UNIVERSIDADE CATÓLICA PORTUGUESA

Product Innovation Performance: a case in Food Retailing Industry

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Product Innovation Performance: a case in Food Retailing Industry

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By

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But this is just a tiny challenge. Looking forward to what's coming

Resumo

A importância da inovação no contexto empresarial continua a crescer, o que suscitou uma grande discussão sobre a forma adequada da sua avaliação, uma vez que não existem métricas pré-estabelecidas para assegurar uma medição eficiente. Para tentar resolver esta lacuna, este estudo criou um modelo para medir o desempenho de produtos inovadores, na indústria de retalho alimentar, em Portugal. Neste sentido, esta investigação avalia, partindo da opinião dos clientes sobre inovações de produtos, o impacto de dois fatores - *consummer innovativeness* e a perceção de inovação dos produtos - e de um moderador, o valor percebido na satisfação dos clientes e nas intenções de recompra de productos inovadores. Os resultados do modelo, que foram analisados com base na modelação de equações estruturais de mínimos quadrados parciais (*PL-SEM)*, sugerem uma correlação positiva entre o valor percebido e a satisfação do cliente na intenção de recompra de produtos inovadores. No entanto, não corroboram totalmente um impacto positivo das variáveis *consummer innovativeness e perceção de inovação dos produtos* na intenção de recompra de novos produtos. Desta forma, os resultados salientam, não só a importância de utilizar esta informação como ponto de partida para a definição de uma estratégia eficaz, mas também alertaram para a potencial necessidade de melhorar o modelo, acrescentando mais fatores, testando-o noutros contextos empresariais e tentando recolher mais respostas para apoiar o modelo.

Palavras-chave: Inovação empresarial; *Performance* de produtos inovadores; Indústria Retalho Alimentar; Modelação de equações estruturais de mínimos quadrados parciais

Abstract

Business innovation importance is growing, but its´s measurement is undergoing tremendous discussion, as there are no pre-established metrics to ensure its efficient measure. To try to solve this gap, this study purposes a model to measure product innovation performance in the food retailing industry, in Portugal. Based on customers´ feedback about product innovations, this research assesses the impact of two drivers, consumer innovativeness and product perceived innovativeness and one moderator, perceived value, on customer satisfaction and new product repurchase intentions. Model´s results, which were analysed based on Partial Least Squares Structural Equation modelling, suggest a positive correlation between perceived value and customer satisfaction on new product repurchases. However, they don´t fully endorse a positive impact of product innovation drivers on new product repurchase intentions. Findings highlighted the importance of using this information as a starting point for defining an effective strategy. They also warned us about the potential need to improve the model by adding more drivers, testing the model on other businesses and trying to collect more responses to endorse the framework.

Keywords: Business Innovation; Product innovation performance; Food retailing Industry; PLS-SEM

9592 words

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Glossary

Alpha: Cronbach´s alpha

AVE: convergent validity

BECX: Best European Customer Experience

BIC: Bayesian Information Criterion

CI: Confidence interval

Eurostat: European Statistical office

F^2: effect size of the predictor constructs

HTMT: heterotrait-monotrait ratio of correlations

IMP: Innovation management practices

LM: Linear Model

OECD: Organisation for Economic Cooperation and Development

OLS: ordinary least squares

PIP: Product Innovation Performance

PLS-SEM: Partial Least Squares Structural Equation Modelling

R^2: R-squared

rhoA: reliability coefficient

rhoC: composite reliability

RMSE: Root Mean Squared Error

SEM: Structural Equation Modelling

SEMinR: package in Rstudio that enables the application of Partial Least Squares Structural Equation Modelling

VIF: variance inflation factor

Introduction

Innovation´s role in living standards, institutions, economic sectors and countries is undeniable (Organisation for Economic Cooperation and Development [OECD] & European Statistical Office [Eurostat], 2018). The knowledge that arises from innovation development is crucial "because all types of innovations entail some degree of novelty that has not existed before (at least for the firm) and can be only introduced through knowledge generation" (Tavassoli & Karlsson, 2015, p.1888). Furthermore, innovation management practices, which represent a means to codify and apply innovation research and management practices, are associated with higher innovation outcomes (Tidd & Thuriaux-Alemán, 2016).

Therefore, companies should have an innovation vision because it will "provide not only direction but an identity that will create a distinctive market position" (Reynaldo et al., 2019, p.483). "For companies, indicators are indispensable to manage and control the plethora of innovative ideas and concepts that are submitted to them" (Dziallas & Blind, 2019, p.3). Nevertheless, measuring innovation within companies is still a challenge (Hao et al., 2017).

Metrics of innovation performance measurement vary. Innovation management practices (IMP) and metrics depend on companies' objectives and their context- "the adoption and effectiveness of IMPs may not be universal, but rather vary by sector and context" (Tidd & Thuriaux-Alemán,2016, p.1125). If financial performance is still the most important and studied goal, reputation and customer satisfaction are also two business goals of innovative companies, which are gaining more relevance (Hao et al., 2017). "For product indicators, a large number of indicators and factors have already been published, but more specific product indicators are needed to evaluate innovations" (Dziallas & Blind, 2019, p.16).

This study addresses two questions to respond to those gaps: What are the key drivers and the key outputs of product innovation performance? What is the impact of product perceived innovativeness, consumer innovativeness and perceived value on product innovation performance?

To answer these questions, the present research is going to focus on a case study within the food retailing industry, in Portugal. This sector was chosen because retailing is one of the most relevant sectors, as they imply wide innovations and direct interactions with end customers (Sorescu et al., 2011).

This study is relevant, because by trying to 1) understand the drivers which are leveraging and hampering product innovation performance; 2) identify if they have a direct or indirect effect on product innovation outcomes and 3) check their explanatory power regarding customer satisfaction and new product repurchase intentions, it is providing managers, in the organization and the sector, information that can "indirectly influence managerial decisions by raising awareness of potential innovation resources" (OECD & Eurostat, 2018, p.49). Managers can also "use aggregated results for their industry to benchmark their organisation's innovation activities and outcomes" (OECD & Eurostat, 2018, p.49). Academics can also benefit, as they "have a strong interest in research that can provide (…) causal interpretations of innovation outcomes" (OECD & Eurostat, 2018, p.48).

Concerning study structure, it comprises six sections. The first section comprises the main literature on business and product innovation measurement. It compares several theoretical perspectives about product innovation performance. Section 2 describes the methodological approach and data. In the following section, the 3rd one, the main results are reported. In the 4th part, the results are discussed. Section 5, provides the study's main conclusion, summarizing managerial and theoretical implications and its limitations and potential future research opportunities.

1.Business Innovation classifications

Innovations and "innovative activities are the central determinant of firm-level economic development and growth" (Alhusen et al., 2021). Its persistence "highlights the influence of past and current innovation on future innovation" (Tavassoli & Karlsson, 2015, p.1887).

Even though innovation importance is recognized, its notion is often considered a "too fuzzy concept to be measured and accounted for" (OECD & Eurostat, 2018, p.3). There is no objective way to define and differentiate innovations from non-innovations (Varis & Littunen, 2010).

The innovation concept has unique features. According to the OECD & Eurostat (2018), innovation is distinctive from non-innovations, because it requires implementation and is a knowledge-based concept. Companies that pursue innovation should seek novelty, utility, and value creation (OECD & Eurostat, 2018).

Different taxonomies have been developed based on these common features to distinguish innovations. The first classification is based on the extent of change and the second one is based on the object of change (Varis & Littunen, 2010).

Following the first classification, Tidd (2001) clustered innovation into disruptive innovation, radical innovation, complex innovation, and continuous incremental innovation. Each one of them enhances a distinctive competitive advantage for the companies. The disruptive innovation creates a new value proposition. Radical innovation is concerned with offering a "highly novel or unique product or service, at a premium pricing" (Tidd, 2001, p.170). Continuous incremental innovation provides a competitive advantage through the "continuous movement of the cost/performance frontier" (Tidd, 2001, p.170). The complex innovation confers advantage by the difficulty of learning the technology used.

Still, this classification is not unanimous. Oke (2007) uses the same criteria differently (he considers radical and incremental innovation as innovativeness degrees) and adds the object of the innovation- service innovation and service products innovation.

Concerning the classification based on the object of change, Tavassoli & Karlsson (2015) clustered innovation into four types: product innovation; process innovation; marketing innovation, and organizational innovation. According to the authors, product innovation “emerge when a new product or a new variety of an existing product is introduced in the market”(Tavassoli & Karlsson, 2015, p.1888). If it becomes successful, this type of innovation is crucial, once it “reduces the financial constraints of the innovating firm” (Tavassoli & Karlsson, 2015, p.1889). The second category of innovation is process innovations. This one differs from product innovation, because it “involve the introduction of new methods of production” (Tavassoli & Karlsson, 2015, p.1890).

Marketing innovation and organizational innovation are the other two types of innovations presented. The first one implies changes or improvements in the target markets. The organizational one “involving changes in firms' routines aiming at improving efficiency and productivity” (Tavassoli & Karlsson, 2015,p.1890).

However, recent studies developed by OECD & Eurostat (2018) revised Tavassoli & Karlsson’s (2015) classification and proposed another one. First, the authors highlighted the need to distinguish between innovations seen as processes and outcomes. Therefore, they provided two definitions - innovations activities and business innovations. The innovation activities “include all developmental, financial and commercial activities undertaken by a firm that is intended to result in an innovation for the firm” (OECD & Eurostat, 2018, p.20).

The business innovation comprises either a new product or a new business process.

In business innovation, OECD & Eurostat (2018) comprised the four types of innovations proposed by Tavassoli & Karlsson (2015) into just two types: product innovations and business process innovations.

Given its complexity, the innovation concept and its classification vary among different authors. Thus, this research will only focus on the object of change classification, following the classifications proposed by OECD & Eurostat (2018): business innovations; product innovations, and business process innovations.

1.1. Innovation performance in companies: business innovation measurement & product innovation measurement

Innovating and monitoring innovation performance is crucial for companies. However, the way companies approach innovation is complex and varies among them. "Some companies still use the "gate" system to track innovation (1st and 2nd generations models)"(Hao et al., 2017, p.5) and others use new models based on "platform business and big data/predictive analytics" (Hao et al., 2017, p.5). Depending on the model, different measurement systems are used. However, there is still "little guidance towards framing the "black box" of the innovation processes" (Hao et al., 2017, p.8).

In 1991, there was established the first "agreement within the global community of practitioners in the OECD Working Party of National Experts on Science and Technology Indicators on how to conceptualize and measure business innovation" (OECD & Eurostat, 2018, p.3). Since then, different frameworks have been developed.

Hao et al. (2017) proposed a framework based on six signposts - technology, digitization, environmental & social sustainability, consumer experience & branding, internal innovation networks, and external innovation ecosystems. Each dimension has a metric along the value delivery chain, using inputs, throughput, and output metrics. By disposing measures within the value delivery chain, companies provide timely information on ongoing innovation projects and can halt the innovation process. El Bassiti & Ajhoun (2017) underline the need to focus innovation measurement on the "processes in-between" and not only "on the measurement of innovation inputs and outputs in terms of spend, speed to market and numbers of new products" (p.99). Despite this, El Bassiti & Ajhoun (2017) suggested different principles to measure innovation performance and comprised them into three complementary components: innovation granularity scales, innovation capability stages and innovation maturity stages.

However, "finding a consistent measurement framework applicable to a wide range of companies still has a long way to go "(Hao et al., 2017, p.8), because there is "no present-day assessment of how widely accepted and how applicable company-level models of innovation are, and ideas about innovation measurement are highly variable" (Hao et al., 2017, p.8). Besides, these frameworks neglect the need to evaluate and assess product innovation performance, justifying the need for the development of such models.

Hannachi (2015) developed a Product Innovation Scale (PIP Scale) based on a multidimensional approach. The scale is composed of five dimensions - financial, market, technical; strategic and consumer.

Financial and market dimensions are related to profits and sales, respectively. The technical performance comprises its quality, features to reduce environmental damage and products´ characteristics that improve health (Hannachi, 2015). The consumer dimension and the strategic one are concerned with consumer satisfaction and consumer loyalty and the company´s effectiveness and reputation. These dimensions focus mainly on "consumers´ acceptance but ignore the influence of the innovation itself on consumers' intention" (Zhang et al., 2020, p.10). This is criticised by Zhang et al (2020), who believe that focusing only on adoption behaviours on new products must not be enough to evaluate consumer satisfaction.

Zhang et al. (2020) proposed a different approach for product innovation measurement. The authors focus on consumers´ paying behaviour. It assesses if consumer innovativeness, perceived product innovativeness and perceived value influence consumers´ willingness to pay. Perceived product innovativeness corresponds to "the degree to which a product viewed by consumers possesses new and unique attributes as compared with other homogenous products" (Zhang et al., 2020, p.3)

Al-Jundi et al. (2019) approach doesn´t differ much from the previous one. The authors measure product innovation performance as new product purchases intentions. To understand this, the authors study the effect of consumer innovativeness, perceived value, and learning process on new product purchases intentions.

All these models about product innovation performance have a common feature. All of them represent product innovation performance as a latent variable - a variable measured indirectly by other constructs (Hair et al., 2021) and highlight the need to understand consumer responses to new products. Given this need and "the critical role of product innovations for the long-term competitiveness of firms" (Tavassoli & Karlsson, 2015, p.1889), this research is going to focus on developing a product innovation performance model.

