative model, leading to conclude that the variables observed represent different dimensions, it contains aspects of the construct domain determining the construct meaning. The items, however, may not be related contributing to form the latent variable (Ribeiro et al., 2024).

The model was evaluated according to the work developed by (Lima et al., 2024; Ramos et al., 2023; Ribeiro et al., 2024). The correlation between formative construct and its reflexive measure for each variable was studied through convergent validity, where path coefficient values over 0.80 were verified. The indicator's variance inflation, multicollinearity was ($[VIF] < 5$). A bootstrap procedure over 1145 resamples (one third of the total resamples) was applied to test path model coefficients and significance. A 5% significance level was set critical to study t-values of path coefficients ($t > 1.96$). A regression analysis was used to evaluate the model's internal multicollinearity and direct effects, examining size and significance of the path coefficients between variables. The R^2 and Q^2 values permitted the evaluation of the

predictive capacity (Ribeiro et al., 2024). The R^2 statistic was calculated to identify the percentage of variation in the endogenous latent variable that is explained by its exogenous latent variables. To evaluate predictive performance, Q^2 values were generated using the PLSpredict algorithm, applying a ten-fold cross-validation method (Lima et al., 2024).

4. RESULTS AND DISCUSSION

4.1. MEASUREMENT MODEL EVALUATION

All indicators in the measurement analysis of the model explain the variables showing a high correlation between the constructs and their reflective measure, since their path coefficients were higher than 0.80 in all constructs. Multicollinearity also proved not to be a problem when evaluating the model, presenting values under 3 ($1.000 \leq VIF \leq 1.102$) suggesting that the variables are not excessively correlated, and the coefficient estimations are reliable. A bootstrap estimation of 1145 samples were used to test relevance of the formative indicators and a 5% significance level as p-values < 0.05 . The results of this analysis can be seen in table 2.

Table 2 - Outer Weights, t-values(p-values) and outer loadings to a 5% significance level

| Variable/Indicators | Outer Weights | t-values (p-values) | Outer Loadings |
|--|---------------|---------------------|----------------|
| Product/Service Personalisation | | | |
| Personalisation | 0.292 | 5.221 (0.000) | 0.375 |
| Product Offer | 0.272 | 4.468 (0.000) | 0.427 |
| Product Characteristics | 0.624 | 10.666 (0.000) | 0.794 |
| Packaging | 0.425 | 6.246 (0.000) | 0.656 |
| Value Perception | | | |
| Satisfaction | 0.963 | 46.175 (0.000) | 0.974 |
| Convenience | 0.224 | 3.808 (0.000) | 0.228 |
| Targeted Health Benefits | 0.046 | 0.848 (0.396) | 0.235 |
| Price | | | |
| Price | N/A | N/A | N/A |
| Shopping Channels | | | |
| Shopping Channels | N/A | N/A | N/A |
| Purchase Intention | | | |
| Purchase Intention | N/A | N/A | N/A |

Note: N/A = not applicable
Source: Created by authors

The variable Product/Service Personalisation analysed, has its four indicators outer weights statistically significant ($p\text{-value} = 0.000 < p\text{-value recommended} < 0.05$). The outer loadings for personalisation, and product offer are lower than 0.50. Although, since its outer weights has $p\text{-value} < 0.05$ they're all statistically significant (Ribeiro et al., 2024). The outer loadings of product characteristics and packaging indicators are higher than 0.50, which can represent a significant influence in product/service personalisation. Consumers probably have valued these two indicators more than Product offer and Personalisation.

