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Determining the Antecedents of Quality of Life Factors from the Use of Smart Technologies in Supermarket Retail

Luis Hernan Contreras Pinochet [a]*, Cesar Alexandre de Souza [b], Adriana Backx Noronha Viana [b], Guillermo Rodríguez-Abitia [c], Vanessa Itacaramby Pardim [b]

[a]*Federal University of Sao Paulo, Osasco, SP 06120-042, Brazil*
[b]*University of Sao Paulo, São Paulo, SP 05508-010, Brazil*
[c]*Raymond A. Mason School of Business, William & Mary, Williamsburg, VA, 23187-8795, United States*

Abstract

This study aims to identify the determining factors of the advances of smart technologies in supermarket retail that influence citizens' quality of life during the COVID-19 crisis. Thus, this research aims to identify and analyze crucial factors that influence users' quality of life who shopped in Brazilian supermarkets, primarily from smart technologies, employing Covariance-based Structural Equation Modeling (CB-SEM) to collect data from 469 users of smart technologies in supermarket retail. The study provided support to observe that, in a way, a large part of the respondents felt good, and their expectations were met when assessing smart technology services in supermarket retail and will continue using them, even after the pandemic. Finally, the proposed model showed consistency and can be applied for future research.

Keywords: Smart technologies; supermarket retail; quality of life; covariance-based structural equation modeling.

1. Introduction

Companies from different segments are currently being challenged to rethink their business models to respond to the pressures arising from the digital transformation process [1]. Far beyond the intensive use of advanced technologies, digital transformation requires organizations to align processes with cultural changes to meet the demand for agility requisitioned by consumers [2,3]. In retail, the digital transformation changed the dynamics and the business model, especially with the expansion of online sales, to adapt and generate new value propositions, thus creating new channels from smart technologies for smart retail [4–6].

* Corresponding author. Tel.: +5511963807777
E-mail address: luis.hernan@unifesp.br

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Smart technologies allow communication with autonomy and integrate it into that network to make life easier for those who use it. This is done by aggregating and analyzing data and helping the user get to know and better prepare, for example, the company's application virtual assistant and others. However, this is not restricted to physical locations but also virtual channels (e-commerce, marketplace, and delivery applications). These technologies offered 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 public and private sectors [7].

The current perspective of smart cities requires an integrated view of all its infrastructure and components, which must consider a series of dimensions that are not related to technology (e.g., social and political) [8]. Thus, the proposal of a humanistic look at technical advances raises deeper discussions regarding ethical and human aspects inherent to smart city initiatives [9]. In addition, the pandemic has caused a severe downturn in economic activity. However, there is an expansion of services in supermarket retail that involve smart technologies mediated by digital platforms.

Therefore, this study aims to identify the determining factors of the advances of smart technologies in supermarket retail that influence citizens' quality of life during the COVID-19 crisis. Thus, this research aims to identify and analyze crucial factors that influence users' quality of life who shopped in Brazilian supermarkets, primarily from smart technologies, employing Covariance-based Structural Equation Modeling (CB-SEM) to collect data from 469 users of smart technologies in supermarket retail.

2. Innovation in the Brazilian supermarket retail sector, theoretical research model and research hypotheses

The supermarket retailer is responsible for maintaining the stock of its products, offering variety to consumers, and providing distribution services to manufacturers. In addition to selling small quantities to the final consumer, the retailer adds value to the product or service it sells. A retail sector characterized by competitiveness and innovation consists of a proliferating range of establishments that are continuously influenced by a highly heterogeneous and dynamic milieu. Pantano et al. [10] summarize the benefits deriving from smart retail, based on three main pillars: 1) availability of products, services, and information (e.g., use of an app to locate products in physical stores that allows retailers to collect data on consumers' behavior within the store regarding the type of product researched); 2) information sharing between companies and customers (e.g., mobile applications that allow retailers to create and send personalized offers to each consumer, based on their preferences/purchase history); and To enhance the interaction between retailers and both sellers (e.g., cashiers) and consumers, it is crucial to establish intelligent partnerships that effectively address the challenges typically encountered in traditional company-customer relationships. The successful implementation of smart retail largely hinges on addressing concerns related to technological dependence, accessibility, risk, and technological obsolescence. These aspects are recognized as fundamental pillars for reaping the advantages offered by this business model [11].

Innovative technological trends in smart retail seek to meet the desire to streamline consumer purchase transactions by providing minimal barriers, such as time and location [12]. This smart retail proposal learns to collect data about its consumers and, thus, promotes personalized service and offers products and services that meet their expectations. This improves the quality of life and appeases the customers' demands through convenience and simplifying 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 combining innovative technological trends as promoters of innovation and quality of life for consumers [5]. According to Pantano and Timmermans [13], the concept of smart retail goes beyond applying modern and innovative technology to retail processes and includes an additional level of intelligence correlated with the use of technology.

In this section, we introduce the theoretical research model on smart technologies that we derived from the literature. To seek answers for this research, we developed a structural model containing the constructs adapted for this context. We formulated the following research hypotheses, listed within each of their respective constructs (see Fig. 1). The seminal references followed the following scales: Perceived User Experience [14], Perceived Usefulness [15,16], Trust [17,18], Perceived Convenience [19,20], Engagement [21], Subjective Security [22,23], and Quality of Life [24,25]. In this sense, the following hypotheses were formulated:

H1a: Perceived user experience has a positive influence on perceived usefulness.