1.2. Product innovation performance

Despite its importance, product innovation measurement is quite heterogeneous, as performance "can be presented from many points of view: commercial, financial, technical, global" (Hannachi, 2015, p.24). Moreover, product innovation measurement depends on companies' goals and must be aligned with the company´s culture and the way it defines progress (Hao et al., 2017). Hence, product innovation performance is going to be depicted on the two key outcomes of product innovation mentioned by the studied company - customer satisfaction and new product repurchase intentions.

Additionally to product innovation performance outcomes, it is also crucial to understand its potential drivers. Perceived Product Innovativeness, Consumer Innovativeness and Perceived Value are the key drivers which will be studied. In the following subsection, they are going to be presented, as well as their relation with product innovation performance.

1.2.1. Perceived Product Innovativeness

Product innovation has a crucial role in company development (Zhang et al., 2020), not only due to its contribution to ensuring companies´ long-term competitiveness (Zhang et al., 2020) but also due to its increasing market power (Tavassoli & Karlsson, 2015).

To ensure new product adoption, companies and marketers "strive to identify the best persuasion strategies to induce attitude and behavioral change among consumers"(Fu & Elliott, 2013, p. 258). However, before studying consumers ´attitudes towards new products, is important to understand their perception of the innovation. Zhang (et al., 2020) comprises this perception into a notion -

perceived product innovativeness, which is "defined as the degree to which a product viewed by consumers possesses new and unique attributes" (p. 3). Based on this concept, several authors studied the impact of product perceived innovativeness either in new product profitability, new product purchase intentions or willingness to pay.

1.2.1.1. Perceived Product Innovativeness impact on perceived value and new product repurchase intentions

Fu & Elliott (2013) studied the influence of product perceived innovativeness on consumers' purchase intention and stated it "may influence consumers' purchase intention both directly and indirectly through other variables" (p.258). Calantone et al.'s (2006) research on how product innovativeness influences new product profitability shows a substantial impact of product innovativeness on products success. Thought, this result is indirect "indicating the primary means of achieving new product success is through gaining product advantage, and the primary means of improving product advantage is through producing an innovative product"(Calantone et al., 2006, p.412). Zhang et al. (2020) tested if a consumer who had higher perceived product innovativeness would be "more willing to buy, even willing to pay a higher price" (p.4), as innovative products tend to be more attractive to them. The author endorsed a positive correlation between product perceived innovativeness and willingness to pay. According to Fu & Elliott (2013), "the sales results imply that most consumers have positive feelings toward new products and the effects of product innovativeness on product adoption are generally positive" (p.260). Therefore hypothesis 1 is formulated as follows:

H1: Perceived product innovativeness positively influences new product repurchase intentions.

Consumers´ perceived product innovativeness can also enhance perceived value regarding product innovations. Consumers tend to "believe that innovative design, new or improved attributes can lead to a better experience with the product"(Zhang et al., 2020). Hence, they are more likely to perceive a higher value in the product. The positive relation between product perceived innovativeness and perceived value was studied by Yu et al. (2017), who highlighted its mediation effect on perceived risk. According to the authors, the perceived innovativeness acts offsets perceived risks and consequently enhances the perceived value. Hence, it´s hypothesized:

H2: Perceived product innovativeness has a positive influence on perceived value.

1.2.2. Consumer innovativeness

Consumers are crucial for the success of new products (Dziallas & Blind, 2019). The consumers who adopt new products play an essential role in innovation diffusion.

However, not every individual tends to purchase new products. It depends on the consumer innovativeness degree. Consumer innovativeness is a general personality trait towards innovations - innate innovativeness; a predisposition towards a product class and its tendency to learn - domain-specific innovativeness - or actual "innovative behaviour" (Bartels & Reinders, 2011). If the consumer is a person who already tends to make innovative and risky decisions, he has an innate innovativeness capability. If the consumer is seeking information about new products or reveals purchases intentions and adoption behaviours, he has an innovative behaviour (Bartels & Reinders, 2011).

Concerning its measurement, Zhang et al. (2020) use a similar classification to the one proposed by Bartels & Reinders (2011). The authors consider two constructs to classify consumer innovativeness: innate innovativeness and actualized innovativeness. The first one refers to consumers' traits and behaviours towards innovative products. The second one "is defined as how fast an individual accepts innovative things." (Zhang et al., 2020, p.3).

Though other authors do not agree with this. Al-Jundi et al. (2019) state that consumers assess the innovation's novelty, ease of use, and functional performance. Zhang (2010) emphasizes self-congruity. If the consumers determine the product–user image matches their self-image, there is a high self-congruity.

Vandecasteele & Geuens (2010) highlights four dimensions within the consumer innovativeness concept: functional, hedonic, social and cognitive. The first one refers to consumers´ attraction to functional or useful products; The hedonic dimension is motivated by "affective or sensory stimulation and gratification" (Vandecasteele & Geuens, 2010, p.310), and the social one is motivated by a social need to differentiate from others. The cognitive dimension is driven by "the need for mental stimulation" (Vandecasteele & Geuens, 2010, p.310).

1.2.2.1. Consumer Innovativeness impact perceived value and new product repurchase intentions

Despite the different classifications and distinctive factors emphasized to measure consumer innovativeness, there is a common proposition in studies regarding consumer innovativeness: "New product responses are related to consumer innovativeness" (Zhang et al., 2020, p.3). Consumers who have this personal trait realize faster than a customer who doesn´t have this characteristic the usefulness of the new product (Al-Jundi et al., 2019). This happens, not only because these consumers seek new excitement and experiences (Al-Jundi et al., 2019), but also because product acquisition itself is important. Individuals with this orientation obtain approval from others by buying innovations" (Vandecasteele & Geuens, 2010, p.309). The impact of consumer innovativeness on new product purchase intentions has been studied by several authors, (Arts et al., 2011; Al-Jundi et al., 2019; Cowart et al., 2008) who found a positive correlation between them. As consumers with this trait have a positive attitude toward product innovation purchases, they are more likely to repurchase them. Therefore, the following hypothesis is made:

H3: Consumer innovativeness positively impacts new product repurchase intention.

The judgment made by consumers may influence their perceptions of products, either new products or not. "In the adoption decision, consumers tend to consider salient incentives and threats" (Cowart et al., 2008, p.1114).

Innovative consumers are "less attuned to the potential threats in the new product purchase environment" (Cowart et al., 2008, p. 1112). Moreover, "consumer innate innovativeness stimulate innovators to perceive a value-added in the innovative products" (Al-Jundi et al., 2019, p.8). Consumers with a "high level of consumer innovativeness "realize the usefulness on a new product easier than late consumers" (Al-Jundi et al., 2019, p.7). Therefore, consumer innovativeness can also trigger consumers' perceived value regarding new products.

Hence it´s hypothesized:

H4: Consumer innovativeness positively impacts perceived value.

1.2.3. Perceived value

In the 90s, perceived value was developed as a predictor of consumer consumption behaviour (Zhang et al., 2020). Since then, researchers developed several classification methods. Value creation is a key component for companies as "they strive to acquire quality consumer relationships and consumer-perceived value" (Yeh, 2016, p.450). Companies treat this variable as a business approach "mutually co-created between firms and consumers…" (Yeh,2016, p.450).

Zhang et al. (2020) studied perceived value by dividing it into functional value; emotional value; money value and social value. The functional value was explored by asking questions regarding product quality and performance. The emotional value comprises questions related to the emotions triggered by the product. The social one includes the perceived image of others. The money is related to innovation pricing. Nevertheless, this classification does not directly relate perceived value with product innovation.

Al-Jundi et al. (2019) used a similar classification. The authors enhance the importance of "the judgment or ratings of overall attributes" (p.8) on new product adoption. Coutelle-Brillet et al. (2014) propose clustering perceived value into extrinsic and intrinsic value. The extrinsic one is related to products efficiency –product capability to improve productivity; product´s performance and flexibility compared to other products. Emotional value and ethical value are the two dimensions of intrinsic value. Despite the disagreement regarding the perceived value definition, both authors highlight perceived value´ importance on innovation. Coutelle-Brillet et al. (2014) state product innovation adoption is more linked to the perceived functional performance of the product. Companies´ perceived value can also benefit from innovation as it enhances the image consumers have.

1.2.3.1. Perceived Value impact on customer satisfaction and new product repurchase intentions

Evaluating consumer assessments regarding a product does not rely only on a trade-off between products´ price and quality. Behavioural intentions and customer satisfaction are critical outputs in its evaluation. Thought, Boksberger & Melsen (2011) argue that "for almost as long as perceived value has been studied, its interdependence to other widely researched marketing concepts such as service quality and customer satisfaction has been discussed controversially." (p.230).

According to Erjave et al. (2016), the perceived price impact on customer satisfaction is not very strong. This perspective is examined by Samudro et al. (2020), which endorsed a positive impact of perceived value on customer satisfaction. Askariazad & Babakhani (2015) extend the model proposed for the European Customer Satisfaction Index, in which the latent variables, customer expectation, perceived quality and perceived value are drivers of customers satisfaction. They reported that perceived value explains almost 71% of customer satisfaction. Based on this, the following hypothesis is made:

H5: Perceived Value positively influences customer satisfaction.

People with a higher consumer innovativeness degree tend to perceive attributes of new products faster. Their "strong desire for new experiences pushes them to look for new information to learn about attributes of innovations (…) (Al-Jundi et al., 2019, p.9). Therefore, their perceived value in product innovation tends to be higher and they are more likely to purchase new product innovations. There is a correlation of 0.703 between perceived value and new product purchase intentions (Al-Jundi et al., 2019).

As customers easily perceive the value added of new products (Al-Jundi et al., 2019) and customers repurchase intentions tend to rely on the perceived value from previous transactions (Ariffin et al., 2016), "customers derive value from the exchanges and the purchases they make" (Hume & Mort, 2010, p.174). Therefore, it´s hypothesized:

H6: Perceived Value positively influences new product repurchase intentions

1.2.4. Customer satisfaction

Customer satisfaction is a common business goal in companies that pursue innovation and it's gaining more relevance (Hao et al., 2017). Thus, "monitoring customer satisfaction and diagnosing what factors drive customers' satisfaction should be an essential activity of every firm"(Chakraborty et al., 2007, p.21). Knowing if the customer is satisfied or not is, not only a source of competitive advantage (Cowart et al., 2008) but also a way to enhance a firm's bottom line in multiple ways (Chakraborty et al., 2007).

General speaking, consumers tend to be more satisfied when their goals are satisfied (Cowart et al., 2008). However, consumers´ satisfaction depends on several items. Goić et al. (2021) depicted customer satisfaction in the grocery retail industry and concluded that prices, price information and availability are the variables that influence the most customer satisfaction. Nevertheless, this study highlighted that customer satisfaction also depended on the store format. Lee & Zhao (2014) also reported that price information increases consumers' preferences.

Chakraborty et al. (2007) highlighted a different issue. The author underlined that customer satisfaction is influenced by "each of the salient product components that form the total product" (p.21). Considering this view, Tudoran et al. (2012) state that consumer satisfaction depends on primary cognition and secondary cognition. Based on the products´ features, consumers "evaluate (…) favourable versus unfavourable or positive versus negative orientation towards an object", (p. 391) and then reassess their first view, which can support or not the first evaluation.

1.2.4.1. Customer satisfaction impact on new product repurchase intentions

Customer satisfaction evaluation is critical for managers to correctly diagnose product success or failure, being especially important when talking about new products (Tudoran et al., 2012). Tudoran et al. (2012) "indicated that satisfaction exerts a significant main effect on purchasing intention" (p.398).

However, "links between (…) satisfaction and behavioural outcomes are neither linear nor straightforward" (Erjave et al., 2016, p.810). It depends on the strength by which consumers hold that satisfaction (Tudoran et al., 2012). When consumers are satisfied it is more likely they repeat their purchase intention. "Continuous consumption behaviour comes from customer satisfaction"(Huarng & Yu, 2019, p.638). Hence it´s hypothesized:

H7: Customer Satisfaction positively influences new product repurchase intentions

1.2.5. New Product Repurchase Intentions

When assessing the product innovation performance, variables and metrics "should be adapted to firm-specific objectives of measurement" (Brattström et al., 2018, p.65). As previously stated, for product indicators several indicators have been published (Dziallas & Blind, 2019, p.16), but judging product innovations´ success is still a challenge for companies.

Thought, measuring purchase intentions and repurchase intentions towards product innovation is relevant. From a short-time perspective "measuring purchase intentions significantly increases the percentage of consumers making at least one repeat purchase (…) decreases the time until the first repeat purchase, and significantly increases the net profits per customer" (Chandon et al., 2004, p.567).

In "a repeat-purchase context, the product is more likely to be accessible in memory than it is for a first-time purchase" (Chandon et al., 2004). Therefore, this research will assess new product repurchase intention as an output measure of product innovation performance.

2. Methodology

This research aims to "understand a real-life phenomenon in-depth" (Yin, 2009, paras 2) in the Portuguese food retailing industry. To explain this phenomenon and to respond to the research questions: "What are the key drivers and the key outputs of product innovation performance?" and "What is the impact of product perceived innovativeness, consumer innovativeness and perceived value on product innovation performance?", some casual links, and theoretical propositions are presumed. Therefore, this section begins with the research model [1] where "a clear set of propositions" is established (Yin, 2009, paras 2).