Additionally, the value perception variable showed all its indicators outer weights were statistically significant, except for the Targeted Health Benefits item, which is not significant in explaining the value perception construct ($p\text{-value} = 0.396 > p\text{-value} = 0.05$; $t\text{-value} = 0.848 < t\text{-value recommended} \leq 1.96$). Its outer loading is also insignificant, lower than 0.50. However, since an elimination of an item could omit unique parts of the composite variable

reducing its theoretical validity, it must be wisely analysed (Lima et al., 2024). This item was maintained because it is seen in this study as a benefit. The benefit is part of the value perception concept, described in the literature review as the trade-off between benefit and sacrifice (Hyun & Fairhurst, 2018; Saif et al., 2024) and evaluated when consumers compare the cost-benefit of a product/service (Saif et al., 2024). The indicator satisfaction has an outer loading over 0.50 (0.974) that contributed and suggested a significant influence on value perception, representing the indicator with greatest impact in this variable. Although, the same is not true for the convenience indicator. Still, convenience is statistically significant for the formative measure of the value perception variable.

4.2. STRUCTURAL MODEL EVALUATION

In the internal structural model evaluation VIF values were under 3.0 for all variables, leading to observe the non-existence of multicollinearity (Galhoz et al., 2024). To verify the study hypothesis and gather insights between variables, a bootstrapping analysis was performed making possible to test its relationships. The path coefficient values between variables ranging from 0.379 to 0.020, are disposed on table 3.

Table 3 - Path Coefficients, t-values(p-values) and variable effect

| Path | Coefficients (β) | t-values (p-values) | Effect |
|---|--------------------------|---------------------|-----------------|
| Product/Service personalisation → Value Perception | 0.379 | 15.556 (0.000) | Direct effect |
| Value Perception → Purchase Intention | 0.214 | 9.498 (0.000) | Direct effect |
| Price x Value Perception → Purchase Intention | 0.027 | 1.085 (0.278) | Moderate effect |
| Shopping Channels x Value Perception → Purchase Intention | 0.020 | 0.686 (0.493) | Moderate effect |

Source: Created by authors

Product/Service personalisation has a positive direct effect on value perception ($\beta = 0.379$; $p < 0.000$). The same can be seen when the effect of value perception on purchase intention ($\beta = 0.214$; $p < 0.000$) was analysed. Both support the hypothesis H1 (Product/Service Personalisation positively influences Value Perception) and H2 (Value Perception positively affects the Purchase Intentions). On the other hand, the path coefficients for variables that moderate value perception and purchase intentions didn't show the same behaviour. The indirect effect of value perception on purchase intention through the moderator price was negative ($\beta = 0.027$; $p < 0.278$), as well as value perception negatively impacts purchase intention through the moderator shopping channels ($\beta = 0.020$; $p < 0.493$).

The structural model explains 14.4% of value perception variance ($R^2 = 0.144$) and 13.5% of purchase intention variance ($R^2 = 0.135$). These values should be interpreted according to the context of the study. Since the R^2 results are under 0.25, the model has a weaker explanatory power for both variables (J. F. Hair et al., 2019). The study concerns to consumer behaviour where values of 0.20 are considered high (Lima et al., 2024). However, these values

did not reach 0.20 and could possibly represent, at best, a moderate explanatory power model.

The Q^2 values for the endogenous variable were both above 0 ensuring that the model has a predictive capacity. The predictive capacity was higher for purchase intention variable ($Q^2 = 0.138 > 0$) than for value perception ($Q^2 = 0.117$). However, it is considered a small predictive relevance for path model ($Q^2 < 0.20$) (J. F. Hair et al., 2019). The summary of R^2 and Q^2 analysis is presented in table 4.

Table 4 - Explain variance (R^2) and predictive capacity (Q^2)

| Variable | Explained Variance | Predictive Capacity |
|----------------------------|--------------------|---------------------|
| Value Perception | $R^2 = 0.144$ | $Q^2 = 0.117$ |
| Purchase Intention | $R^2 = 0.135$ | $Q^2 = 0.138$ |
| Source: Created by authors | | |

4.3. DISCUSSION

This study contributes to the theory by acknowledging how mass personalisation influences purchase intentions, through the mediation of customer value perception. Only secondary data was used to discover the relationship between these variables. The database was developed using 3,500 Online reviews from Trustpilot, processed through text mining and applied to the conceptual model using a structural equation model approach, distancing the study from traditionally used methodologies to test the relationship between the variables Product/Service Personalisation, Value Perception, and Purchase Intention with Price and Shopping Channels as moderators.

