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Smart technologies in supermarket retail and their influence on citizens' quality of life during the COVID-19 pandemic

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Abstract

Purpose – This research aims to propose the development of a model that identifies, in essential services, the determining factors affecting the technological advances offered by different smart technologies in supermarket retail channels that influence citizens' quality of life, amidst the coronavirus disease 2019 (COVID-19) pandemic.

Design/methodology/approach – The data were collected using a cross-sectional questionnaire survey ($n = 469$). The authors applied the structural equation modeling (SEM) technique to test the hypotheses, along with the partial least squares (PLS) method for estimating latent variables and combining with the necessary condition analysis (NCA) method.

Findings – According to the results of the NCA method, the results were adequate, and more attention should be paid to the quality of life construct after finding the bottleneck point of 50%. In this sense, adaptive resilience was characterized as the main necessary predictor construct for quality of life. In addition, Generation Z and Millennials have the highest frequency of use in all smart technologies, with "assisted purchase" being the most widely used.

Social implications – Finally, the effect of the pandemic changed the consumption routine with supermarkets, not being a mere option but a necessity in the context of a smart city.

Originality/value – As a result, the proposed model was consistent, showing that all direct and indirect SEM paths were validated, highlighting data security and privacy and resilience issues. In addition, the NCA method complemented the procedures performed in the SEM phase.

Keywords Smart technologies, Smart cities, Supermarket retail, Quality of life

Paper type Research paper

1. Introduction

Smart technologies are disruptive innovations that give the industry the impetus to digital transformation, and have been presenting rapid advances in recent decades. Many of these

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technologies allow an entity to function appropriately in the process of automation, customer engagement, personalization and optimization (Duan, Edwards, & Dwivedi, 2019).

Similarly, smart technologies can provide opportunities to facilitate entrepreneurship, creativity and innovation, to drive economic growth (Kraus, Richter, Papagiannidis, & Durst, 2015). This type of initiation can also be observed from a strategic perspective, triggering the emergence of new value chains in companies and stakeholders involved in the design and execution of smart city projects (Paroutis, Bennett, & Heracleous, 2014).

In addition, smart technologies incorporated into an object allow it to communicate autonomously and render it part of that network to make life easier for those using it. This is not restricted to physical locations but also pertains to virtual channels (e-commerce, marketplace and delivery applications). These technologies, provided in the form of services, become more efficient for citizens, monitoring and optimizing the existing infrastructure, increasing collaboration between different economic actors, and encouraging innovative business models in the public and private sectors (Marsal-Llacuna, Colomer-Llinàs, & Meléndez-Frigola, 2015). Therefore, increased competitiveness occurs through innovation (Appio, Lima, & Paroutis, 2018).

The concept of a smart city is based on the use of information and communication technologies (ICTs), together with human capital, to solve urban problems and improve processes within the city, seeking to achieve an improvement in citizens' quality of life, as well as in economic development and resource management. The exponential growth of urban populations increases the importance of smart cities, as it seeks to expand the city's capacity, better manage its resources, increase the quality of life of citizens, and improve the efficiency and quality of services provided (Habib, Alsmadi, & Prybutok, 2019), mainly by government entities and companies. It is currently possible to go to a supermarket and complete a transaction without the presence of an attendant, thanks to smart technologies.

Society has been tested by the coronavirus disease 2019 (COVID-19) pandemic, needing an immediate solution with a transversal impact on its various domains that must remain active (Sheth, 2020). The city must be flexible and continue to be responsive, by allocating resources to keep the ecosystem functioning to avoid chaos. Given this, by the guidance of the World Health Organization (WHO), cities worldwide determined they needed to implement strategies to avoid the disease transmission. Among the main strategies, we noted the observance of social distance, new learning forms, the redefinition of work activities and a change in logistics, among others.

Retail e-commerce sales amounted to approximately US$4.9tn worldwide, growing by 50% over the following years, reaching about US$7.4tn by 2025. According to STATISTA (2022), the pandemic's impact on retail e-commerce sites global traffic grew by 6% between January and March in 2020 (the initial phase of the pandemic) and the same period in 2021. Therefore, this moment of growth should be used to develop business strategies for e-commerce.

Selecting services offered by the retail sector as a research object is justified since they belong to the group of services called "essential" and are controlled by laws or decrees. Essential services are activities that need to be maintained in the face of the pandemic circumstances which are considered essential to guarantee services to the population. Among the main ones are healthcare and production, distribution, and marketing of health, hygiene, food and beverage products throughout the country (BRAZIL, 2020).

In São Paulo, retail e-commerce sector's turnover reached approximately R$108bn in 2020, which represented a real growth of 2.32% over 2019, in addition to an increase of 10% to 15% in sales (APAS, 2021). In addition, there was a marked growth in purchasing products in supermarkets, mainly in online services through e-commerce, marketplace or applications resulting in many companies improving their sales services.

Some research has investigated how smart technologies promote consumer behavior by adopting different interfaces and functionalities (Chang & Chen, 2021; Dacko, 2017; Pillai, Sivathanu, & Dwivedi, 2020). Faced with this, many people need to adapt by trying new technologies to satisfy their curiosity in the search for a more pleasant and satisfying shopping experience, even in the COVID-19 pandemic. In this sense, the literature leads us to a process of reflection on purchasing behavior from customers' points of view (Khan *et al.*, 2021).

Therefore, this research aims to propose the development of a model that identifies, in essential services, the determining factors affecting the technological advances offered by different smart technologies in supermarket retail channels that influence citizens' quality of life, within the context of the COVID-19 pandemic.

2. Literature review

2.1 The dynamics of the Brazilian supermarket retail sector vis-à-vis COVID-19

Competitive, innovation-driven retail comprises a growing variety of institutions that are constantly affected by a highly diverse and dynamic environment. The supermarket retailer considers keeping products it sells stocked, offering variety to consumers and providing distribution services to manufacturers. In addition to selling small quantities of products or services to the final consumer, the retailer adds value to what is being sold.