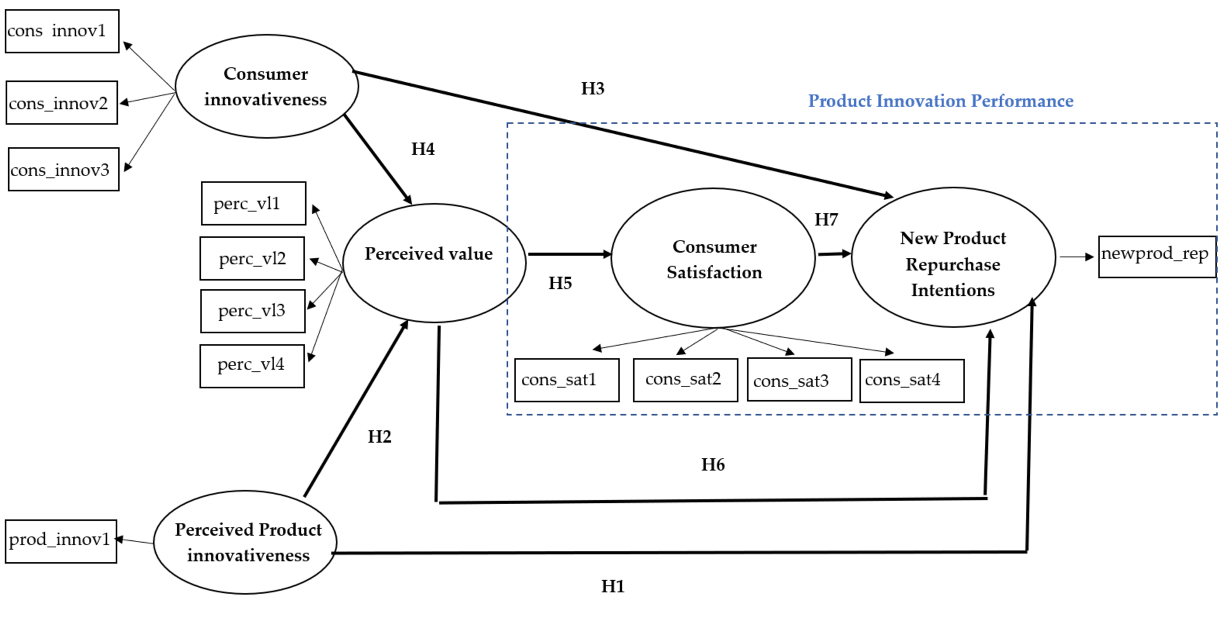

Figure 1: Research Model

[1] All the endogenous model´s constructs, Perceived Value, Consumer Satisfaction and New Product Repurchase Intentions, correspond to latent constructs as they are indirectly measured by other constructs (Hair et al., 2022) The construct on the exogenous model, Consumer Innovativeness and Perceived Product Innovativeness, are the key drivers of Consumer Satisfaction and New Product Repurchase Intentions. The perceived value variable is a mediator between drivers and the main outcomes. The variables in rectangles correspond to the manifested variables, the variables that are going to be measured.
Regarding the arrows, the ones in dark black correspond to the paths which are going to be assessed.

The hypotheses were designed to: 1) understand the drivers which are leveraging and hampering product innovation performance; 2) identify if they have a direct or indirect effect on product innovation outcomes, and 3) check their explanatory power regarding customer satisfaction and new product repurchase intentions. However, the hypotheses ", as well as the circumstances within which the propositions are believed to be true" (Yin, 2009, paras 2), are not, totally, theoretically endorsed. Therefore, this case study is exploratory.

Even though the analysis is only about a single organization, "the (…) case (…) involve more than one unit of analysis." (Yin, 2009, paras 3). The analysis includes customers view about product innovation and PLS-SEM analysis of product innovation performance model. Therefore, it can be classified as an embedded case study.

2.1. Data Collection & Sample

First, it was conducted a preliminary study through a survey. The respondents of the survey had to fulfil one criterion: they had to be customers of the *Food Lab corner* of Sonae *MC*, and they must have purchased a group of *Food Lab´s* products between 1st September of 2021 and 16th January of 2022. The study focused on the brand by which *MC* introduces product innovations - *Food Lab-,* because it´s concerned with the customer's evaluation of product innovation. However, the brand has products that are exclusively sold in the corner and others that are sold in the corner and on the normal shelves (double implemented products). Therefore, from the products with the highest number of customers, the sample was composed of 12 products: half of them were exclusively sold in the *Food Lab* and the other half were of double implementation.

The query, which was made in the checkbox platform, was sent through SMS and newsletter, due to the higher response rates in these channels. The data was collected between 10th February and 21st of February.

A total of 25 635 customers received a survey composed of 2 sections. The first one is about product identification. In the second one the customers were asked to reply to a group of questions based on a Likert scale – 1- totally disagree; 2-disagree; 3-neutral; 4-agree; 5-totally agree. To maximize product innovation evaluations, customers were allowed to give their opinion on two products. The indicators can be consulted bellow.

Indicators	**Scale & authors**
Al-Jundi et al. (2019); Vandecasteele & Geuens (2010) & Cowart et al. (2008)	
cons_innov1	The product improved my social image
cons_innov2	I felt more important when I bought it
cons_innov3	People think I´m trendy because I bought that product
Zhang et al. (2020)	
prod_innov_1	I consider the product is innovative
Al-Jundi et al. (2019) & Zhang et al. (2020)	
perc_vl1	The product is environmentally friendly
perc_vl2	I consider the product a healthy option
perc_vl3	The product is convenient
perc_vl4	The product fits my lifestyle
Goić et al. (2021); Lee & Zhao (2014) & Hannachi (2015)	
cons_sat1	I´m pleased with the products´ texture
cons_sat2	I´m pleased with the products ‘flavour
cons_sat3	I´m pleased with the products ‘price
cons_sat4	I´m pleased with the products ‘packaging
Tudoran et al. (2012) & Al-Jundi et al. (2019)	
newprod_rep1	I would repurchase the product

Table 1: Manifested indicators and their assessment

Before analysing the data, it is useful to characterize the consumers of the sample. First, it´s important to notice that only 4% of the target population answered the questionnaire, which represents a total of 1031 product evaluations. Due to general data protection regulations and companies´ privacy policies, it was not possible to collect demographic or personal data about consumers. Hence, sample characterization was based on consumers´ learning process- the channels through which consumers learnt about product innovation.

Characteristics	**Respondents (n=1031)**	
Learning Process	Number	Percentage (%)
Store	733	71.10%
Friends/ Family	108	10.48%
Social Media	162	15.72%
***Continente* site**	100	9.70%
***Food Lab* site**	11	1.07%
Continente Lab´s Community	7	0.68%
Other [2]	21	2.04%

Table 2: Sample characteristics

The results [2] (Table 2) show that from the 1031 respondents, 733 had their first contact with product innovation in store. Social Media was the second most frequent answer with 162 responses. Friends and *Continente's* website got 108 and 100 answers, respectively. *Continent Lab´s Community*[3] had the least number of responses.

[2] It´s important to notice respondents could select more than one learning process indicator. For example, a consumer could select a store and friends. Therefore, the total percentage of respondents is not 100%.
[3] Continent Lab´s Community is a platform of *Continente Lab,* where users can give their feedback regarding product innovations launched

2.2. Research model: data analysis

The data collected is going to be analysed based on Structural Equation Modelling (SEM). This model integrates "the measurements (the so-called measurement model) and the hypothesized causal paths (the so-called structural model) into a simultaneous assessment" (Gefen et al., 2011, p.4). The measurement structure and structural model can be estimated based on a Covariance-Based SEM or on Partial Least Squares SEM (Gefen et al., 2011).

This research's main goal is theory building (Barroso et al., 2010) and has an exploratory purpose (Hair et al., 2011). It focuses "on the prediction of the dependent variables (both latent and manifest)" (Barroso et al., 2010, p.429), maximising the explained variance of dependent latent constructs (Hair et al., 2011). Thus, data is going to be analysed based on PLS-SEM. This technique, which is "designed to reflect the theoretical and empirical conditions (…) where these are habitual situations with no solid theories and scarce knowledge" (Barroso et al., 2010, p.431), is valuable, not only because it enables testing "complex models with many constructs, indicator variables and structural paths without imposing distributional assumptions on the data"(Hair et al., 2019, p.9), but also due to its higher fit "for analysing secondary data from a measurement theory perspective" (Hair et al., 2019, p.6).

The research model (see figure 1) is a reflective measurement model, because the constructs cause the covariation of the indicators, meaning the arrows are pointing from the latent variables to the indicators (Hair et al., 2011). Therefore, data analysis is going to be based on structural model assessment and measurement model assessment.

3. Results

This section displays the main results from the application of the SEMinR package – "it enables applied practitioners of PLS-SEM to use terminology that is very close to their familiar modelling terms" (Hair et al., 2021, p.50) - in Rstudio.

3.1. Descriptive analysis

Before starting the analysis, data was cleaned, meaning it was checked out for possible outliers (check the appendice Figure 7-18) and missing values.

Descriptive analysis began with the analysis of the mean and the median of manifested variables. The results can be checked out in the table presented below.

Manifest indicator	Mean	1st quartile	Median	3rd quartile
cons_innov1	2.45	1	3	3
cons_innov2	2.29	1	2	3
cons_innov3	2.17	1	2	3
prod_innov1	3.85	3	4	5
perc_vl1	3.46	3	3	4
perc_vl2	3.84	3	4	4
perc_vl3	3.88	3	4	5
perc_vl4	3.91	3	4	4.5
cons_sat1	4.08	4	4	5
cons_sat2	3.85	3	4	5
cons_sat3	2.97	2	3	4
cons_sat4	3.62	3	4	4
newprod_rep1	3.80	3	4	5

Table 3: Descriptive analysis of manifested indicators

Manifested variables mean varies between 2.17 and 4.08. *Cons_sat1* and *perc_vl4* are the ones with the highest scores, indicating consumers, on average, are more satisfied with the product innovation texture and product innovation fit in their lifestyle. On the other hand, they disagree on feeling more important when buying product innovation. Most of them also disagree with the statement regarding people's positive thoughts about them when buying innovations.

Nevertheless, almost 61% of the total manifest variables have a median of 4, indicating that most consumers agree with the manifested indicators statements. Consumer Innovativeness indicators are the only ones where two indicators (*cons_innov2* and *cons_innov3*) median is on a disagreement value (2: disagree).

To check correlations between indicators, the following matrix (figure 2) was created. In the matrix, the lighter and smaller bullets mean a lower correlation value (value closer to 0), whereas a bigger and darker bullet means a higher correlation value (value closer to 1).

According to its results, it's possible to state that there aren't negative correlations between indicators (in the image do not appear red dots). Moreover, the matrix shows a high correlation between *cons_sat1* and *cons_sat2* with the new product repurchase intention manifest variable. *Perc_vl3* and *perc_vl4* are also highly correlated with *newprod_rep1*. *Cons_sat1* and *cons_sat2* also show a correlation with *perc_vl3* and *perc_vl4* higher than 0.4.

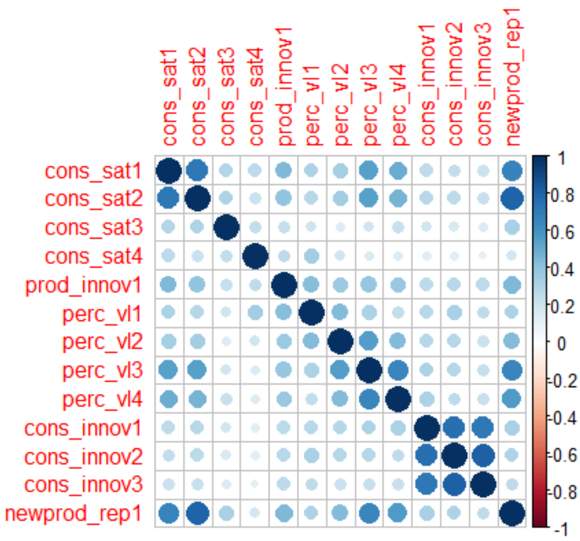

Figure 2: Correlation Matrix. Source: author script from RStudio

3.2. Measurement Model Assessment

"The measurement model defines the latent variables that the model will use and assigns observed variables (indicators) to each" (Barroso et al., 2010, p.432). It is applied by measuring reliability and validity. Reliability comprises indicator reliability; internal consistency reliability; composite reliability. Validity includes convergent validity and discriminant validity. The main goal of evaluating these measures is "to analyze whether the theoretical constructs are correctly measured by the manifest variables" (Barroso et al., 2010, p.432).

Regarding the indicator reliability (Table 4 [4]), which indicates the "communality of an indicator" (Hair et al., 2021, p.77), only two of the items are below the recommended value of 0.708, namely "cons_sat3" and "cons_sat4" with a 0.523 and 0.425 respectively. To check if *cons_sat3* and *cons_sat4* values should be eliminated a test has been made. According to Hair et al. (2021) "indicators with loadings between 0.40 and 0.708 should be considered for removal only when deleting the indicator leads to an increase in the internal consistency reliability or convergent validity(..) above the suggested threshold value" (p.77). As presented in Table 5, convergent validity (AVE) is above the value mentioned. Only internal consistency reliability is not. Therefore, indicators were eliminated, and the alpha value was tested (see the internal consistency reliability table in the appendices). Without *cons_sat3* and *cons_sat4, alpha* accounts for 0.835, which is above the reference value. According to Hair et al. (2021) perspective, they should be deleted. Nevertheless, both indicators were

[4] All tables are conditionally formatted. Thus:

- Bold corresponds to the highest value and the lowest value
- Green colour to a value within the recommended value
- Light red values not within the recommended value
- Yellow corresponds to a value which is closer to the threshold value

maintained, because other authors (Taber, 2018) consider values above 0.6 satisfactory.