The structural model showed that the personalisation of products/services presented in the reviews has a direct positive effect on consumers' perception of value, supporting H1, and revealing consistent results to previous studies (Sharma & Fatima, 2024) corroborating the idea that consumers prefer products/services with high perceived value (Saif et al., 2024) which occurs when customers are able to personalise products, improving the product functionality or the look of the product to match customers' tastes and preferences (Mugge et al., 2009). This study shows that Companies shall consider implementing ways of doing mass personalised products to achieve customers' value expectations.

In addition, the perception of value of MP products also positively affects purchase intentions, confirming that the value realised by the consumer is very relevant in the decision-making process (Ahn & Lee, 2019). The literature tells us that purchase intention is assessed by considering the high or low price (Antwi, 2021) and the perceived value analysing the characteristics and attributes (Costa et al., 2021) or quality of the product (Casidy & Wymer, 2016). For mass personalised products, the latter two are confirmed, but the same cannot be concluded when relating to price. Companies shall use mass personalisation methods to

produce MP products in scale, and at the same time do it in co-creation with the client. In this process, co-creation is key to generate the perceived value and the purchase intention.

The moderating effect of price on the relationship between perceived value of MP products and purchase intention was insignificant (H3), contradicting the premise that price plays an important role in purchase intention (Antwi, 2021; Lima et al., 2024) and corroborating the idea that consumers would be willing to pay more for this type of product as they are not affected by price due to the perceived value they attribute to them (Casidy & Wymer, 2016; Deloitte, 2015). In order to answer the drivers that must be understood by companies and that lead customers to be willing to pay (Casidy & Wymer, 2016), we can consider that a personalised mass product is one of the factors that may drive customers' willingness to pay for their preferences, reinforcing the fact that personalised products are in high demand (Witek-Krowiak et al., 2024) and, as mentioned above, can be a relevant asset in a company's product and marketing strategy.

The same insignificant relationship was shown for moderating effect of shopping channels on perceived value of MP products and purchase intention (H4) revealing that shopping channels do not influence the relationship between these 2 variables, which means in this case, that the value perceived by customers and their purchase intention is not dependent on the channel, contradicting what was found in the literature about purchase journey being influenced by the customer interactions with shopping channels (Van Nguyen et al., 2024) and the strong relationship between perceived value and the shopping habits (Sharma & Fatima, 2024). This leads to the conclusion that the theory that value perception in the purchasing decision process continues to focus on product attributes rather than channel attributes (J. Wang & Wang, 2024), at least for MP products. For this case, motivations behind customer behaviour are inconclusive for companies to position their channels (Zielke & Komor, 2025). It is also possible to conclude that the main reason behind consumer behaviour pointed out in the literature regarding the online channel (high cost-effectiveness) does not apply in this case either, since price does not have a relevant moderate relationship between variables and the brand analysed only has an online channel (J. Wang & Wang, 2024).

5. CONCLUSIONS AND FUTURE RESEARCH

The study elaborates on the relationships between mass personalised products, value perception and purchase intention with price and shopping channels as moderators whose relationships require further development and literature support. The obtained results advocate towards developing products tailored in co-creation with clients is a critical factor to enhance value perception and purchase intention leading customers to behave indifferently towards the price. Nevertheless, shopping channels are also irrelevant in the moderation of the relationship between value perception and purchase intention.

The results of the study do answer positively to the queries it proposes providing critical information to the relevant retail companies and retail industry. This highlights the fact that the attributes and product/service value perception are the relevant motives for the purchase intention of MP products/services. Considering mass personalisation should be part of retail marketing strategies. The study also contributes to the literature on mass personalisation including on its other topics besides the manufacturing paradigm, and differences between personalisation and customisation, allowing to enrich the subject with research in the marketing area.