The retail sector is one of the most important in the Brazilian economy, representing around 20% of the gross domestic product (GDP) and generating approximately 7.6 m direct jobs. Brazilian supermarkets sell 87.3% of all food, cleaning and personal care products in the country, totaling 89 thousand stores. In 2019, this sector generated 1,881 m direct jobs, 28,700 more jobs than in 2018 (SBVC, 2018; ABRAS, 2020). The sector's profits reached BRL 378.3 bn in 2019, with nominal growth of 6.4%, when compared to 2018 (ABRAS, 2020), which represents around 5.2% of GDP, generating 1.8 m direct jobs and another 5 m indirect jobs. Federal decree no. 10,282, of March 20, 2020, which establishes the rule that an essential service is characterized by urgent care to the community, which, when not performed, endangers survival and/or the health or safety of the population, officially declared supermarket services as essential, (BRASIL, 2020). In the socioeconomic aspect, activities performed by the supermarket sector are highly relevant, given their contribution to meeting the population's basic consumption needs, so that an eventual supply disruption has significant impacts on the economy and society, changing their demands.

The "Me, My Life, My Wallet" report carried out by KPMG (2021) during the COVID-19 pandemic observed some characteristics commonly attributed to Generations Baby Boomers (ages 55–73), X (ages 39–54), Millennials (ages 23–38) and Z (ages 7–22) that accelerated digital proficiency throughout generations, yet anticipating the concern with economy, financial stability and future for the younger ones (Dimock, 2019). The study also indicates that the experience of social isolation shared by people of all age groups – and especially the relationship with digital – is bringing different generations together and making them gain more common characteristics than ever, including the purchase of products (e.g. supermarket retail sector).

Indeed, digital transformation is perceived as a fundamental transition of society, driven by generations called "digital" (including Generation Y and Z), for which digital technologies are deeply rooted in their culture and daily practices. In this context, companies must be able to adapt themselves by changing their business model or developing a new one. However, the process leads to highly corrosive consequences for the urban digital society. This gives rise to a socially divided and highly conflicted ecosystem. While some celebrate the new world of digital technologies, others think this world is driving cities towards greater dehumanization because, unlike human qualities, they bring concerns that affect the quality of life (García-Fernández, Gálvez-Ruíz, Fernández-Gavira, Vélez-Colón, Pitts, & Bernal-García, 2018).

2.2 Smart technologies in retail

Innovative technological trends in smart retailing seek to meet the desire to streamline consumer purchase transactions by providing minimal barriers, such as time and location (Vrontis, Thrassou, & Amirkhanpour, 2017). This smart retail proposal learns to collect data about its consumers, and thus promotes personalized services and offers products and services that meet their expectations, improving the quality of life, and offering the ease demanded by consumers through convenience and simplification of the purchase process without queues and checkouts.

Smart retail emerges as part of an expanded concept of smart cities, exploring the city as a laboratory of innovation, focusing on a new perspective for retail management, by bringing integrating innovative technological trends as promoters of innovation and quality of life for consumers. According to Pantano and Timmermans (2014), the concept of smart retail goes beyond the application of modern and innovative technology to retail processes, as it includes an additional level of intelligence correlated to the use of technology. Thus, according to the authors, smart technology for retail generates the new concept of smart retail, which can be evaluated according to organizational and practical dimensions, encompassing sales activities.

The consumer's purchasing behavior, habits, needs and expectations have changed. The consumer journey is no longer predictable, and the retailer needs to respond to this reality (KPMG, 2020). The exponential growth of e-commerce naturally occurred not only in Brazil but all over the world. Thus, it is essential to understand the customer experience given that customers interact with numerous touchpoints in various channels and media, and this is becoming an increasingly complex process. These changes require companies to integrate multiple business functions and even external partners (Lemon & Verhoef, 2016).

Supermarket consumers are changing their habits in response to the pandemic. They want more information about the product, availability of touchless purchases, flexibility in the means of payment, delivery, etc. One of the biggest challenges in this sector is to find patterns and similarities between different classes of information to increase the efficiency of activities, through artificial intelligence, big data, machine learning and business analytics. In this direction, smart technologies have been investigated to understand their impacts and benefits in smart retail (Dacko, 2017; Chang & Chen, 2021).

Some of the leading smart technologies for online shopping in supermarket retail can be observed in the literature (Capgemini, 2020), such as the supermarket's application (offer discounts, promote products, etc.); assisted purchase (an application that connects supermarket and customer, acting as a purchasing intermediary, e.g. iFood, Rappi, Cornershop, UberEats, etc.); quick response (QR) code (provide additional information about products, promotional coupons, among others, by scanning an image with your smartphone); chatbots (virtual agents) and self-checkout (allows the customer to complete their purchases alone at ATMs).

Within the same context, we identified conveniences observed in the literature review that favor smart technologies for supermarkets (Capgemini, 2020). Following are the main ones identified in the literature: shorter purchase time; greater power to compare prices; exclusive offers for anyone using the website, or app, or in a standalone marketplace; being able to consult the technical datasheets of the products; possibility to make purchases out of business hours; perception of ease when receiving products at home; receive communication with the latest releases (e.g. notification in-app or browser); science of evaluating the quality of the product that is purchased; real-time order tracking during the delivery process; and real-time communication channel to answer questions and solve problems.

2.3 Construction of the model and research hypotheses

This section presents the theoretical research model of smart technologies derived from the literature and developed from the formulation of the respective research hypotheses listed within each of their respective constructs (see Figure 1). The seminal references followed the