On the other hand, the "Con_Innov" construct indicators are the highest ones, ranging from 0.904 to 0.935, which stresses the relevance of consumer innovativeness assessment.

	Cons_Innov	Prod_Innov	Perc_Vl	Cons_Sat	Newprod_Rep
cons_innov1	0.910				
cons_innov2	**0.935**				
cons_innov3	0.904				
prod_innov1		1.000			
perc_vl1			0.601		
perc_vl2			0.772		
perc_vl3			0.867		
perc_vl4			0.799		
cons_sat1				0.889	
cons_sat2				0.898	
cons_sat3				0.523	
cons_sat4				**0.425**	
newprod_rep					1.00

Table 4: Indicator Reliability

Concerning the internal consistency reliability (table 5), it is assessed Cronbach's alpha (alpha); the composite reliability (rhoC); the convergent validity (AVE) and the reliability coefficient rhoA.

Alpha indicators range between 0.674 and 0.905 meaning that only "Cons_Sat" is not above the threshold value of 0.7. Internal consistency reliability of "Prod_Innov" and "NewProd_Rep" should not "be interpreted as an indication of perfect reliability" (Hair et al., 2021, p.84) since both are measured by a single indicator and therefore "its internal consistency reliability is by definition 1" (Hair et al., 2021, p.84). The values of composite reliability are all above the value considered acceptable: 0.7 (Hair et al., 2011). The highest value – the one of the "Cons_Innov" construct - is 0.940. This value is not problematic, once it does not exceed the maximum limit referred by Hair et al. (2021) - 0.95. Values above 0.95 can be problematic because they "suggest the possibility of undesirable response patterns (e.g., straight-lining), thereby triggering inflated correlations among the error terms of the indicators" (Hair et al., 2021, p.77).

Regarding the explanation of the variance of its indicators, all the constructs are above the 0.50 threshold values (Hair et al., 2011). Therefore, all the constructs explain more than 50 per cent of its indicators - *Cons_Innov* explains 84% of its indicator's variance; *Perc_Vl* explains 58.7% and *Cons_Sat* 51.3%.

Cons_Innov (0.918) *Cons_Sat* (0.827) and *Perc_Vl* (0.787) have the highest levels of reliability coefficient.

These results validate research model´s constructs- consumer innovativeness, product innovativeness, perceived value- and product innovation performance constructs: customer satisfaction and new product repurchase intentions.

Constructs	**alpha**	**rhoC**	**AVE**	**rhoaA**
Cons_Innov	**0.905**	**0.940**	**0.840**	**0.918**
Prod_Innov	1.00	1.00	1.00	1.00
Perc_Vl	0.760	0.848	0.587	**0.787**
Cons_Sat	**0.674**	**0.793**	**0.513**	0.827
NewProd_Rep	1.00	1.00	1.00	1.00

Table 5: Internal consistency reliability

Concerning discriminate validity, it was assessed the square roots of the AVEs for the reflectively measured constructs (Table 6).

	Cons_Innov	*Prod_Innov*	*Perc_Vl*	*Cons_Sat*	*NewProd_Rep*
Cons_Innov	**0.916**				
Prod_Innov	0.292	**1.00**			
Perc_Vl	0.388	0.501	**0.766**		
Cons_Sat	0.311	0.476	0.608	**0.716**	
NewProd_Rep	0.325	0.447	0.660	0.778	**1.00**

Table 6: Discriminate validity

Cons_Innov (0.916*), Prod_innov* (1), *Perc_Vl* (0.766) are higher than the correlations of each construct with other latent variables. This pattern is not recognizable in the *Cons_Sat* construct whereas the correlation with *NewProd_Rep* is higher than the square roots of its AVE (0.778>0.716). This can happen due to correlations issues. *Cons_Sat* has already reliability issues as it has a AVE=0.513 and Alpha=0.674. Hence, is reasonable its´ square root of AVE is lower than the correlated construct.

Despite its importance, the square roots of AVE, Fornell–Larcker criterion, does not allow for reliably detecting discriminant validity issue" (Hair et al., 2021, p.86). Thus, it´s performed a second validity criterion: the HTMT criterion. HTMT criterion corresponds to "the mean value of the indicator correlations across constructs (…) relative to the (geometric) mean of the average correlations for the indicators measuring the same construct" (Hair et al., 2021, p.79).

	Cons_Innov	**Prod_Innov**	**Perc_Vl**	**Cons_Sat**	**NewProd_Rep**
Cons_Innov					
Prod_Innov	**0.306**				
Perc_Vl	0.469	0.584			
Cons_Sat	0.386	0.568	0.795		
NewProd_Rep	0.338	0.447	0.738	**0.846**	

Table 7: Discriminate validity HTMT criterion

According to the HTMT criterion results (Table 7), the reflective constructs are below 0.85, which is the threshold value of conceptually different constructs (Hair et al., 2021). *Cons_Sat* and *NewProd_Rep* is the only relation with an HTMT value equal to the threshold value, accounting for 0.846, which supports that *Cons_Sat´s* square root of AVE is lower than its correlated construct.

3.3. Structural Model Assessment

After the measurement model assessment, the structural model should be evaluated. The structural model links together the constructs (Hair et al., 2011). According to Barroso et al. (2010), structural model assessment relies mainly upon two items: path coefficients and R^2 values. Nevertheless, before evaluating the significance and relevance of the structural model relationships, it´s essential to check collinearity issues. Hair et al. (2021) highlighted the importance of this step:

> The reason is that the estimation of path coefficients in the structural models is based on ordinary least squares (OLS) regressions of each endogenous construct on its corresponding predictor constructs. Just as in an OLS regression, the path coefficients might be biased if the estimation involves high levels of collinearity among predictor constructs. (p. 116)

Hence, this section will firstly assess collinearity issues and then paths correlations. Following this, there is a segment to check model explanatory power and predictive power. Was also added a model comparison, to enhance the model fit.

3.3.1. Collinearity- VIF issues

Collinearity issues are only problematic when variance inflation factor (VIF) values are above 5 or between 3- 5. As shown in the tables below, none of the predictor constructs is below these values- *Perc_Vl* and *NewProd_Rep* values range between 1.093 -1.202.

Predictor constructs	VIF value
Perc_Vl	*Cons_Innov*: 1.903
	Prod_Innov: 1.903
NewProd_Rep	*Cons_Innov*: 1.202
	Prod_Innov: 1.437
	Per_Vl: 1.839
	Cons_Sat: 1.701

Table 8: Predictors and VIF value

Therefore, it is now possible to assess path coefficients.

3.3.2. Significance and relevance of the path coefficients

Path coefficient (β) values range between -1 and +1. "Coefficients closer to -1 representing strong negative relationships and those closer to +1 indicating strong positive relationships" (Hair et al., 2021, p.118). Its significance depends on the values in the confidence interval (CI). For example, "A path coefficient is significant at the 5% level if the value zero does not fall into the 95% confidence interval" (Hair et al., 2021, p.117).

Paths	β	T-value	CI2.5%-97.5%
Cons_Innov ➡ *Perc_Vl*	0,264	10,228	[0,213- 0,312]
Cons_Innov ➡ *NewProd_Rep*	0,027	1,93	[-0,013-0,069]
Prod_Innov ➡ *Perc_Vl*	0,423	1,542	[0,368-0,475]
Prod_Innov ➡ *NewProd_Rep*	**0,017**	**0,689**	**[-0,032-0,066]**
Perc_Vl ⟶ *Cons_Sat*	**0,608**	**26,866**	**[0,565-0,652]**
Perc_Vl ⟶ *NewProd_Rep*	0,283	10,522	[0,229-0,336]
Cons_Sat ⟶ *NewProd_Rep*	0,589	23,132	[0,537-0,637]

Table 9: Significant and relevance of paths

First, let's consider the original estimation of path coefficients. The exogenous constructs have the lowest impact in one of the output variables, *NewProd_Rep* (*Cons_Innov*➡ *NewProd_Rep*=0.027 and Prod_Innov ➡ *NewProd_Rep*= 0.017). On the other hand, *Perc_Vl* exerts a higher impact either in *Cons_Sat* or *NewProd_Rep* (*Perc_Vl* ➡*Cons_Sat*= 0.608; *Perc_Vl*➡ *NewProd_Rep*=0.283). These results show consumer innovativeness and perceived product innovativeness don´t impact much on product innovation performance. In contrast, perceived value does impact new product repurchase intentions.

Cons_Sat is the construct with the biggest effect on *NewProd_Rep* (*Cons_Sat*➡ *NewProd_Rep*=0.589). This result is aligned with hypothesis 7.

Concerning the t-value, according to Hair et al. (2021), its value "from the bootstrapping should exceed the value of 1.960" (p.126). It's possible to check that the relationships between the exogenous constructs and *NewProd_Rep* are not significant (*Cons_Innov* ⟶ *NewProd_Rep*, t stat=1.93 and *Prod_Innov* *NewProd_Rep*, t stat= 0.689). This is supported by the confidence interval range. Both path coefficients are not meaningful at 2.5% level as 0 falls into the interval

(*Cons_Innov* ⟶ *NewProd_Rep*, CI= [-0.013-0.069]; Prod_Innov NewProd_Rep, CI= [-0.032-0.066]).

Nevertheless, the relationships between the exogenous constructs and the moderator, as well as the ones between the endogenous constructs have a statistical significance.

Now the bootstrapped total paths will be assessed to understand the impact of the exogenous constructs, *Cons_Innov* and *Prod_Innov* on both outcome constructs, *Cons_Sat and NewProd_Rep*.

Prod_Innov has the highest effect either in *Cons_Sat* (0.257) and in *NewProd_Rep* (0.289). The influence of *Cons_Innov* on *Cons_Sat* and (0.161) on *NewProd_Rep* (0.196) has also some significance, but it is lower than the *Prod_Innov* one. On one hand, these results do not reject hypotheses H1 and H3. On the other hand, they suggest a higher impact of Product Innovativeness on both product innovations performance constructs. Hence, the company should focus more on developing strategies to enhance perceived consumer innovativeness.

	β	**T-value**	**CI 2.5%-97.5%**
Cons_Innov ➡ Perc_Vl	0,264	10,228	[0,213-0,312]
Cons_ Innov ➡ Cons_Sat	**0,161**	**9,363**	[0,127-0,194]
Cons_Innov ➡ NewProd_Rep	0,196	7,558	[0,148-0,245]
Prod_Innov ➡ Perc_Vl	0,423	15,542	[0,368-0,475]
Prod_Innov ➡ Cons_Sat	0,257	11,878	[0,216-0,300]
Prod_ Innov ➡ NewProd_Rep	0,289	10,055	[0,234-0,346]
Perc_Vl ⟶ Cons_Sat	0,608	**26,866**	[0,565-0,652]
Perc_Vl ⟶ NewProd_Rep	**0,641**	26,143	[0,593-0,688]
Cons_Sat ⟶ NewProd_ Rep	0,589	23,132	[0,537-0,637]

Table 10: Bootstrapped total paths

Regarding the paths, the ones with the highest values are those in the endogenous model (*Perc_VL; Cons_Sat and NewProd_Rep*) - the correlation between *Perc_VL* and *NewProd_Rep* and between *Cons_Sat* and *New_Prod_Rep* have the highest values: 0.608 and 0.589. These results support the positive impact referred on the literature, in which several authors highlighted, not only the influence of perceived value on new product repurchase intentions, but also the effect of consumer satisfaction on new product repurchase intentions.

3.3.3. Model explanatory Power

According to Hair et al. (2011), as PLS-SEM´s main goal is to explain the variation of the endogenous constructs, the R^2 values should be higher.

	Perc_Vl	*NewProd_Rep*	*Cons_Sat*
R^2	**0.314**	**0.661**	0.370

Table 11: R^2

The values of the target constructs aren´t very similar. *NewProd_Rep* has the highest value with a 0.661 score. *Cons_Sat* and *Perc_Vl* have a lower value, accounting, respectively, with 0.370 and 0.314 R^2 values. Nevertheless, new product repurchase intentions and customer satisfaction have the highest scores, meaning the research model has a good explanatory power, which reinforces hypothesis´ ability to explain product innovation performance.

Another important value to assess is f^2 (Table 12). These values show the effect size of the predictor constructs (Hair et al., 2021).

	Perc_Vl	*Cons_Sat*	*NewProd_Rep*
Cons_Innov	**0.094**		0.002
Prod_Innov	0.241		0.001
Perc_Vl		0.586	0.131
Cons_Sat			**0.603**

Table 12: Effect size of predictor constructs

Perc_Vl and *Cons_Sat* have the highest effect sizes in *NewProd_Rep* (0.131 and 0.603, respectively). On the other hand, Prod_Innov have a higher effect size in Per_Vl than Cons_Innov (Prod_Innov ➡ Perc_Vl= 0.241 and Cons_innov Perc_Vl= 0.094).

3.3.4. Model comparisons

To check if the research model is the best, Hair et al. (2021) suggest the creation and comparison of different model configurations. Hence, it was created a new version of the research model. Model 2[5] is presented below.