5.1. THEORETICAL IMPLICATIONS

Following the abovementioned market trends, it is relevant that retailers adopt new forms of products' personalisation, focusing on customers' demand and their wishes (Y. Wang et al., 2017). MP allows the production of unique and personalised products at affordable costs through customers' active and individual participation in the design process (Qin et al., 2023). It is a promising strategy that makes "the one-person market" a reality (Zhou et al., 2013).

However, the research on MP is limited, as no study approaches the impact of MP on customer experience. This is what this study aims to do, addressing this gap by acknowledging how MP influences purchase intentions, mediated by value perception. Thus, it contributes to the literature on mass personalisation beyond the mainstream topics aforementioned, with five (5) key theoretical implications, as follows:

Firstly, this study broadens the understanding of MP by exploring how product/service personalisation directly influences consumers' value perception. This finding supports and extends existing theories suggesting that consumers prefer products/services with high perceived value, especially when they can personalise these products to meet their individual preferences (Saif et al., 2024; Mugge et al., 2009).

Secondly, the research demonstrates that value perception mediated by personalisation positively impacts purchase intentions. This is crucial as it integrates two previously isolated areas of study: product personalisation and value perception theory. It

suggests that personalisation not only enhances customer satisfaction but also directly drives purchase intentions (Ahn & Lee, 2019; Costa et al., 2021).

Thirdly, the results show that neither price nor shopping channels significantly moderate the relationship between value perception and purchase intentions for mass personalised products. These findings challenge existing theories that suggest price and shopping channels are critical moderators in purchase decisions. It implies that, for mass personalised products, the value perceived by the customer is more influential than price or shopping channel (Antwi, 2021; Van Nguyen et al., 2024; J. Wang & Wang, 2024).

Fourthly, the research highlights the importance of co-creation in generating perceived value. By involving customers in the design and production process, companies can significantly enhance the perceived value of personalised products. This finding offers a perspective on co-creation, suggesting it is an essential component for the success of mass personalisation (Hsiao et al., 2015; Ramaswamy & Ozcan, 2018).

Lastly, this study contributes to marketing and retail management theory by demonstrating that mass personalisation should be an integral part of marketing strategies. The ability to personalise products at scale, while maintaining co-creation with the customer, is crucial for meeting consumer value expectations and increasing purchase intentions (Alexander & Kent, 2022; Both & Steinmann, 2023).

These theoretical implications not only enrich the existing literature on MP but also provide a solid foundation for future research to explore other dimensions of value perception and their relationships with different marketing variables.

5.2. MANAGERIAL IMPLICATIONS

The managerial implications of this study translate into several practical insights for managers aiming to leverage MP to enhance customer value perception and purchase intentions. Considering the findings in the literature and the results of this study, companies should consider adopting mass personalisation methods to meet individual customer preferences. This involves allowing customers to personalise products, actively involving them in the design and production processes, thereby enhancing the perceived value and relevance of the products. By enabling customers to personalise products according to their individual tastes and preferences, firms can significantly improve the perceived value of their offerings.

The study also highlights the critical role of engaging customers in the personalisation co-creation process. It is imperative for companies to facilitate and encourage customer participation in product development. This interaction is essential for creating products that meet the specific needs of individual customers, thereby enhancing both the functional and emotional value perceived by the consumers and lead to a stronger sense of ownership over the product.

While price is traditionally considered a pivotal factor in purchase decisions, the results suggest that for mass personalised products, the perceived value is a more significant determinant. This indicates that customers may be willing to pay a premium for products that offer high personal relevance and satisfaction. Therefore, companies can consider pricing strategies that reflect the added value of personalisation without worrying excessively about price sensitivity. Highlighting the unique benefits and value of personalised products can justify premium pricing and attract customers willing to pay more for personalised offerings.

Furthermore, the study reveals that the shopping channel does not significantly moderate the relationship between perceived value and purchase intention for mass personalised products. This consistency across different shopping channels suggests that the value derived from personalisation remains stable regardless of the purchasing channel. However, companies shall ensure that their personalisation strategies are seamlessly integrated across all channels, providing a consistent and high-quality customer experience whether online or offline.