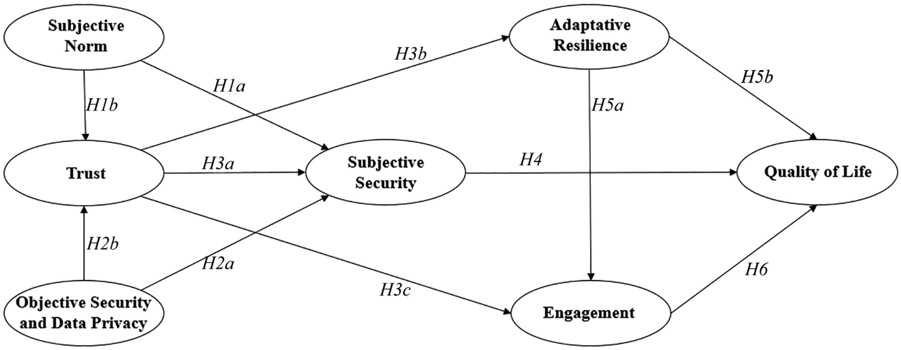

Figure 1.
Research model

corresponding scales: Subjective Norm (Urmetzer & Walinski, 2014), Objective Security and Data Privacy (Cimperman, Brenčič, & Trkman, 2016; Abu-Shanab, 2017; Sepasgozar, Hawken, Sargolzaei, & Foroozanfa, 2019), Trust (Mittendorf, 2016; Chang, Liu, & Shen, 2017), Subjective Security (Cui, Lin, & Qu, 2018; Urmetzer & Walinski, 2014), Adaptive Resilience (Nilakant, Walker, Van Heugten, Baird, & De Vries, 2014), Engagement (Vivek, Beatty, Dalela, & Morgan, 2014) and Quality of Life (Ejdys & Halicka, 2018; De Guimarães, Severo, Felix Júnior, Da Costa, & Salmoria, 2020).

2.3.1 Subjective norm (SN). The subjective norm influences the individual's perception of normative pressures, beliefs and opinions of society, which include the views and expectations of other people and the degree to which the individual is inclined to agree and consider these aspects in their judgment and thought formation. It consists of the individual's concern about the probability of people or groups important to him approving or disapproving a particular action (Meskaran, Ismail, & Shanmugam, 2013). In the context of this research, the subjective norm is the influence of what the social environment thinks about smart technologies and their use. If this opinion is favorable, the adherence rate will not only increase, but it can turn into a viral acceptance process (Urmetzer & Walinski, 2014), and thus, likewise exert a positive influence on subjective security and trust. Therefore, the following hypotheses are formulated:

H1a. Subjective norm has a positive influence on subjective security.

H1b. Subjective norm has a positive influence on trust.

2.3.2 Objective security and data privacy (OSDP). Objective security is a tangible technical characteristic; in the context of the smart city, it is the actual technological solution, such as antivirus, encryption, among other systems or devices (Urmetzer & Walinski, 2014). As for data privacy, structural guarantees are the main factors influencing trust. Thus, as it is strongly related to technical issues, it is inconvenient to separate this from the concept of objective security: they have then been coupled into a variable for this study. In the context of the smart city, the existence of objective security and data privacy is a critical factor for the development of citizens' trust, as it is a guarantee that they have safeguards, both in relation to receiving purchased service or product as regarding leakage or inappropriate use of personal information (Chang *et al.*, 2017; Abu-Shanab, 2017; Cimperman *et al.*, 2016; Sepasgozar *et al.*, 2019). Furthermore, although subjective security does not affect objective security, the opposite happens. The level of technical protection influences the individual's perception of security. Given this context, a considerable objective security level is necessary, capable of influencing the individual in his/her perception of subjective security and trust in smart technology to adopt it as a result. Therefore, we established the following hypotheses:

H2a. Objective security and data privacy have a positive influence on subjective security.

H2b. Objective security and data privacy have a positive influence on trust.

2.3.3 Trust (TR). It is valuable to draw on the extensive information systems literature on the role of trust in technology adoption (e.g. MISQ's trusteeship on trust – Söllner, Benbasat, Gefen, Leimeister, & Pavlou, 2016) and examine whether the COVID-19 pandemic has instigated a shift in people's attitudes towards mobile contact rather than human contact. People may be more inclined to consider investing in new applications that combine technologies they became familiar with during social distancing (Coombs, 2020). According to AlHogail (2018), trust is considered an influential variable to minimize uncertainty and create a sense of security, influenced by perceived risk and previous experiences (familiarity). In the context of technology, it is the belief that expectations are met and that what is expected will be delivered (Chang *et al.*, 2017). It is pertinent to note that new technologies are emerging to face the growing challenges of urban cities with many inhabitants which often occur in large metropoles. Trust is the currency for people to have faith in a system, in devices that work with each other, and in a city that is transparently governed by consensus among its inhabitants and organizations (Mittendorf, 2016). Thus, it is considered that trust plays an important role in the acceptance of smart technologies concerning subjective security, adaptive resilience and engagement. Thus, the following hypotheses were formulated:

H3a. Trust in technology positively affects subjective security.

H3b. Trust in technology positively affects adaptive resilience.

H3c. Trust in technology positively affects engagement.

2.3.4 Subjective security (SS). Subjective security is the intangible aspect of security, which is the user's perceived sense of general security, which is influenced by social opinions (subjective norms), in addition to the objective security factor and data privacy (Urmetzer & Walinski, 2014). Research indicates that safety is not just a technical issue but a human and organizational one (Meskaran *et al.*, 2013) and by recognizing the impact of subjective safety on the individual's propensity, many studies have started to investigate the influence of perceived safety (subjective) rather than objective security (Cui *et al.*, 2018). In the context of the smart city, this concept is the perceived feeling the potential user has about the security of the technology, regardless of the technical safeguards. Thus, if he has the perception that there may be security problems, this potential user will not become a real user, even though it is guaranteed from a technological point of view (Urmetzer & Walinski, 2014; Sepasgozar *et al.*, 2019). The perception of security is considered an essential factor in adopting new products or services, directly impacting the user's quality of life factor, and consequently the adoption of smart technologies (AlHogail, 2018).

H4. Subjective security in technology positively affects quality of life.

2.3.5 Adaptive resilience (AR). When a city is planned to be smart, it must also be prepared to always be resilient. Resilience is the ability to quickly adapt or recover in unexpected situations (Fiksel, Polyviou, Croxton, & Pettit, 2015). An organization that seeks to have a resilient culture achieves performance and can grow during a crisis. For companies to thrive in the face of turbulent change, organizations need to improve the way they address their customers and their internal processes (e.g. the supply chain to cater their customers). Companies must be able to quickly and effectively recover from operational disruptions (Nilakant *et al.*, 2014). Adaptive resilience plays an important role in accepting smart technologies when addressing issues such as citizen engagement and quality of life. Thus, the following hypotheses were formulated:

H5a. Adaptive resilience positively affects engagement.

H5b. Adaptive resilience positively affects quality of life.