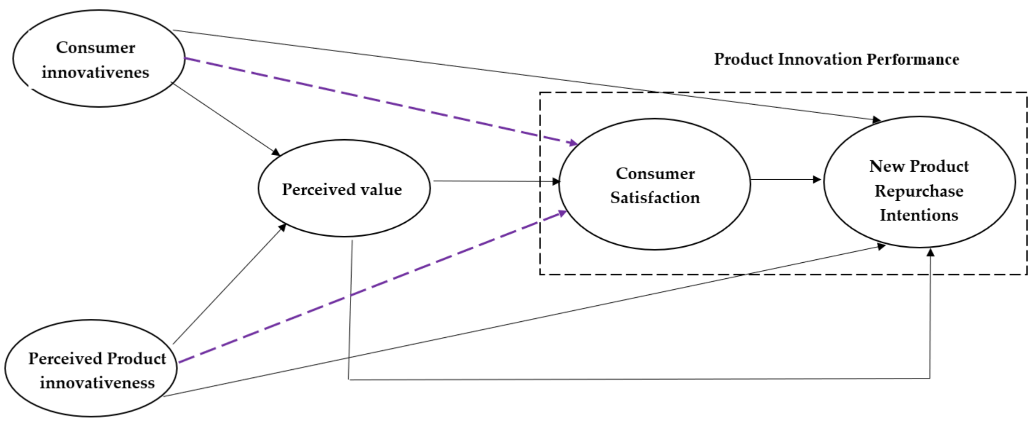

Figure 3: Model 2

[5] The coloured arrows correspond to the correlations added. It was added a direct correlation between the exogenous constructs and the other construct.

Created the model for comparison purposes, it was necessary to assess the model fit. To do so it was checked BIC value and BIC-based Akaike weights.

	Its criteria for competing models	BIC Akaike weights
Model1	-1082.294	0.977922494
Model2	-1074.712	0.02207751

Table 13: Criterions for a model fit assessment

Table 13 results show that Model1 has a higher model fit (-1082.294) than Model2 (-1074.712). We can consult the BIC-based Akaike weights regarding the models' relative likelihoods. According to these values, Model1 has a strong weighting accounting for more than 0.956 than Model2.

These results allow us to state Model1 is the superior model, which corresponds to the initial model proposed.

3.3.5. Predictive Power

Lastly, it was assessed the structural model's predictive power. Even though the main research goal is not the model´s predictive capability, it was assessed because one of the main purposes of PLS-SEM is prediction (Hair et al., 2011). To do so, it was applied PLS predict, "a holdout sample-based procedure that applies k-fold cross-validation to estimate the model parameters" (Hair et al., 2021, p.135). To evaluate the distribution of predictive error research focused on the key output - New Product Repurchase Intentions (*NewProd_Rep*).

Prediction error distribution (Figure 4) is like a normal distribution, indicating symmetric distribution. Hence, to test the model's predictive power, it was used RMSE (Root Mean Squared Error) and Linear Model metrics.

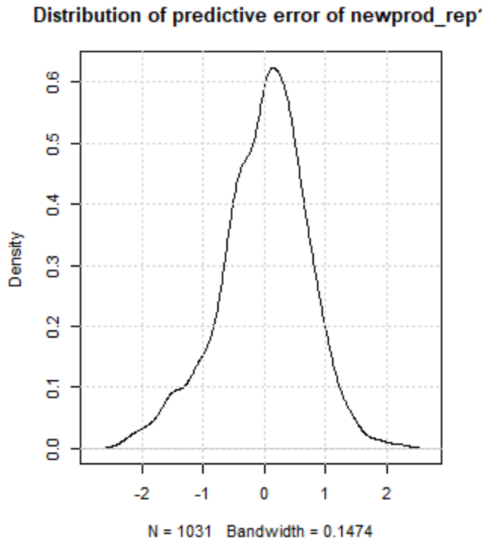

Figure 4: Prediction error distribution

According to Shmueli et al. (2019) when the RMSE in the PLS sample are higher than those in the LM sample the model has lower predictive power - the PLS sample has a higher predictive error than the LM model benchmark- *newprod_rep1*= 0.712 and LM=0.639.

	The predictive error of predictor construct newprod_rep1
PLS RMSE	0.712
LM RMSE	0.639

Table 14: Predictive Power of predictor construct - PLS vs RMSE

3.4. Hypotheses validation

The results suggest that product innovation performance does not depend much on consumer innovativeness and perceived innovativeness. Therefore, there is no support for hypotheses 1 and hypotheses 3, as consumer innovativeness and product perceived innovativeness have an impact lower than 0.1 in the key output of product innovation performance: new product repurchase intentions.

Nevertheless, it was found a moderate impact of perceived value either on consumer satisfaction and new product repurchase intentions, non-contradicting hypotheses 5 and hypothesis 6. Then, it's important to test the total effect of consumer innovativeness and perceived product innovativeness on customer satisfaction and new product repurchase intentions, because the exogenous constructs have, not only a direct effect on the target constructs but also an indirect effect, which means their total effect is "the sum of the direct and indirect effect" (Hair et al., 2021, p.140). According to Hair et al. (2021), it's possible to not contradict a hypothesis based on a significant indirect effect.

As presented in the table below the indirect effect of *Cons_Innov* on *NewProd_Rep* is 0.169 and 0.161 on *Cons_Sat*. Product Innovativeness (*Prod_Innov*) has a bigger effect, accounting for 0.271 on *NewProd_Rep* and 0.257 on *Cons_Sat*.

	PIP constructs	
	Cons_Sat	***NewProd_Rep***
Cons_Innov	0.161	0.169
Prod_Innov	0.257	0.271

Table 15: Indirect effect of exogenous constructs on Product Innovation Performance constructs

When inspecting the bootstrapped confidence intervals, neither includes 0, which means the indirect effect is significant (Hair et al., 2021).

Paths	**CI (2.5%-97.5%)**
Cons_Innov ➡ *Perc_Vl* ➡ *NewProd_Rep*	[0.056-0.096]
Prod_Innov ➡ *Perc_Vl* ➡ *NewProd_Rep*	**[0.093-0.150]**

Table 16: Confidence intervals of indirect effects

Concerning the direct effect, as shown in Table 8, *Cons_Innov* has an impact of 0.027 on *NewProd_Rep* and *Prod_Innov* an impact of 0.017 on *NewProd_Rep*. Both confidence intervals include 0, which means the effect is less substantial ([-0.013-0.069]; [-0.032-0.066]). This means that both relations with product innovation performance indicators are fully mediated by *Perc_Vl*, but it does not act as a competitive mediator, as the result of multiple paths is positive (0.0020). Despite the relevant indirect effect, hypotheses 1 and 3 were not rejected. Further explanations are given in the discussion section.

It was found a positive impact of the exogenous variables on the mediator (Perceived Value), which allow us to not reject hypotheses 2 and 4. The impact of consumer satisfaction on new product repurchase intention (hypothesis 7) is also confirmed.

The table presented below summarises the main indicators used to check the hypothesis's results.

Paths	β	t-value	Hypotheses result
Prod_Innov ➡ NewProd_Rep	**0,017**	**0.689**	**H1-Not rejected**
Prod_Innov ➡ Perc_Vl	0,423	15.542	**H2- Not rejected**
Cons_Innov ➡ NewProd_Rep	0,027	1.293	**H3- Not rejected**
Cons_Innov ➡ Perc_Vl	0,264	10.228	**H4- Not rejected**
Perc_Vl ⟶ Cons_Sat	**0,608**	26.866	**H5- Not rejected**
Perc_Vl ⟶ NewProd_Rep	0,283	10.522	**H6- Not rejected**
Cons_Sat ⟶ NewProd_Rep	0,589	23.132	**H7- Not rejected**

Table 17: Hypotheses results

4. Discussion

The main objective of this research is to investigate the drivers and their impact on product innovation performance in the food retailing industry, in Portugal. The findings (figure 5)[6] show a good explanatory power of the model, which explains a 66% variation in consumer satisfaction (*Cons_Sat*) and justifies 37% of the variation in new product repurchase intentions (*NewProd_Rep*). Therefore, the model proposed has a good fit for the food retailing industry.

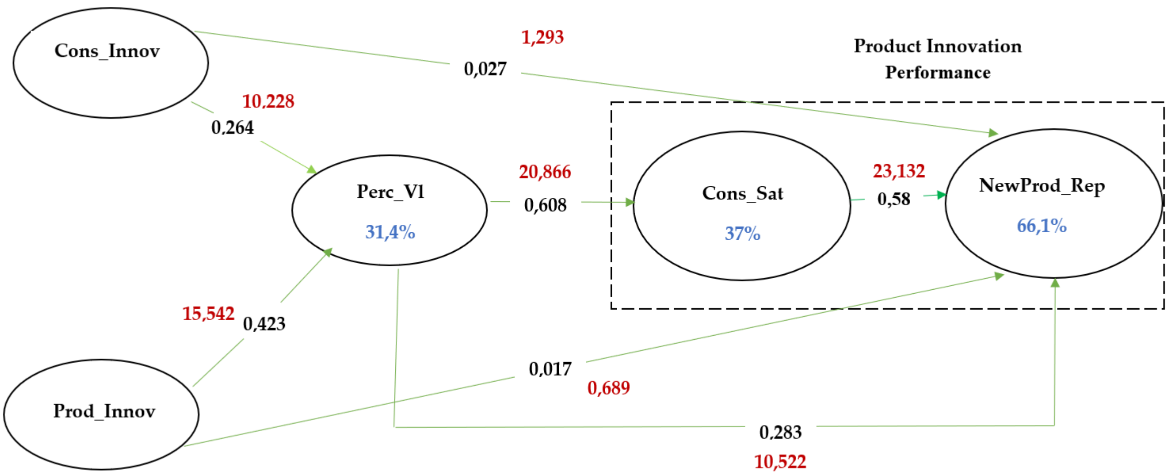

Figure 5: Research model with final results

"The consumer experience measurement should be at the forefront when launching a new product" (Tudoran et al., 2012). If companies want to develop long term and meaningful relationships (Erjave et al., 2016), consumer experience measurement should focus on customer satisfaction. This measurement becomes

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[6] The colours are deliberately used. Concerning the arrows, the ones with green colour represent not rejected hypotheses. Regarding values, colours represent different indicators results. The ones in dark black represent path coefficients; the red ones correspond to t-values and the blue ones refer to R^2 values.

even more important in the retailing context, once “retailers engage in direct interactions with end customers”(Sorescu et al., 2011).

The relation between consumer satisfaction and consumers’ tendency to repurchase was already studied. Cowart et al. (2008) stress that satisfied consumers were more likely to purchase and repurchase products than those who were not satisfied. Notwithstanding, consumer satisfaction’s influence on purchasing, it depends on the strength with which consumers hold that satisfaction (Tudoran et al., 2012). Research findings strengthen a positive influence of consumer satisfaction and new product repurchase intentions within the food retailing industry.

Implementing “differentiating actions must be taken into account based on perceived value”(Coutelle-Brillet et al., 2014, p.170), as they can influence consumers’ adoption decisions. This principle becomes even more relevant when talking about new products. According to Florack et al.(2021, p.686) a “differentiation principle is highly relevant for the introduction of new food products to the market because these will be evaluated compared to the already existing and more familiar ones”. Results endorse a positive correlation between perceived value and new product repurchase intentions, which reinforces Al-Jundi et al. (2019) and Wu et al. (2014) studies.

The impact of perceived value on customer satisfaction is also supported with a 0.608 path correlation. Research on this topic is not new. In the earlies 90s, it was developed a specific methodology to measure customer experience - Best European Customer Experience (BECX). BECX measurement model already included customers satisfaction. It was measured by several latent variables, including perceived value, which reinforces the correlation found between them. The current results are in line with those.

Concerning the influence of the two exogenous constructs on the mediator, the research found a positive influence between them. “The decision of whether or not to adopt an innovative product represents a goal conflict for many consumers” (Cowart et al., 2008, p.1113). Nevertheless, consumers with innovativeness traits tend to perceive an added value in product innovations (Al-Jundi et al., 2019). This assumption is endorsed by current research findings. The impact of perceived product innovativeness on perceived value has also been studied. According to Zhang et al. (2020) “consumers may believe that innovative design, new or improved attributes can lead to a better experience with the products (p.5). This is proven in Zhang et al. (2020) study where the authors found a positive influence of product perceived innovativeness on perceived value.

Despite the findings being aligned with other research findings, the results of this study raise some doubts about two hypotheses. The influence of consumer innovativeness and perceived product innovativeness on new product repurchase intentions is not rejected, but it can be questioned. If the direct effects of *Prod_Innov* on *NewProd_Rep* and of *Cons_Innov* on *NewProd_Rep* are not significant, the indirect effect is significant. Both relations with product innovation performance indicators are fully mediated by *Perc_Vl*, which act as a complementary mediator.

These findings are aligned with hypothesis result validation. Hair et al. (2021) state a hypothesis can be reinforced based on a significant indirect effect. Conversely, Cowart et al. (2008) states that “The intervening psychological process between the individual trait of innovativeness and the behaviour of new product adoption is not well understood” (p.1112). Notwithstanding those perspectives, this study is based on a different context - it studies the food retailing industry and therefore the product innovation performance relates to food products. Research findings endorse the statement of Cowart et al. (2008), as it raises a doubt. This also leads us to the next section: as the different views can be a starting point for future research or a research limitation.

5. Conclusion

Innovating and differentiating products within the food retailing industry is crucial, once customers tend to compare them to non-innovative products (Erjavec et al., 2016). This research proposed a model to measure product innovation performance in the food retailing industry in Portugal, based on two key outcomes - customer satisfaction (*Cons_Sat*) and New Product Repurchase Intentions (*NewProd_Rep);* two key drivers - consumer innovativeness (*Cons_Innov)* and Perceived Product Innovativeness (*Prod_Innov*), and a moderator - perceived value (*Perc_Vl*).