For customers to understand value is essential for companies to ensure effective communication of the benefits and availability of personalised products. Companies shall use targeted marketing campaigns to educate customers about the advantages of personalisation and how it can meet their specific needs. This can help in building awareness and driving demand for personalised products. Co-create and MP assumes that collecting and analysing customer feedback is also vital for continuous improvement. Companies should use customer reviews and feedback to refine their personalisation processes and product offerings. This can help in identifying areas for improvement and ensuring that the personalisation strategies remain aligned with customer expectations.

By implementing these strategies, companies can enhance the perceived value of their products, improve customer satisfaction, adopt MP strategies that focus on customer involvement and co-creation and ultimately drive higher purchase intentions. By prioritising the perceived value of personalised products over price competition or shopping channels, companies can enhance customer satisfaction, and ultimately, purchase intentions. These managerial implications provide a roadmap for leveraging mass personalisation to achieve competitive advantage.

5.3. LIMITATIONS AND FUTURE RESEARCH

When analysing this study a set of limitations shall be considered. Despite the big data that can be obtained via online platforms which allows for a wide perspective based on large samples (reviews), it is nonetheless limited to the available features, whilst a study conducted via questionnaires, focus groups or interviews shall provide more insightful conclusions. Secondly, a validated dictionary by three independent experts was used to structure the constructs and items. Therefore, subjectivity and human bias should be taken into consideration when looking at the results (Galhoz et al., 2024). Additionally, the data extracted and used for this study relates to one brand only, that may have its specific nuances that may

have been absorbed if other brands were included in the sample, softening/normalising the results. Next future studies may analyse individually or a group of reviews from other brands. The same goes for the fact that this brand only has an online shopping channel, thus, providing a limited universe of shopping experience. The moderated relationship by shopping channels between value perception and purchase intentions was irrelevant. However, what happens to the results of a brand that sells omnichannel (Van Nguyen et al., 2024)? Future research may focus on exploring this relationship through a brand that sells online and offline.

The moderated relationship by price between value perception and purchase intentions was also irrelevant, making it impossible to know more about the subject. Next studies on different brands shall analyse this relationship to confirm the results. Another interesting future question would be how much are the customers willing to pay for mass personalised products according to the segment of customers, type of product and geographic location?

Another limitation is this study considered in the value perceived analysis all its dimensions except social value (Ahn & Lee, 2019). This dimension was not explored through the reviews. Future studies may deepen the relationship between this specific dimension of the value perceived by customers and purchase intention of mass personalised products. Additionally, Care/Of's offer is just for B2C (Business to Consumer) and for that reason reviews from B2B (Business to Business) companies were not analysed. In the future research would also be interesting to analyse the relationships for B2B market.

Despite its limitations, this research reveals important insights about mass personalisation products relationships and provides valuable directions for future research about this subject.