2.3.6 Engagement (EN). Smart city planning begins with creating digital urban space: an agglomeration of digital hardware and software, public administration datasets, smart sensors and meters, social media and new electronic services across all domains of the city. This new layer of digital space and technologies can change and optimize all aspects of cities: economy, life, utilities and governance (Komninos, Kakderi, Panori, & Tsarchopoulos, 2019). Current smart city strategies outsource environmental and social resilience activities to different sectors using new technologies to pursue democratic engagement and alternative strategies for environmental and social progress (Viitanen & Kingston, 2014). Furthermore, engagement is associated with the behavior change process, making the individual an active agent in the communication process (Vivek *et al.*, 2014). Thus, it is considered that engagement plays an essential role in the acceptance of smart technologies and directly affects citizens' quality of life. Accordingly, the following hypothesis was formulated:

H6. Engagement positively affects quality of life.

2.3.7 Quality of life (QL). Quality of life is a human perception that seeks to reflect a degree of satisfaction found in personal, family, love, social and environmental life, assuming the ability to attain a cultural synthesis of all the elements that a given society considers its standard of comfort and well-being. However, historical, cultural and social aspects are factors that can interfere in the concept of quality of life, as these are linked to the expectations of individuals over time, to what is right or wrong in their culture and their social stratification or social class. Quality of life is present in everyday actions and is reflected in people's attitudes and values. These actions are then inserted in the formation of human behavior (including purchasing behavior) and are the product of experiences previously lived by the individual (Ejdys & Halicka, 2018; De Guimarães *et al.*, 2020).

3. Method

3.1 Data collection and sample

We based this article on a cross-selection analysis of participants obtained through a collection with individuals in the city of São Paulo, who had made purchases in virtual channels (e-commerce, marketplace or applications) (e.g. Rappi, iFood, Uber Eats etc.) or a face-to-face environment using technologies for some promotions (e.g. Pão de Açúcar, Extra Supermercado, Carrefour, Mambo, Sonda, etc.) or in autonomous markets (e.g. Zaitt) during the period of the pandemic. Participation was voluntary, and the respondents remained anonymous. We chose São Paulo since it is considered the smartest city in Brazil by Urban Systems' Connected Smart Cities ranking (Urban Systems, 2021), and it occupies the 42nd position in the world by the Global Power City Index (GPCI Index, 2020). We collected data for convenience, and we conducted the collection process through a survey, which was made available on the online research platform QuestionPro on social networks (LinkedIn and WhatsApp) in February 2021. A pre-test was conducted with 20 respondents. Out of the participants, 526 completed the survey and, after data purification using the Mahalanobis distance criterion (D^2) to identify outliers ($n = 57$), 469 respondents remained. No data were missing, so we did not need to use an imputation method. In the data analysis, we utilized IBM SPSS, Smart partial least squares (PLS) Professional and RStudio (package NCA).

3.2 Instrument development

The research includes a sociodemographic portion of the respondent's profile and psychometric scales of the proposed model. In the analysis phase of sociodemographic data, we sought to incorporate questions to cover aspects of consumption in supermarket retail based on technologies for these analyses. We built the model with 40 questions anchored on a seven-point Likert-type scale, 1 – totally disagree to 7 – strongly agree (see Table A1 in Supplementary file). The instrument used reverse translation and was validated by four experts in the field. Using structural equation modeling (SEM) with PLS, we performed multivariate analysis for estimating latent variables and combining with the necessary condition analysis (NCA) method.

3.3 Common method bias, non-responder bias and collinearity

We verified the variance of the common method by applying the Harman's single factor test (Podsakoff & Organ, 1986) on the 40 items and extracted five components with an eigenvalue greater than 1.0. The variance extracted from the first component was 40.32%, lower than the minimum of 50%. In addition, the authors conducted a non-respondent bias analysis. When performing these tests, we found that both the common method bias and the non-respondent bias do not represent a problem for the continuity of the study. By analyzing the collinearity, we have identified that all the variance inflation factors (VIFs) of the constructs were below 3.3 based on Kock (2015). The values obtained were SN = 2.941, SS = 2.450, OSDP = 2.657, TR = 2.554, AR = 2.152; EN = 3.087 and QL = 2.577. This indicates that there is no multicollinearity between the constructs. Therefore, we can assume that the regression coefficients are well-estimated and adequate for the model. Skewness ($\beta = 6.161$; $z = 481.628$; $p < 0.001$) and kurtosis ($\beta = 76.217$; $z = 12.750$; $p < 0.001$) verified data normality through Mardia's multivariate test. These tests for the indicators were "highly significant" with $p < 0.001$, indicating non-normality, which we expected. This procedure was necessary to limit the possibility of using some statistical analysis techniques with the normal distribution of data as a characteristic.

4. Results

4.1 Demographic information

The sample has an audience of 44.6% ($n = 209$) male and 55.4% ($n = 260$) female. Out of the respondents, 42.9% have an undergraduate degree and 57.1% are undergraduate students; 75.9% of respondents are employed and 24.1% participate in non-paid activities. The average income is concentrated in the "up to 6 minimum wages" bracket (65.9%) – the minimum wage used was 1,100 BRL (214.22 USD) – January 2021 data. Smartphone is the most used device (66.3%) followed by notebook (24.5%). In this study, we analyzed the generations defined by the Pew Research Center to understand the use of smart technologies (Dimock, 2019). The results presented in Table A2 (see in Supplementary file) indicated that Generation Z and Millennials are the ones that more often use smart technologies, highlighting "assisted purchase".

4.2 Evaluation of the measurement model

After the first interaction, the results of the factor loadings obtained by the variables were presented: the authors found that it was not necessary to exclude variables (all factors were above 0.5) to adjust the model. Next, we verified the convergent validity, and the discriminant validity involved the correlation between the constructs of the theoretical model. The analysis of the measurement model must precede the analysis of the relationships between the latent constructs or variables. The next step was to examine the measurement model, which involved: Cronbach's alpha (CA), Dillon Goldestein's p-rho, composite reliability (CR), average variance extracted (AVE), coefficients of determination (R^2) and the GoF (goodness-of-fit) (Hair, Hult, & Ringle, 2016) exhibited in Table A3 (see in Supplementary file).