The research findings endorsed a positive impact of perceived value on customer satisfaction and new product repurchase intentions. Concerning the drivers of product innovation performance, the correlation between them was not fully supported. However, as the indirect effect of *Cons_Innov* and *Prod_Innov* on *NewProd_Rep* and *Cons_Sat is* significant, the correlation between the driver's constructs and the output ones should be further tested. The detailed assessment of the product innovation performance model has several implications for managers who want to achieve efficiency in product innovation in food retailing.

First, better-informed managers can leverage the efficiency of product innovation performance. This research highlights which drivers are contributing positively and negatively to product innovation performance. By examining the correlation between the drivers proposed and product innovation performance variables, they can easily proceed with adequate investments in innovation. Besides that, a closer look at the results also provides them with information on the indirect impacts of other variables in their expected outputs. The results show a positive correlation between perceived value mediator and consumer satisfaction and new product repurchase intentions. They have also raised a question about the role of perceived value on the influence between consumer innovativeness and product perceived innovativeness. "The act of collecting data on innovation in an organisation can indirectly influence managerial decisions by raising awareness of potential innovation activities and resources" (OECD & Eurostat, 2018, p.49).

Secondly, the unveiling of relations provided by the research model can also contribute to the long-term profitability of the firm, as the organization can develop product innovations that satisfy consumer needs (Hume & Mort, 2010).

This work findings also extend business innovation knowledge. First, this study focuses on the service industry, which only "account for 1–4% of the relevant publications" (Dziallas & Blind, 2019, p.7) on innovation measurement. It also scopes on non-technological product innovation, specifically food product innovation within retailing industry. The model proposed for assessing product innovation performance also explores a gap in the literature - the measurement of innovation within companies. As previously mentioned, there is "little guidance towards framing the "black box" of the innovation processes" (Hao et al., 2017, p.8).

Despite the managerial effects and theoretical implications, the findings from this study need to be interpreted with caution. As the results focus only on one case study, they should not be generalised to the food retailing industry as a whole, nor other industries. Future research can include another case study within the same industry to check if the results are rugged, as "analytic conclusions independently arising from two cases, as with two experiments, will be more powerful than those coming from a single case…" (Yin, 2009, paras. 2). It could also be interesting to compare results between them, evaluating potential mismatches and similarities.

Notwithstanding the good number of responses (1031), especially considering the shorter period to collect the data, it corresponds only to 4% of the target population. There is a modest response rate, which raises a doubt: if the results would be similar if the sample were larger.

Concerning manifested indicators measurement, product perceived innovativeness construct and new product repurchase intentions are measured using single items. Why not evaluate them with multi-items? Despite single items' importance (they are more likely to increase responses rates- survey becomes shorter and therefore respondents are more likely to answer- ; they also avoid "common method bias" (Petrescu, 2013, p.101)), multi-items avoid validity issues, increase reliability and have a higher correlation with the variable measured.

Moreover, research findings did not stress a direct influence of consumer innovativeness and perceived product innovativeness on new product repurchase intentions (one of the outputs of product innovation performance). Therefore, it could be interesting to test the model by including more constructs. Consumers´ learning process could be a noteworthy variable to be added. The influence of consumer innovativeness on the process of acquiring information about product innovations is already proven by Al-Jundi et al. (2019), who states that "Consumer innovativeness improves the learning process for new products" (p.6). Furthermore, the corporate image could also be added as a driver construct. Askariazad & Babakhani (2015) found a positive impact of it on customer satisfaction. However, none of these constructs was tested in the food retailing industry, which reinforces the relevance of its inclusion in future research.

Finally, in upcoming explorations, the research model could be analysed from a different perspective. Instead of analysing product innovation feedback as a whole, product innovation could be clustered by brands. Then, it could be assessed the impact of brands on product innovation performance.

6. Bibliography

Al-Jundi, S. A., Shuhaiber, A., & Augustine, R. (2019). Effect of consumer innovativeness on new product purchase intentions through learning process and perceived value. *Cogent Business and Management*, *6*(1), 1-15. https://doi.org/10.1080/23311975.2019.1698849

Alhusen, H., Bennat, T., Bizer, K., Cantner, U., Horstmann, E., Kalthaus, M., Proeger, T., Sternberg, R., & Töpfer, S. (2021). A New Measurement Conception for the 'Doing-Using-Interacting' Mode of Innovation. *Research Policy*, *50*(4). https://doi.org/10.1016/j.respol.2021.104214

Ariffin, S., Yusof, J. M., Putit, L., & Shah, M. I. A. (2016). Factors Influencing Perceived Quality and Repurchase Intention Towards Green Products. *Procedia Economics and Finance*, *37*(16), 391–396. https://doi.org/10.1016/s2212-5671(16)30142-3

Arts, J. W. C., Frambach, R. T., & Bijmolt, T. H. A. (2011). Generalizations on consumer innovation adoption: A meta-analysis on drivers of intention and behavior. *International Journal of Research in Marketing*, *28*(2), 134–144. https://doi.org/10.1016/j.ijresmar.2010.11.002

Askariazad, M. H., & Babakhani, N. (2015). An application of European Customer Satisfaction Index (ECSI) in Business to Business (B2B) Context. *Journal of Business and Industrial Marketing*, *30*(1), 17–31. https://doi.org/10.1108/JBIM-07-2011-0093

Barroso, C., Carrión, G. C., & Roldán, J. L. (2010). Applying maximum likelihood and PLS on different sample sizes: studies on SERVQUAL model and employee behavior model. In *Handbook of partial least squares* (pp. 427-447). Springer.

Bartels, J., & Reinders, M. J. (2011). Consumer innovativeness and its correlates: A propositional inventory for future research. *Journal of Business Research*, *64*(6), 601–609. https://doi.org/10.1016/j.jbusres.2010.05.002

Boksberger, P. E., & Melsen, L. (2011). Perceived value: A critical examination of definitions, concepts and measures for the service industry. *Journal of Services Marketing*, *25*(3), 229–240. https://doi.org/10.1108/08876041111129209

Brattström, A., Frishammar, J., Richtnér, A., & Pflueger, D. (2018). Can innovation be measured? A framework of how measurement of innovation engages attention in firms. *Journal of Engineering and Technology Management - JET-M*, *48*(1), 64–75. https://doi.org/10.1016/j.jengtecman.2018.04.003

Calantone, R. J., Chan, K., & Cui, A. S. (2006). Decomposing product innovativeness and its effects on new product success. *Journal of Product Innovation Management*, *23*(5), 408–421. https://doi.org/10.1111/j.1540-5885.2006.00213.x

Cowart, K., O., Gavin, L.F., & Wilson, A.,E. (2008).A structural look at consumer innovativeness and sel-conguence in new product purchases. *Psychology & Marketing*, *25*(12), 461–469. https://doi.org/10.1002/mar.20256

Chakraborty, G., Srivastava, P., & Marshall, F. (2007). Are drivers of customer satisfaction different for buyers/users from different functional areas? *Journal of Business and Industrial Marketing*, *22*(1), 20–28. https://doi.org/10.1108/08858620710722798

Chandon, P., Morwitz, V. G., & Reinartz, W. J. (2004). The short- And long-term effects of measuring intent to repurchase. *Journal of Consumer Research*, *31*(3), 566–572. https://doi.org/10.1086/425091

Coutelle-Brillet, P., Riviere, A., & des Garets, V. (2014). Perceived value of service innovation: A conceptual framework. *Journal of Business and Industrial Marketing*, *29*(2), 164–172. https://doi.org/10.1108/JBIM-04-2012-0066

Dziallas, M., & Blind, K. (2019). Innovation indicators throughout the innovation process: An extensive literature analysis. *Technovation*, *80–81*(1), 3–29. https://doi.org/10.1016/j.technovation.2018.05.005

El Bassiti, L., & Ajhoun, R. (2017, January 16). *Towards Innovation Excellence: Why* *and How to Measure Innovation Performance?* In International Conference on Information and Communication Technology for The Muslim World (ICT4M), Jakarta, Indonesia. https://doi.org/10.1109/ict4m.2016.031

Florack, A., Koch, T., Haasova, S., Kunz, S., & Alves, H. (2021). The Differentiation Principle: Why Consumers Often Neglect Positive Attributes of Novel Food Products. *Journal of Consumer Psychology*, *31*(4), 684–705. https://doi.org/10.1002/jcpy.1222

Fu, F., & Elliott, M. (2013). The moderating effect of perceived product innovativeness and product knowledge on new product adoption: An integrated model. *Journal of Marketing Theory and Practice*, *21*(3), 257–272. https://doi.org/10.2753/MTP1069-6679210302

Gefen, D., Rigdon, E. E., & Straub, D. (2011). Editor´s comments: an update and extension to SEM guidelines for administrative and social science research. *MIS quarterly, 35*(2), 3-14. https://www.jstor.org/stable/23044042

Goić, M., Levenier, C., & Montoya, R. (2021). Drivers of customer satisfaction in the grocery retail industry: A longitudinal analysis across store formats. *Journal of Retailing and Consumer Services*, *60*(1). https://doi.org/10.1016/j.jretconser.2021.102505

Erjave, H.,S., Dmitrovic,T., D., & Brzan, P., P. (2016). Drivers of customer satisfaction and loyalty in service industries. In *journal of Businees Economics and Management*, *17(*5), 810-823. https://doi.org/10.3846/16111699.2013.860614

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial Least Squares Structural Equation Modeling (PLS-SEM) using R*. Springer. https://doi.org/10.1007/978-3-319-57413-4_15

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–152. https://doi.org/10.2753/MTP1069-6679190202

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

Hannachi, Y. (2015). Development and Validation of a Measure for Product Innovation Performance : The PIP Scale. *Journal of Business Studies Quarterly*, *6*(3), 23–35. https://www.proquest.com/docview/1667167862?pq-origsite=gscholar&fromopenview=true

Hao, X., J. ,van Ark, B., & Ozyildirim, A. (2017, May). *Signposts of Innovation: A Review of Innovation Metrics.* Working paper No.17-01. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.2970648

Huarng, K. H., & Yu, M. F. (2019). Customer satisfaction and repurchase intention theory for the online sharing economy. *Review of Managerial Science*, *13*(3), 635–647. https://doi.org/10.1007/s11846-018-0321-0

Hume, M., & Mort, G. S. (2010). The consequence of appraisal emotion, service quality, perceived value and customer satisfaction on repurchase intent in the performing arts. *Journal of Services Marketing*, *24*(2), 170–182. https://doi.org/10.1108/08876041011031136

Lee, K. K., & Zhao, M. (2014). The effect of price on preference consistency over time. *Journal of Consumer Research*, *41*(1), 109–118. https://doi.org/10.1086/675219

Organisation for Economic Cooperation and Development [OECD] & European Statistical Office [Eurostat]. (2018). Oslo Manual 2018: Guidelines for collecting, reporting and using data on innovation (4th edition). OECD Publishing. https://doi.org/10.1787/9789264304604-en%0Ahttps://www.oecd-ilibrary.org/science-and-technology/oslo-manual-2018_9789264304604-en%0Ahttps://www.oecd-ilibrary.org/science-and-technology/oslo-manual-2018_9789264304604-en

Oke, A. (2007). Innovation types and innovation management practices in service companies. *International Journal of Operations and Production Management*, *27*(6), 564–587. https://doi.org/10.1108/01443570710750268

Petrescu, M. (2013). Marketing research using single-item indicators in structural equation models. *Journal of Marketing Analytics*, *1*(2), 99–117. https://doi.org/10.1057/jma.2013.7

Samudro, A., Sumarwan, U., Simanjuntak, M., & Yusuf, E. Z. (2020). Assessing the effects of perceived quality and perceived value on customer satisfaction. *Management Science Letters*, *10*(5), 1077–1084. https://doi.org/10.5267/j.msl.2019.11.001

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *European Journal of Marketing*, *53*(11), 2322–2347. https://doi.org/10.1108/EJM-02-2019-0189

Taber, K. (2018). The use of cronbach´s alpha when developing and reporting research intruments in science education. *Research in Science Education*, *1*(48), 1273-1296. https://doi.org/10.1007/s11165-016-9602-2

Tavassoli, S., & Karlsson, C. (2015). Persistence of various types of innovation analyzed and explained. *Research Policy*, *44*(10), 1887–1901. https://doi.org/10.1016/j.respol.2015.06.001

Tidd, J. (2001). Innovation management in context: Environment, organization and performance. *International Journal of Management Reviews*, *3*(3), 169–183. https://doi.org/10.1111/1468-2370.00062

Tidd, J. & Thuriax-Alemán, B. (2016). Innovation management practices: cross-sectorial, variation and effectiveness. *R&D Management*, *46*(3), 1024-1043. https://doi.org/10.1111/radm.12199

Tudoran, A. L., Olsen, S.O., & Dopico, D. C. (2012). Satisfaction strength and intention to purchase a new product. *Journal of Consumer Behaviour*, *50*(1), 391–405. https://doi.org/10.1002/cb.1384

Vandecasteele, B., & Geuens, M. (2010). Motivated consumer innovativeness: Concept, measurement, and validation. *International Journal of Research in Marketing*, *27*(4), 308–318. https://doi.org/10.1016/j.ijresmar.2010.08.004

Varis, M., & Littunen, H. (2010). Types of innovation, sources of information and performance in entrepreneurial SMEs. *European Journal of Innovation Management*, *13*(2), 128–154. https://doi.org/10.1108/14601061011040221

Yin, R. K. (2009). *Case Study Research: Design and Methods* (4th edition). Sage.