BIBLIOGRAPHICAL REFERENCES

- About Us | Browse AI. (s.d.). Scrape and Monitor Data from Any Website with No Code. <https://www.browse.ai/about-us>. (n.d.).*
- Ahn, S. J., & Lee, S. H. (2019). The effect of consumers' perceived value on acceptance of an internet-only bank service. *Sustainability (Switzerland)*, 11(17). <https://doi.org/10.3390/su11174599>
- Alexander, B., & Kent, A. (2022). Change in technology-enabled omnichannel customer experiences in-store. *Journal of Retailing and Consumer Services*, 65. <https://doi.org/10.1016/j.jretconser.2020.102338>
- Antwi, S. (2021). "I just like this e-Retailer": Understanding online consumers repurchase intention from relationship quality perspective. *Journal of Retailing and Consumer Services*, 61. <https://doi.org/10.1016/j.jretconser.2021.102568>
- Barata, J., Cardoso, J. C. S., & Cunha, P. R. (2023). Mass customization and mass personalization meet at the crossroads of Industry 4.0: A case of augmented digital engineering. *Systems Engineering*, 26(6), 715–727. <https://doi.org/10.1002/sys.21682>
- Bascur, C., & Rusu, C. (2020). Customer experience in retail: A systematic literature review. *Applied Sciences (Switzerland)*, 10(21), 1–18. <https://doi.org/10.3390/app10217644>
- Ben-Jebara, M., & Modi, S. B. (2021). Product personalization and firm performance: An empirical analysis of the pharmaceutical industry. *Journal of Operations Management*, 67(1), 82–104. <https://doi.org/10.1002/joom.1109>
- Both, A., & Steinmann, S. (2023). Customer experiences in omnichannel retail environments: a thematic literature review. *International Review of Retail, Distribution and Consumer Research*. <https://doi.org/10.1080/09593969.2023.2256491>
- Büchi, G., Cugno, M., & Castagnoli, R. (2020). Smart factory performance and Industry 4.0. *Technological Forecasting and Social Change*, 150. <https://doi.org/10.1016/j.techfore.2019.119790>
- Casidy, R., & Wymer, W. (2016). A risk worth taking: Perceived risk as moderator of satisfaction, loyalty, and willingness-to-pay premium price. *Journal of Retailing and Consumer Services*, 32, 189–197. <https://doi.org/10.1016/j.jretconser.2016.06.014>
- Castelo-Branco, I., Amaro-Henriques, M., Cruz-Jesus, F., & Oliveira, T. (2023). Assessing the Industry 4.0 European divide through the country/industry dichotomy. *Computers and Industrial Engineering*, 176. <https://doi.org/10.1016/j.cie.2022.108925>
- Contentsquare. (2024). *Quel avenir pour la CX? Tendances de l'expérience client en ligne 2024*.
- Costa, C. S. R., Costa, M. F. da, Maciel, R. G., Aguiar, E. C., & Wanderley, L. O. (2021). Consumer antecedents towards green product purchase intentions. *Journal of Cleaner Production*, 313. <https://doi.org/10.1016/j.jclepro.2021.127964>

- Espinoza Pérez, A. T., Rossit, D. A., Tohmé, F., & Vásquez, Ó. C. (2022). Mass customized/personalized manufacturing in Industry 4.0 and blockchain: Research challenges, main problems, and the design of an information architecture. *Information Fusion*, 79, 44–57. <https://doi.org/10.1016/j.inffus.2021.09.021>
- Galhoz, I., Ramos, R. F., & Biscaia, R. (2024). Airline environmental sustainability actions and CSR impact on customer behavior. *Research in Transportation Business and Management*, 53. <https://doi.org/10.1016/j.rtbm.2024.101111>
- Grönroos, C., & Voima, P. (2013). Critical service logic: Making sense of value creation and co-creation. *Journal of the Academy of Marketing Science*, 41(2), 133–150. <https://doi.org/10.1007/s11747-012-0308-3>
- Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, 1(3). <https://doi.org/10.1016/j.rmal.2022.100027>
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. In *European Business Review* (Vol. 31, Issue 1, pp. 2–24). Emerald Group Publishing Ltd. <https://doi.org/10.1108/EBR-11-2018-0203>
- Hsiao, W.-B., Chiu, M.-C., Chu, C.-Y., & Chen, W.-F. (2015). A systematic service design methodology to achieve mass personalisation. In *Int. J. Agile Systems and Management* (Vol. 8).
- Hyun, J., & Fairhurst, A. (2018). Understanding consumers' purchasing behavior of ethnically disparate products. *Journal of Consumer Behaviour*, 17(1), e114–e126. <https://doi.org/10.1002/cb.1691>
- Katoozian, H., & Zanjani, M. K. (2022). Supply network design for mass personalization in Industry 4.0 era. *International Journal of Production Economics*, 244. <https://doi.org/10.1016/j.ijpe.2021.108349>
- Khder, M. A. (2021). Web scraping or web crawling: State of art, techniques, approaches and application. *International Journal of Advances in Soft Computing and Its Applications*, 13(3), 144–168. <https://doi.org/10.15849/ijasca.211128.11>
- Kotras, B. (2020). Mass personalization: Predictive marketing algorithms and the reshaping of consumer knowledge. *Big Data and Society*, 7(2). <https://doi.org/10.1177/2053951720951581>
- Lima, D., Ramos, R. F., & Oliveira, P. M. (2024). Customer satisfaction in the pet food subscription-based online services. *Electronic Commerce Research*. <https://doi.org/10.1007/s10660-024-09807-8>
- Littlechild, S. (2021). Exploring customer satisfaction in Great Britain's retail energy sector part II: The increasing Use of Trustpilot online reviews. *Utilities Policy*, 73. <https://doi.org/10.1016/j.jup.2021.101297>