CA coefficients range between 0.858 and 0.932. These results indicate high internal consistency of the scales used. Dillon Goldestein's p-rho ranged between 0.862 and 0.934. Likewise, the CRs ranged between 0.901 and 0.944, indicating satisfactory results (Hair, Anderson, & Babin, 2009). For this model, AVEs range between 0.616 and 0.716. All latent variables dissipated AVE greater than 50%, indicating the existence of convergent validity.

The discriminant validity of items reflects the correlation between factors. In this research, the AVEs were greater than or equal to the square of the correlation between the factors, as shown in Table A4 (see in Supplementary file), meeting the definitive criterion of Fornell and Larcker (1981) with all factor loadings of each indicator with values above 0.5. Therefore, it was not necessary to exclude variables to fit the model. In addition, the Heterotrait-Monotrait ratio (HTMT) criterion is added, which indicates that the values obtained must be less than 0.85 for conceptually different constructs (Franke & Sarstedt, 2019).

4.3 Evaluation of the structural model

The R^2 values demonstrate that the model has accuracy and predictive relevance in all constructs (see Table A3). The value found for the GoF is 0.582 (58.2%) and was considered large enough for the validity of the model in PLS. To test the significance of the indicated relationships, the resampling or bootstrapping technique was used (see Table A5 in Supplementary file).

As shown in Table A5 (see in Supplementary file), all direct and indirect paths in the research model were positive and statistically significant. Therefore, the proposed model supported all hypotheses as shown in Figure A1 (see in Supplementary file). The mediations observed in the model indicated partial results.

4.4 Necessary condition analysis (NCA)

Dul (2016) developed the NCA method that paves the way for classifying necessary conditions into data sets. Unlike the analysis of relationships between independent and dependent variables, the NCA method shows areas in variable scatter plots that can specify a necessary condition (Richter, Schubring, Hauff, Ringle, & Sarstedt, 2020). This study applied the NCA in the theoretical model of smart technologies as a function of the dependent variable Quality of Life. Figure A2 (in Supplementary file) displays the scatter plots for all proposed relationships. Table A6 (see in Supplementary file) shows the size of the effects. As the accuracy of the ceiling envelopment-free disposal hull (CE-FDH) ceiling line is by definition 100%, a separate column was not added for the ceiling line accuracy. The NCA results (see Table A6 in Supplementary file) specify whether or not the independent variables are necessary conditions when analyzing the effect size ($d \geq 0.1$) and significance ($p < 0.05$) for the Quality of Life variable. Therefore, it was possible to evaluate each necessary condition in detail with the bottleneck tables.

From the results presented, all constructs were of practical importance (effect size) with a medium effect, which for Dul (2016) occurs in 40% of Research in Business Administration, so it is possible to observe the need for these constructs to be present in the model. For example, Table A5 shows that three necessary conditions are required to reach a 50% level in quality of life: AR not less than 16.7%, EN not less than 3.3% and SS not less than 8.3%. Therefore, this condition could only be identified with the NCA method.

5. Discussion

H2b (OSDP → TR; $\beta = 0.711$) had the greatest relationship between the direct paths. For respondents, this relationship was perceived as the main one, due to the association made with the technological systems or devices, according to Urmetzer and Walinski (2014). When analyzing the age of the respondents, we discovered that Generation Z and Millennials presented, in all smart technologies, the highest frequency of use – frequent (39.4%) or occasionally (32.2%). When we analyzed which technology was most used, "assisted purchase" stood out, with Generation Z at 43.4% and Millennials at 33.5%. This technology gained strength during the pandemic period due to applications that mediate interactions between supermarkets and customers, who choose the products and inform the company that provides this intermediation service. If there is stock, the purchase is made and shipped directly to the address. For consumers to trust these digital platforms, they must convey credibility to citizens, especially when the concern lies in the information that is sent (for example personal data, credit cards, access codes, etc.). Objective security and data privacy are critical factors for trust, mainly due to the associated risks behind delivery applications, including the exposure of user data to third parties; unauthorized charges; or access to credit cards registered in the applications. Unfortunately, several scams are reported on social networks or complaint sites (for example, Reclame AQUI website or through videos available on YouTube). Even so, the main platforms that provide these services in the city of São Paulo alert consumers about the existence of these accounts and how their service processes work. If this guarantee is not met by companies providing "assisted purchase" services, users will perceive greater risk in adopting this technology (Abu-Shanab, 2017).

The second-largest list of paths involved three hypotheses having in common the variable "adaptive resilience". First, H5a (AR → EN; β = 0.577) is where companies seek to create online experiences putting customers at the center of their strategy, and think of new ways to connect customers with digital support channels that are effective. One way to demonstrate resilience on the part of companies is to learn from their mistakes, thus demonstrating an adaptive capacity (Komninos *et al.*, 2019). Companies that offer smart interaction technologies allow consumers to feel more involved in choosing, for example, how to pay. If flexibility is not possible, some companies seek to offer amenities or discounts on purchases. Therefore, engagement will occur when the individual becomes an active agent in the communication process, based on smart technologies (Vivek *et al.*, 2014).

Second, the H5b (AR → QL; β = 0.502) brings as a priority the quality of life itself in the search for attention and convenience for users of smart technologies. Consumers look to these digital channels for an immediate environment for payment and receipt of goods. As a result, consumers have changed, and individuals are adapting to new ways of buying their daily groceries. New "Generation Z" and "Millennials" consumers value price above recommendations, brand reputation and product quality. These profiles follow merchandise brands for the discount opportunity. This relationship that is created with companies through digital channels favors a satisfaction that is materialized in the quality of life from the adaptive resilience of those involved in everyday attitudinal actions in purchasing behavior (Ejdys & Halicka, 2018; De Guimarães *et al.*, 2020).