Yeh, Y. P. (2016). Market orientation and service innovation on customer perceived value: The case of supermarket retailers. *Management Research Review*, *39*(4), 449–467. https://doi.org/10.1108/MRR-08-2014-0205

Yu, J., Lee, H., Ha, I., & Zo, H. (2017). User acceptance of media tablets: An empirical examination of perceived value. *Telematics and Informatics*, *34*(4), 206–223. https://doi.org/10.1016/j.tele.2015.11.004

Zhang, F., Sun, S., Liu, C., & Chang, V. (2020). Consumer innovativeness, product innovation and smart toys. *Electronic Commerce Research and Applications*, *41*(1), 100974. https://doi.org/10.1016/j.elerap.2020.100974

7. Appendices

7.1. Product Innovation Sample

Bolas energéticas
Continente
Equilíbrio

Wunda
bebida vegetal

Pure Piraña
Água gaseificada
com álcool

Almôndegas
Vegan
Continente
Fácil&Bom

Picada Vegan
Continente
Fácil&Bom

Hambúrguer
Vegan
Continente
Fácil&Bom

Freeness
Bites 100% naturais
sem 14 alergénios

Seven Seas
Snack crocante de
algas marinhas

KitKat Vegan

True Gum
Pastilhas elásticas
sem plástico

Barras de tenebrio
Barras proteicas
com
farinha de inseto

***Snacks* de tenebrio**
Snacks de inseto
temperado

Figure 6: Product Innovations listed in the survey

7.2. Descriptive analysis of extra data

The first images displayed correspond to the graphs done to evaluate outliers' presence on the data frame.

Product innovativeness indicator

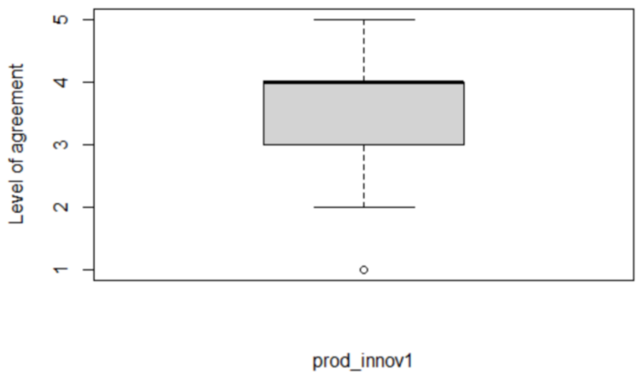


Figure 7: Boxplot of prod_innov1

Consumer innovativeness indicators

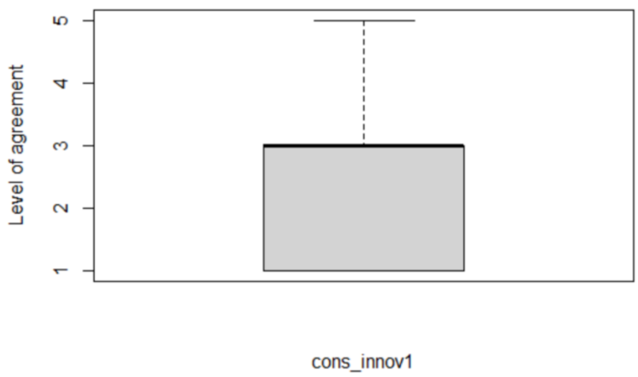


Figure 8: Boxplot of cons_innov1

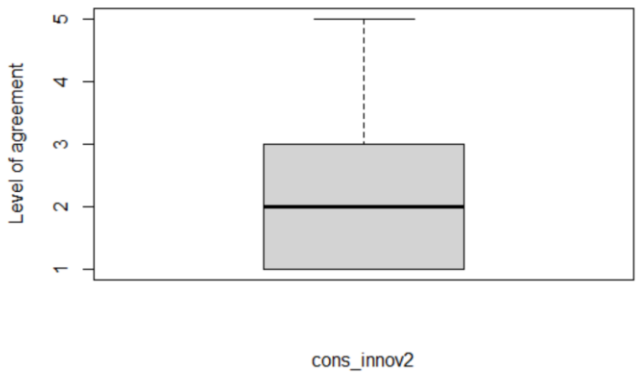


Figure 9: Boxplot of cons_innov2

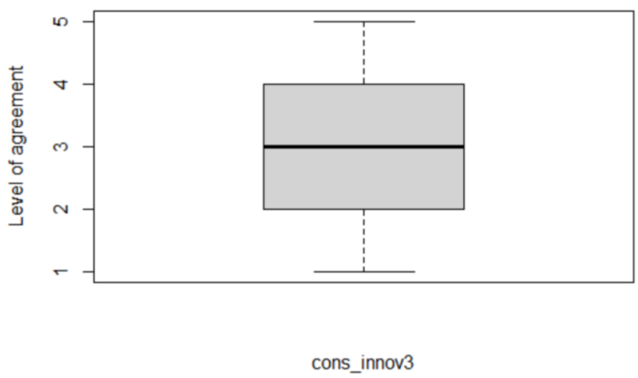


Figure 10: Boxplot of cons_innov3

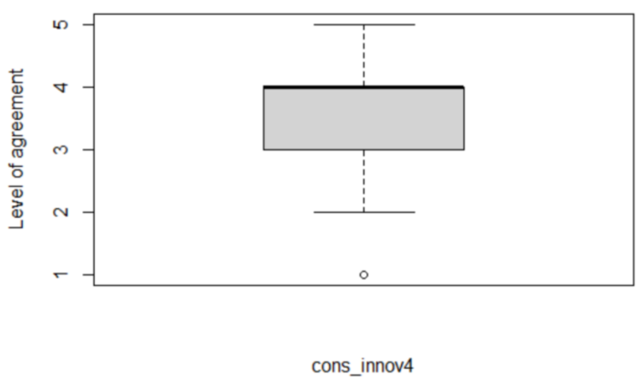


Figure 11: Boxplot of cons_innov4

Perceived value indicators

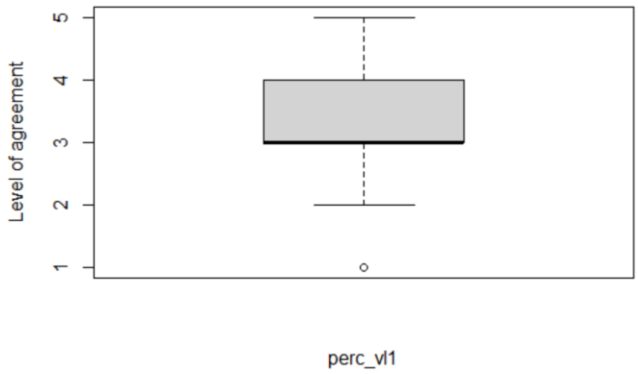


Figure 12: Boxplot perc_vl1

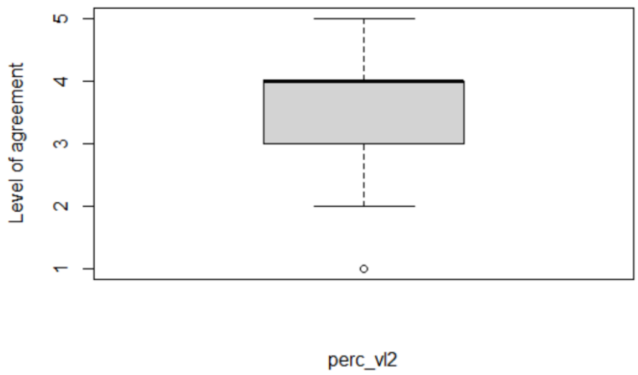
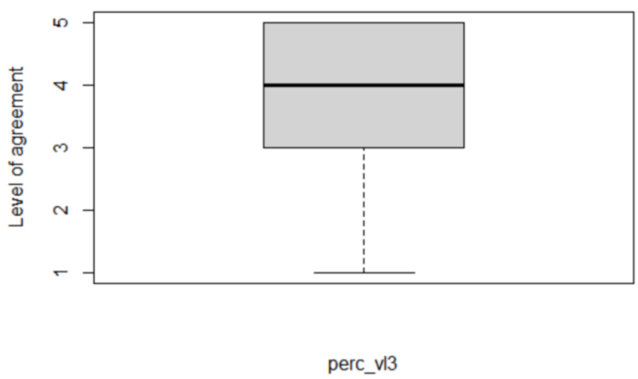


Figure 13: Boxplot perc_vl2



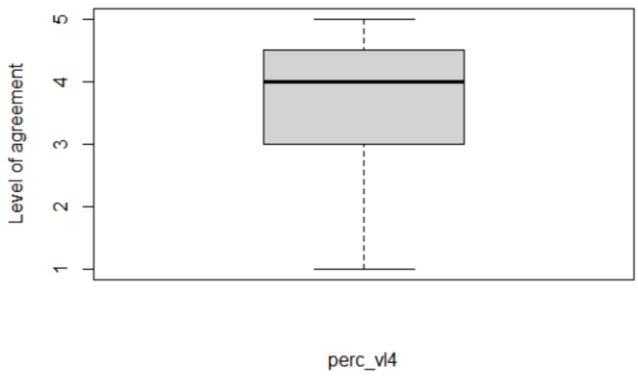


Figure 14: Boxplot of perc_vl4

Consumer Satisfaction indicators

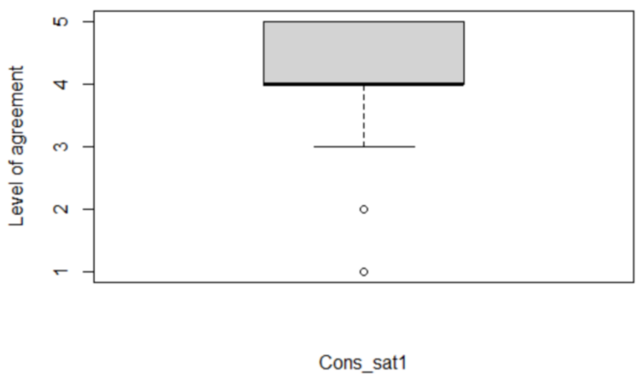


Figure 15: Boxplot of cons_sat1

:

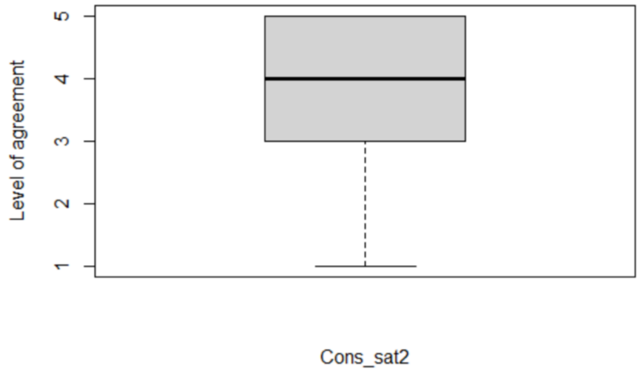


Figure 16: Boxplot of cons_sat2

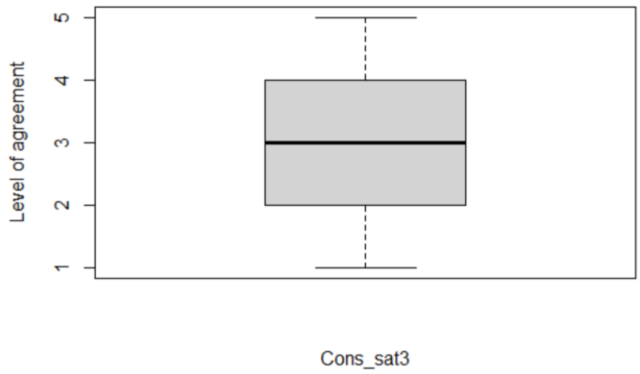


Figure 17: Boxplot of cons_sat3

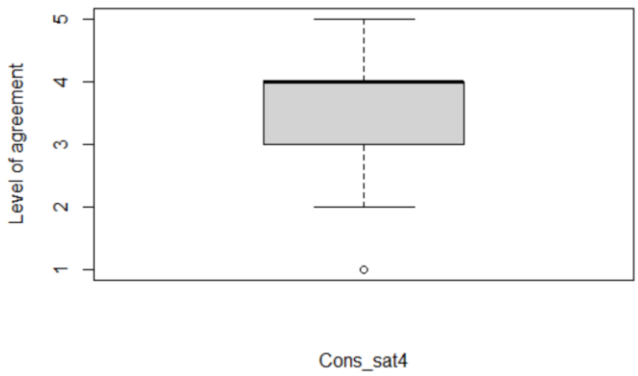


Figure 18: Boxplot of cons_sat4

New Product Repurchase Intentions

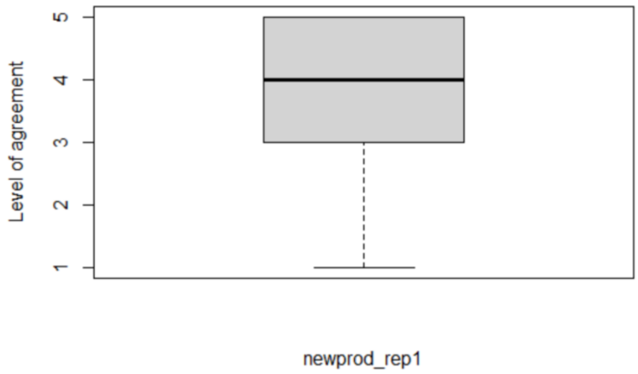


Figure 19: Boxplot of newprod_rep1

The following histograms display the frequency of answers regarding indicators variables.