- Moro, S., Pires, G., Rita, P., Cortez, P., & Ramos, R. F. (2023). Discovering ethnic minority business research directions using text mining and topic modelling. In *Journal of Research in Marketing and Entrepreneurship* (Vol. 25, Issue 1, pp. 83–102). Emerald Publishing. <https://doi.org/10.1108/JRME-01-2022-0004>
- Moro, S., & Rita, P. (2022). Data and text mining from online reviews: An automatic literature analysis. In *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery* (Vol. 12, Issue 3). John Wiley and Sons Inc. <https://doi.org/10.1002/widm.1448>
- Mugge, R., Schoormans, J. P. L., & Schifferstein, H. N. J. (2009). Incorporating consumers in the design of their own products. The dimensions of product personalisation. *CoDesign*, 5(2), 79–97. <https://doi.org/10.1080/15710880802666416>
- Nagy, I. D., Dabija, D. C., Cramarenco, R. E., & Burcă-Voicu, M. I. (2024). The Use of Digital Channels in Omni-Channel Retail—An Empirical Study. *Journal of Theoretical and Applied Electronic Commerce Research*, 19(2), 797–817. <https://doi.org/10.3390/jtaer19020042>
- Qin, Z., Johnson, D., & Lu, Y. (2023). Dynamic production scheduling towards self-organizing mass personalization: A multi-agent dueling deep reinforcement learning approach. *Journal of Manufacturing Systems*, 68, 242–257. <https://doi.org/10.1016/j.jmsy.2023.03.003>
- Rahman, S. M., Carlson, J., Gudergan, S. P., Wetzels, M., & Grewal, D. (2022). Perceived Omnichannel Customer Experience (OCX): Concept, measurement, and impact. *Journal of Retailing*, 98(4), 611–632. <https://doi.org/10.1016/j.jretai.2022.03.003>
- Ramaswamy, V., & Ozcan, K. (2018). What is co-creation? An interactional creation framework and its implications for value creation. *Journal of Business Research*, 84, 196–205. <https://doi.org/10.1016/j.jbusres.2017.11.027>
- Ramos, R. F., Biscaia, R., Moro, S., & Kunkel, T. (2023). Understanding the importance of sport stadium visits to teams and cities through the eyes of online reviewers. *Leisure Studies*, 42(5), 693–708. <https://doi.org/10.1080/02614367.2022.2131888>
- Ribeiro, P., Ramos, R. F., & Moro, S. (2024). Restaurant containment measures and perceived service quality: implications for future pandemics. *Consumer Behavior in Tourism and Hospitality*, 19(1), 116–130. <https://doi.org/10.1108/CBTH-06-2023-0081>
- Rodríguez-Parada, L., Mayuet, P. F., & Gámez, A. J. (2019). Custom design of packaging through advanced technologies: A case study applied to apples. *Materials*, 12(3). <https://doi.org/10.3390/ma12030467>
- Saif, M. A. M., Hussin, N., Husin, M. M., Muneer, A., & Alwadain, A. (2024). Beyond conventions: Unravelling perceived value's role in shaping digital-only banks' adoption. *Technological Forecasting and Social Change*, 203. <https://doi.org/10.1016/j.techfore.2024.123337>