Finally, the H3b (TR → AR; β = 0.518) is when we look at the effect of trust on adaptive resilience. We can understand that retailers are creating a sense of community or ecosystem that is an innovative experience with their smart technologies changing the shopping routine. In this sense, supermarket retailers try to differentiate themselves, offering their brands and building stronger relationships with their consumers, producing increased sales and loyalty. Trust in technologies such as "assisted purchase" is expressed by building a robust social presence among target audience. In addition to the adaptive resilience that supermarkets need to have in their technology platforms, there is a tendency to use issues related to the community's resilience, as noted by Viitanen and Kingston (2014). Many retailers have transformed their physical locations to facilitate safe pick-up by their consumers. As the consumer gets used to a pick-up or delivery structure, the purchasing behavior tends to change. This change in mentality represents the new trend within the concept of adaptive resilience. To meet the high demand during the pandemic, many retailers also adapted their operations, directing efforts towards delivery using their workforce and partnering for a complete service. Many companies are struggling to keep up with the demand to the critical challenges of their operations.

Many people who felt well cared for and experienced this type of service may continue to use it after the pandemic. Therefore, an acceleration in the adoption of e-commerce is noticeable. This is likely because the consumer profile after the COVID-19 pandemic will be different: respondents in this study categorized in Generation Z and Millennials demonstrated that they are involved with all the smart technologies proposed in this study. However, the natural evolution for this type of service is expected to be personalization for each consumer. For that, resources as artificial intelligence, dynamism and personalization of content are consistently in the unique customers' vision.

Despite not being born immersed in smart technologies, Generations X and Baby Boomers are being forced to adapt, but to a lesser degree, as the pandemic turned out to be a milestone and the only viable alternative to getting on with life is to adapt with the new technologies. These older generations drive more significant concerns from different sectors and create investment opportunities. This segment of the population could benefit from this type of smart technology, e.g. to avoid risky situations or infections (health). On the other hand, Generations X and Baby Boomers seem to have delegated purchasing activities to younger generations within the context of supermarket retail.

The common element that sustains both new urbanism and smart cities is the need for a social-level response to the accelerated urbanization of the world's population and its implications for people's quality of life. In this sense, the supermarket retailer has been seeking to expand its presence with the support of smart technologies serving the customer experience, personalization, logistics, omnichannel, and shopping with mobility and through devices that bring convenience (smartphones, tablets, virtual assistants, chatbots, voice recognition, among others). Innovation is also present within digital operations, with strategies involving agile processes to better respond to consumer changes.

The NCA method complemented the procedures performed in the SEM phase. According to the results of the NCA method, the results were adequate, and more attention should be paid to the quality of life construct after finding the bottleneck point of 50%. In this sense, adaptive resilience was characterized as the main necessary predictor construct for quality of life.

6. Conclusion

We reached the objective by proposing the development of a model to identify the determining factors affecting the technological advances in essential services offered by different smart technologies in supermarket retail channels that influence citizens' quality of life in the context of the COVID-19 pandemic.

This article contributes to society by discussing how consumers are learning to improvise from new habits due to the social distance caused by the COVID-19 pandemic. Even if consumers return to old habits, new regulations and procedures will likely modify many in the way they buy products and services due to advances in smart technologies (Sheth, 2020). Given this, there are managerial implications where companies also had to learn to improvise and become more resilient during the pandemic crisis. In short, companies can learn how to make their infrastructure, systems and processes more resilient, which was made clear by the customers' demand in this study.

The proposed model showed consistency and can be applied to future research. The literature review presents us with a specific case of a smart city in São Paulo in which ethical principles and values were observed with concern and the optimization of new technologies. In the case of smart technologies for supermarkets, it was evident in this study that the most significant concern is associated with data security and privacy.

In this sense, the digitization of the city as a whole and the companies that provide essential services (supermarket retail) must be conscious, opening the dialog on what must be built (direct channels or with intermediaries such as "assisted purchase"), as it becomes critical to gain insight into consumer preferences.

Finally, retailers must adapt to changes in purchasing behavior to succeed in a post-COVID-19 environment. The effect of health crises like these makes consumers buy differently, and in the current case, it was not a mere option but a need to find new ways of consumption.

The limitations of this study are mainly related to its external validity. The study had as selection criteria respondents from the city of São Paulo. Although these respondents manage to bring the essence of the study, the extension of the study to other cities and states can be considered for future studies. In addition, it is imperative to conduct a comparative study with other smart cities around the world.

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Supplementary file

Table A1.
Proposed model scales in detail

Construct	Items	Cross-loadings	Scale items	Reference
Subjective norm (SN)	SN1	0.837	I would trust smart technologies if people I care about recommended it	Adapted from Urmetzer and Walinski (2014)
	SN2	0.843	If the media recommended using smart technologies, I would follow the recommendation	
	SN3	0.887	If people who matter to me think smart technologies are safe, so do I	
	SN4	0.887	I trust the judgment of the people who matter to me when it comes to the security of smart technologies	
	SN5	0.771	I want to use smart technologies when I see them being used by other consumers	
Subjective security (SS)	SS1	0.731	I think the company responsible for smart technology is concerned with the security of information transactions	Adapted from Cui *et al.* (2018)
	SS2	0.880	I believe it is safe to use smart technologies daily to make purchases	
	SS3	0.873	I feel comfortable using smart technologies during the purchase process	Adapted from Urmetzer and Walinski (2014)
	SS4	0.864	I believe smart technologies are safe	
Objective security and data privacy (OSDP)	OSDP1	0.774	Smart technologies give enough support for me to feel comfortable using them	Adapted from Sepasgozar *et al.* (2019)
	OSDP2	0.865	Smart technologies are secure enough for me to make my data available to use a service	Adapted from Cimperman *et al.* (2016)
	OSDP3	0.725	I think the person responsible for the smart technology will take full responsibility for any kind of technical failure during use	Adapted from Sepasgozar *et al.* (2019)
	OSDP4	0.868	I believe that smart technologies have legal and technological frameworks (e.g. encryption, up-to-date security systems) that protect my data properly	Adapted from Abu-Shanab (2017) and Sepasgozar *et al.* (2019)
	OSDP5	0.881	I believe that smart technologies can protect my personal information	Adapted from Abu-Shanab (2017)
Trust (TR)	TR1	0.782	Overall, smart technologies are reliable	Adapted from Mittendorf (2016)
	TR2	0.849	I think smart technologies are efficient, safe, and trustworthy	
	TR3	0.724	I tend to rely on smart technologies, even though I know little about them	
	TR4	0.770	I believe that smart technologies stay true to their purpose	
	TR5	0.852	Smart technologies are reliable to carry out my operations	Adapted from Chang *et al.* (2017)
	TR6	0.794	I can rely on smart technologies to carry out useful activities to improve my quality of life	
	TR7	0.772	Smart technologies meet my expectations	

(*continued*)

Table A1.