Product Perceived innovativeness

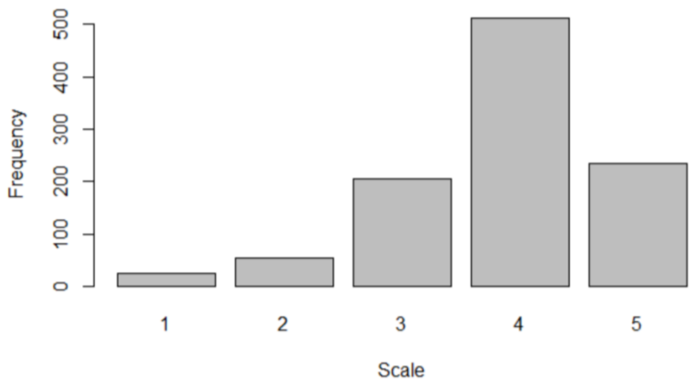


Figure 20: Level of consumers´ agreement regarding product perceived Innovativeness

Consumer Innovativeness

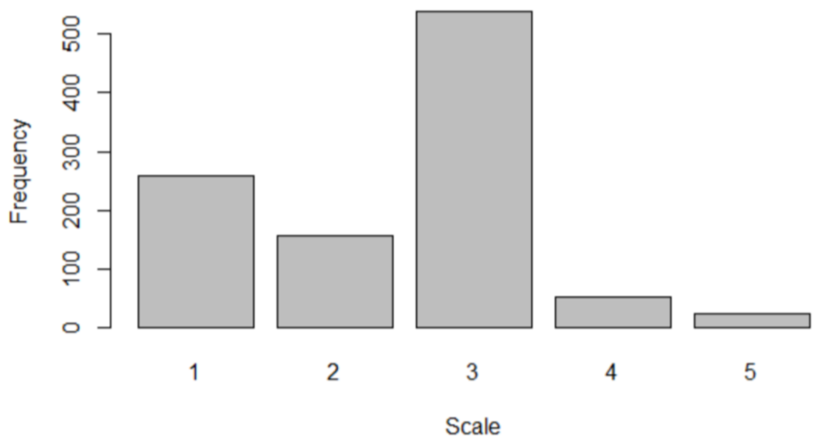


Figure 21: Level of consumers´ agreement regarding product ability to improve social image

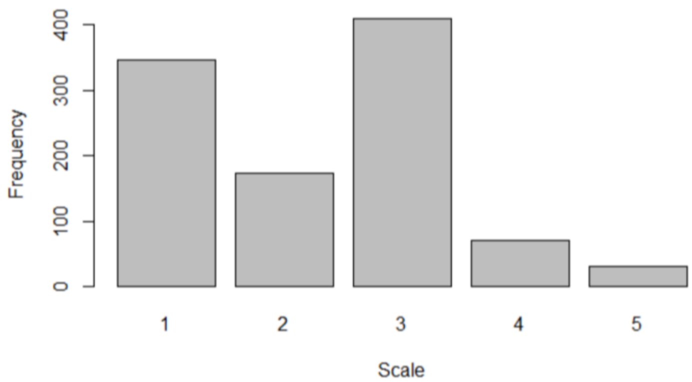


Figure 22: Level of consumers´ agreement regarding product innovation impact on their importance

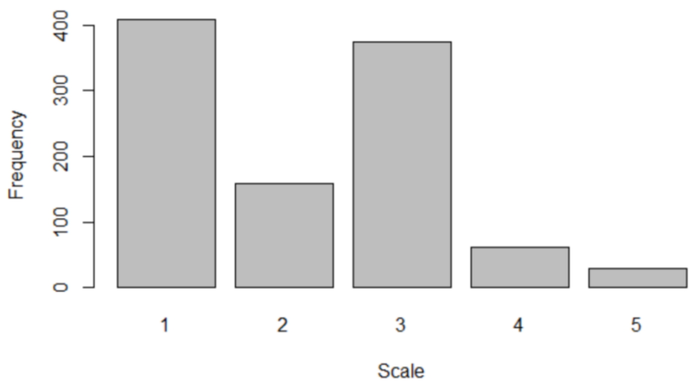


Figure 23: Level of consumers´ agreement regarding cons_innov3

Perceived Value

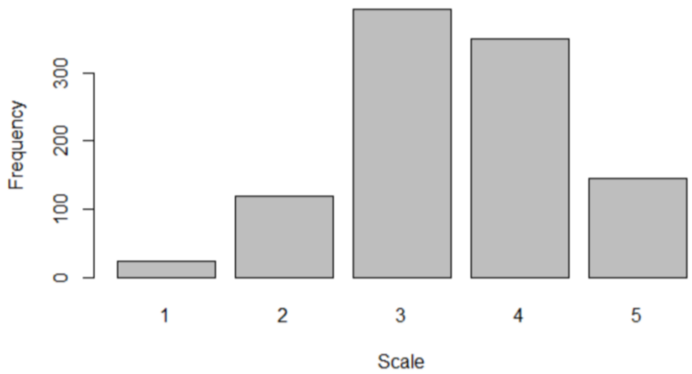


Figure 24: Level of consumers´ agreement regarding perc_vl1

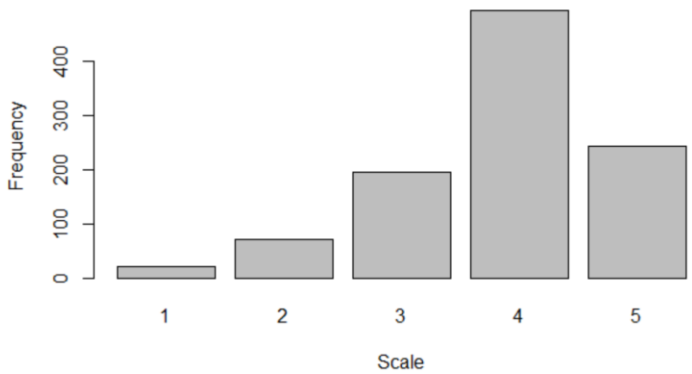


Figure 25: Level of consumers´ agreement regarding perc_vl2

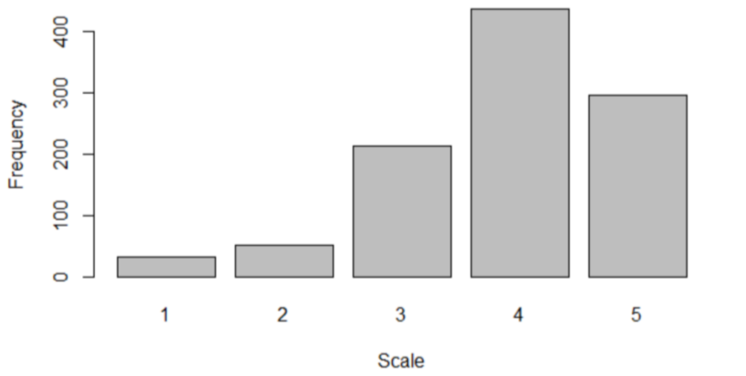


Figure 26: Level of consumers´ agreement regarding perc_vl3

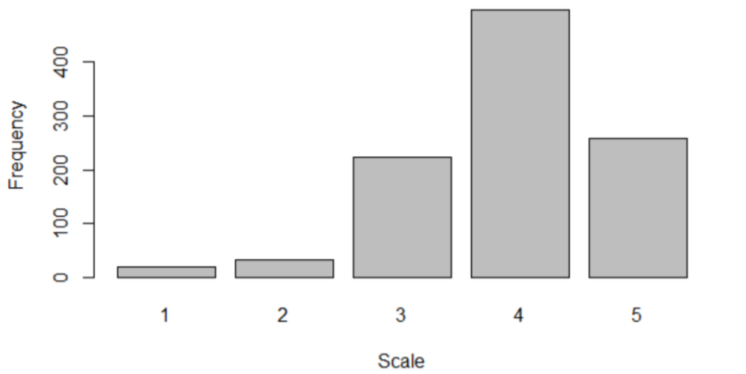


Figure 27: Level of consumers´ agreement regarding perc_vl4

Consumer Satisfaction

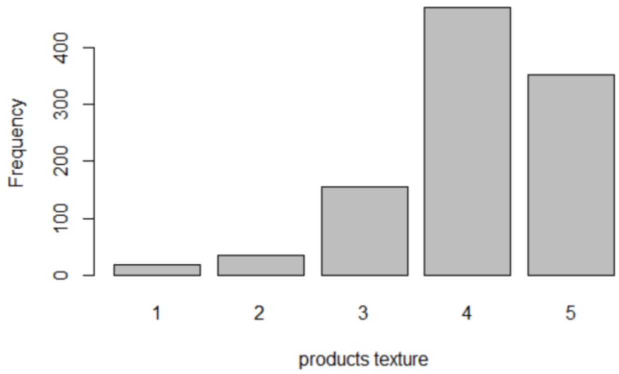


Figure 28: Level of consumers´ agreement regarding cons_sat1

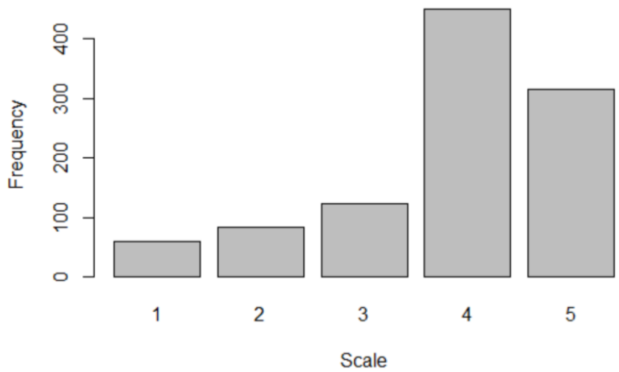


Figure 29: Level of consumers´ agreement regarding cons_sat2

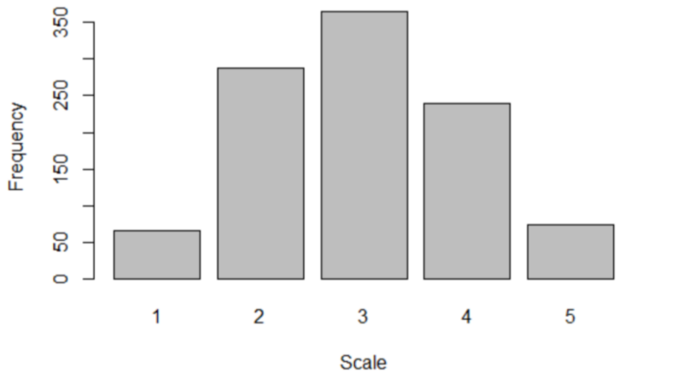


Figure 30: Level of consumers´ agreement regarding cons_sat3

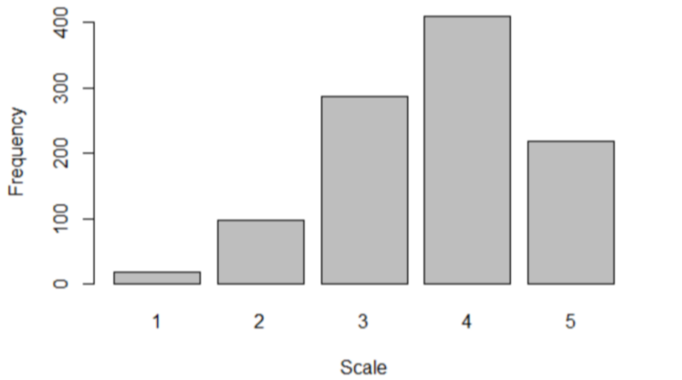


Figure 31: Level of consumers´ agreement regarding cons_sat4

New Product Repurchase Intentions

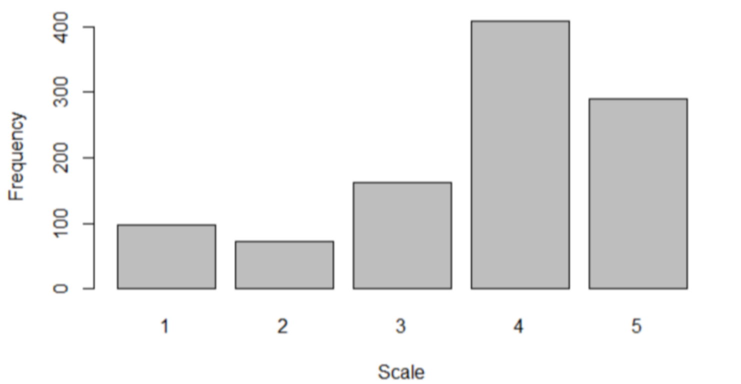


Figure 32: Level of consumers´ agreement regarding new product repurchase intention

7.3. Results

Constructs	alpha	rhoC	AVE	rhoaA
Cons_Innov	**0.905**	**0.940**	0.840	**0.918**
Prod_Innov	1.000	1.000	1.000	1.00
Perc_Vl	**0.760**	**0.848**	**0.587**	**0.787**
Cons_Sat	0.835	0.923	**0.858**	0.842
NewProd_Rep	1.000	1.000	1.00	1.00

Table 18: Internal consistency reliability after deleting *cons_sat3 and cons_sat4*