- Sharma, N., & Fatima, J. (2024). Influence of perceived value on omnichannel usage: Mediating and moderating roles of the omnichannel shopping habit. *Journal of Retailing and Consumer Services*, 77. <https://doi.org/10.1016/j.jretconser.2023.103627>
- Silva, S. C., Silva, F. P., & Dias, J. C. (2023). Exploring omnichannel strategies: a path to improve customer experiences. *International Journal of Retail and Distribution Management*. <https://doi.org/10.1108/IJRDM-03-2023-0198>
- Summerlin, R., & Powell, W. (2022). Effect of Interactivity Level and Price on Online Purchase Intention. *Journal of Theoretical and Applied Electronic Commerce Research*, 17(2), 652–668. <https://doi.org/10.3390/jtaer17020034>
- The Deloitte Consumer Review Made-to-Order: The rise of mass personalization*. (2015). <https://www2.deloitte.com/content/dam/Deloitte/ch/Documents/consumer-business/ch-en-consumer-business-made-to-order-consumer-review.pdf>
- Tseng, M. M., Jiao, R. J., & Wang, C. (2010). Design for mass personalization. *CIRP Annals - Manufacturing Technology*, 59(1), 175–178. <https://doi.org/10.1016/j.cirp.2010.03.097>
- Turner, C., & Oyekan, J. (2023). Personalised Production in the Age of Circular Additive Manufacturing. *Applied Sciences (Switzerland)*, 13(8). <https://doi.org/10.3390/app13084912>
- ul Hasan, H. M. R., Lang, C., & Xia, S. (2023). Investigating Consumer Values of Secondhand Fashion Consumption in the Mass Market vs. Luxury Market: A Text-Mining Approach. *Sustainability (Switzerland)*, 15(1). <https://doi.org/10.3390/su15010254>
- Van Nguyen, A. T., McClelland, R., & Thuan, N. H. (2024). Omni-channel customer segmentation: A personalized customer journey perspective. *Journal of Consumer Behaviour*. <https://doi.org/10.1002/cb.2401>
- Wang, J. J., Wang, L. Y., & Wang, M. M. (2018). Understanding the effects of eWOM social ties on purchase intentions: A moderated mediation investigation. *Electronic Commerce Research and Applications*, 28, 54–62. <https://doi.org/10.1016/j.elerap.2018.01.011>
- Wang, J., & Wang, C. (2024). Understanding shoppers' cross-channel analysis of influencing factors of online and offline channels: Evidence from clothing product. *Journal of Retailing and Consumer Services*, 81. <https://doi.org/10.1016/j.jretconser.2024.104000>
- Wang, Y., Ma, H. S., Yang, J. H., & Wang, K. S. (2017). Industry 4.0: a way from mass customization to mass personalization production. *Advances in Manufacturing*, 5(4), 311–320. <https://doi.org/10.1007/s40436-017-0204-7>
- Witek-Krowiak, A., Szopa, D., & Anwajler, B. (2024). Advanced Packaging Techniques—A Mini-Review of 3D Printing Potential. In *Materials* (Vol. 17, Issue 12). Multidisciplinary Digital Publishing Institute (MDPI). <https://doi.org/10.3390/ma17122997>
- Zhou, F., Ji, Y., & Jiao, R. J. (2013). Affective and cognitive design for mass personalization: Status and prospect. *Journal of Intelligent Manufacturing*, 24(5), 1047–1069. <https://doi.org/10.1007/s10845-012-0673-2>

- Zielke, S., & Komor, M. (2025). Why do customers choose online or offline channels? A framework of motives and its application in an international context. *Journal of Retailing and Consumer Services*, 82. <https://doi.org/10.1016/j.jretconser.2024.104054>
- Zuniga Huertas, M. K., & Pergentino, I. (2020). The effect of “co-creation with consumers” claims on purchase intention: The moderating role of product category performance information. *Creativity and Innovation Management*, 29(S1), 75–89. <https://doi.org/10.1111/caim.12369>



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