Construct	Items	Cross-loadings	Scale items	Reference
	TR8	0.727	Smart technologies emphasize my interests and needs	
Adaptative resilience (AR)	AR1	0.819	I can absorb unexpected changes in the purchasing process related to the use of smart technologies	Adapted from Nilakant *et al.* (2014)
	AR2	0.752	If a company doesn't adopt smart technologies, there will always be others that can fill that role for me	
	AR3	0.774	For me, there will always be companies that adopt smart technologies to improve the purchasing process	
	AR4	0.847	I can adapt my knowledge to the best use of smart technologies	
	AR5	0.821	I can make difficult decisions quickly when I use smart technologies	
Engagement (EN)	EN1	0.785	I spend a lot of my free time following the evolution of smart technologies	Adapted from Vivek *et al.* (2014)
	EN2	0.730	I am interested in using smart technologies to make purchases	
	EN3	0.906	Any information or news related to smart technologies catches my attention	
	EN4	0.872	I like to learn more about smart technologies	
	EN5	0.885	I pay close attention to any news related to smart technologies	
Quality of life (QL)	QL1	0.828	The use of smart technologies will significantly improve the quality of the purchasing process	Adapted from Ejdys and Halicka (2018)
	QL2	0.801	The use of smart technologies will be a source of additional benefits (e.g. 24-h service, sense of security, etc.) that would otherwise not be available	
	QL3	0.848	The widespread use of smart technologies will bring measurable benefits to the purchasing process and quality of life	
	QL4	0.862	Using smart technologies can significantly improve my comfort	
	QL5	0.803	Strengthening the bond with companies by using smart technologies, breaks barriers and brings an innovation that is important for my life	Adapted from De Guimarães *et al.* (2020)
	QL6	0.872	Smart technologies provide me with a better purchasing process	
	QL7	0.746	Transparency and efficiency result from the use of smart technologies during the purchasing process	
	QL8	0.824	The adoption of smart technologies for the purchasing process allows me to prioritize actions that directly impact my quality of life	

Table A2.
Use of smart technologies by generations

Item	Category	n	%	Smart technologies Supermarket app	Assisted purchase	QR code	Chatbots	Self-checkout
Generation (age)	Generation Z (age 18–22)	185	39.45	35.84% (119)	43.35% (137)	37.50% (27)	37.21% (16)	33.34% (30)
	Millennials (ages 23–38)	151	32.20	34.34% (114)	33.54% (106)	37.50% (27)	41.86% (18)	34.44% (31)
	Generation X (ages 39–54)	93	19.83	21.69% (72)	16.46% (52)	15.28% (11)	13.95% (6)	23.33% (21)
	Boomers (ages 55 or older)	40	8.52	8.13% (27)	6.65% (31)	9.72% (7)	6.98% (3)	8.89% (8)
	Total	469	100.00	100.0%	100.0%	100.0%	100.0%	100.0%

Constructs	CA (>0.7)	ρ-rho (>0.7)	CR (>0.7)	AVE (>0.5)	R^2
SN	0.900	0.899	0.926	0.716	
OSDP	0.881	0.889	0.914	0.680	
TR	0.858	0.862	0.905	0.704	0.604
SS	0.910	0.914	0.928	0.616	0.608
AR	0.862	0.866	0.901	0.645	0.268
EN	0.893	0.901	0.922	0.703	0.420
QL	0.932	0.934	0.944	0.679	0.602

Table A3. Evaluation of the convergent validity and values of the model's goodness-of-fit

Constructs	SN	OSDP	TR	SS	AR	EN	QL
SN	*0.846*	0.534	0.516	0.604	0.319	0.244	0.416
OSDP	0.477	*0.825*	0.850	0.822	0.480	0.407	0.536
TR	0.467	0.772	*0.785*	0.797	0.580	0.449	0.651
SS	0.531	0.718	0.708	*0.839*	0.617	0.435	0.659
AR	0.281	0.425	0.518	0.530	*0.803*	0.708	0.816
EN	0.228	0.370	0.420	0.396	0.640	*0.838*	0.593
QL	0.382	0.489	0.600	0.589	0.732	0.563	*0.824*

Note(s): Elements marked diagonally in italic represent the square root of the AVE. Below diagonal elements are the correlations between the constructs

Table A4. Assessment of discriminant validity: Fornell–Larcker criterion (below main diagonal) and HTMT (above main diagonal)

H#	Direct paths	β	Bootstrapping (n = 5000)	Standard deviation	T-test	P-value
H1a	SN → SS	0.202	0.200	0.036	5.538	0.000
H1b	SN → TR	0.128	0.129	0.035	3.653	0.000
H2a	OSDP → SS	0.367	0.369	0.050	7.324	0.000
H2b	OSDP → TR	0.711	0.710	0.031	23.195	0.000
H3a	TR → SS	0.331	0.329	0.053	6.221	0.000
H3b	TR → AR	0.518	0.516	0.044	11.887	0.000
H3c	TR → EN	0.122	0.120	0.044	2.759	0.006
H4	SS → QL	0.269	0.266	0.039	6.912	0.000
H5a	AR → EN	0.577	0.580	0.037	15.396	0.000
H5b	AR → QL	0.502	0.505	0.046	10.867	0.000
H6	EN → QL	0.135	0.135	0.038	3.537	0.000
	Indirect paths (mediations)					
M_1	SN → TR → SS	0.042	0.043	0.014	3.005	0.003 (Partial)
M_2	OSDP → TR → SS	0.235	0.233	0.039	6.086	0.000 (Partial)
M_3	TR → AR → EN	0.299	0.299	0.031	9.696	0.000 (Partial)
M_4	AR → EN → QL	0.078	0.078	0.022	3.583	0.000 (Partial)

Table A5. Confirmation of hypotheses

Bottleneck QL	AR	EN	SS
0	NN	NN	NN
10	16.7	NN	8.3
20	16.7	NN	8.3
30	16.7	NN	8.3
40	16.7	NN	8.3
50	16.7	3.3	8.3
60	23.3	3.3	8.3
70	26.7	13.3	8.3
80	36.7	13.3	8.3
90	46.7	26.7	16.7
100	63.3	26.7	50

NCA effect sizes (accuracy and fit are 100%)

Construct	QL CE-FDH	Slope
AR	0.262 (medium effect)	1.524
EN	0.174 (medium effect)	1.839
SS	0.113 (medium effect)	1.443

Note(s): $p < 0.05$; CE-FDH, ceiling envelopment-free disposal hull

Table A6.
Bottleneck table and NCA effect sizes

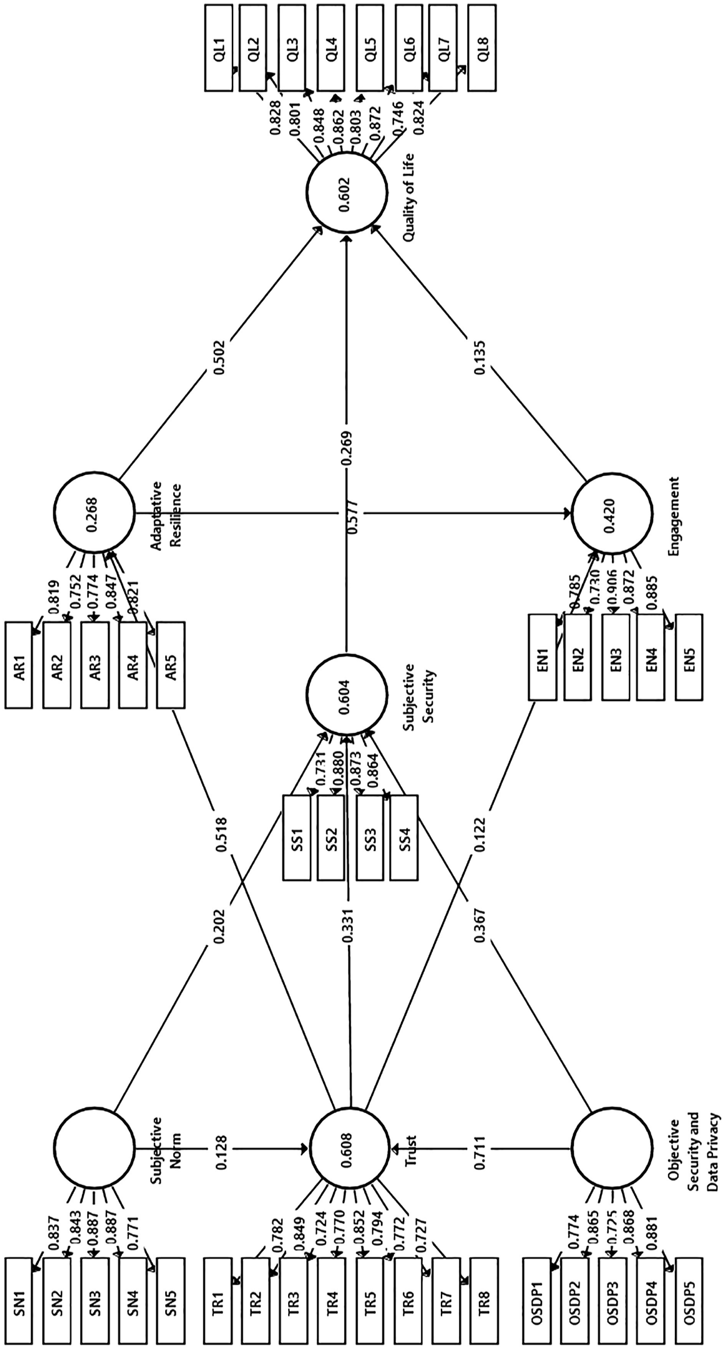

Figure A1.
Results of PLS structural model analysis

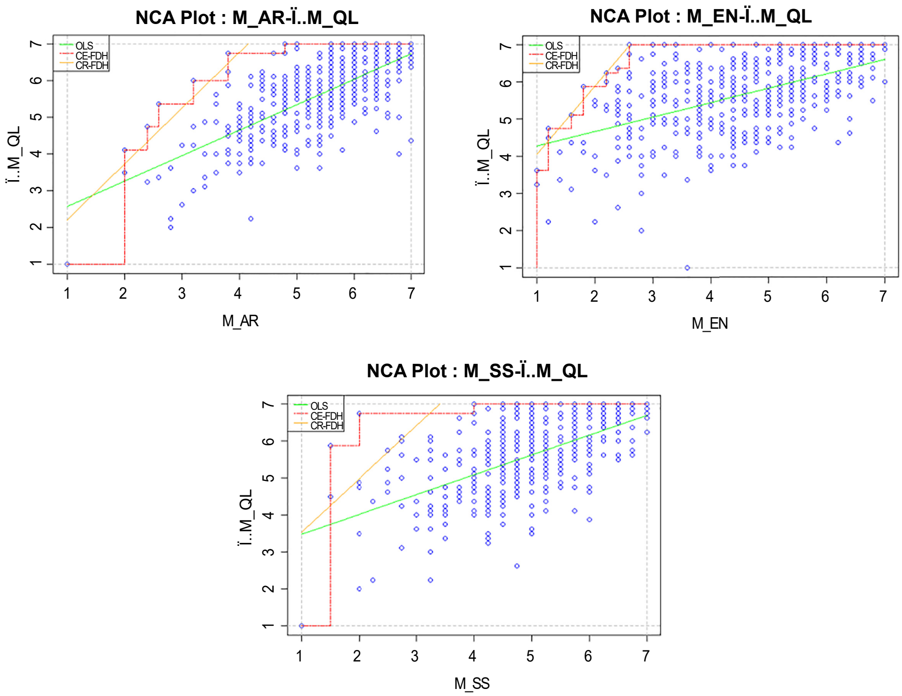

Figure A2.
NCA plot of quality of life predictors

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