H1b: Perceived user experience has a positive influence on quality of life.

H2a: Perceived usefulness has a positive influence on trust.

H2b: Perceived usefulness has a positive influence on engagement.
H2c: Perceived usefulness has a positive influence on quality of life.
H3a: Trust has a positive influence on engagement.
H3b: Trust has a positive influence on quality of life.
H4a: Perceived convenience has a positive influence on trust.
H4b: Perceived convenience has a positive influence on quality of life.
H5: Engagement has a positive influence on quality of life.
H6: Subjective security has a positive influence on quality of life.

3. Method

3.1 Data collection and sample

We conducted our research based on a cross-selection analysis of participants obtained through a collection with individuals who made purchases in the city of São Paulo during the period of the pandemic in virtual channels (e-commerce, marketplace, or applications), or in a face-to-face environment using technologies, or in autonomous markets. Participation was voluntary, and respondents remained anonymous. The city of São Paulo was chosen because it is considered the smartest city in Brazil by the Urban Systems Connected Smart Cities ranking [26] and occupied 42nd position in the world by the Global Power City Index [27]. We collected data using convenience sampling (on social networks, e.g., LinkedIn, WhatsApp, Facebook, Instagram). We conducted the collection process through a survey made available on the online research platform QuestionPro. 526 participants completed the survey and, using the Mahalanobis distance criterion (D^2) to identify outliers (n=57) for data purification, 469 valid responses remained. There were no missing data, so there was no need to use the imputation method. We used G*Power 3.1.9 software to calculate the sample testing power (1-b err prob), which equals 100%. In the data analysis, we utilized the IBM SPSS 25 and AMOS 24.

3.2 Instrument development

The questionnaire included a sociodemographic assessment of the respondents' 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 smart technologies (we used cross tables for these analyses). The model was built with 32 questions anchored on a seven-point Likert-type scale (1- totally disagree to 7- totally agree). The instrument used reverse translation and was validated by four experts in the field. The methods used for this research were: (1) Covariance-based Structural Equation Modeling (CB-SEM) verified the data and tested the structure and hypotheses of the model; (2) CB-SEM is designed for theory building, confirmation, and rejection, alongside rigorous multivariate assumptions; and (3) the SEM approach measures the linear interrelationships.

3.3 Common method bias, non-response bias, and collinearity

As these data were primary, it was necessary to ensure that no systematic bias influenced the collected information. We verified the variance of the common method by applying Harman's single factor test [28] on the 30 items and five components, extracting an eigenvalue greater than 1.0. The variance extracted from the first component was 45.37%, less than 50%, which is the maximum value to be accepted. In addition, we performed non-response bias analysis, according to the recommendations of [29]. When performing these tests, we found that both the common method bias and the non-response bias do not represent a problem for the continuity of the study. As the sample was considered large, we divided the data into two random sub-samples, and, subsequently, we performed an analysis of the multigroup effect of latent variables (t-test). As a result, this process found that both subsamples had similar results. We also examined late response bias, comparing early (first month) and late (last month) responses. However, the results revealed no statistical differences between groups. Considering that all data were collected in a cross-sectional study (survey), it was possible to use the total sample in the survey. By analyzing the collinearity, we found that all the Variance Inflation Factors (VIFs) of the constructs were below 3.3 based on Kock [30]. The values obtained were PUE=2.585, PU=1.893, TR=2.266, PC=2.053, EN=3.294, SS=2.179, and QL=2.522. 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. Therefore, our model can be considered free of common method bias. Finally, we tested normality from the values of multivariate skewness and kurtosis statistics using the Mardia test ($p<.001$).

4. Analysis of Results

4.1 Descriptive Statistics

The demographic profile of respondents is composed of 44.6% (209) men and 55.4% (260) women. 42.9% of the sample have graduated, and of these, 17.1% completed postgraduate studies. According to the analysis, 75.9% of respondents are employed, and the monthly average family income is concentrated up to 6 minimum wages (approximate value - up to U$1,292.52). In this research, we engaged the Pew Research Center [31] criteria to understand the use of smart technologies according to respondents' generations. The results presented in Table 1 provide indications that Generation Z and Millennials are the ones that make more use of smart technologies, highlighting 'Assisted Purchase' and 'Supermarket Apps.'

Table 1. Use of smart technologies by generations

Item	Category	n	%	Smart Technologies				
				Supermarket app	Assisted purchase	QR Code	Chatbots	Self-checkout
Generation (age)	Generation Z	185	39.45	35.8% (119)	43.4% (137)	37.5% (27)	37.2% (16)	33.3% (30)
	Millennials	151	32.20	34.3% (114)	33.5% (106)	37.5% (27)	41.9% (18)	34.4% (31)
	Generation X	93	19.83	21.7% (72)	16.5% (52)	15.3% (11)	14.0% (6)	23.3% (21)
	Boomers	40	8.53	8.1% (27)	6.6% (31)	9.7% (7)	7.0% (3)	8.9% (8)
	Total	469	100.00	100.0%	100.0%	100.0%	100.0%	100.0%

4.2 Confirmatory Factor Analysis (CFA)

CFA determined the validity of the scales' constructs, an integral approach of the SEM, and is very useful for verifying the structure of the constructs and observed variable set (see Fig. 1). The latent variable is measured by the variable observed in this type of analysis. In the first stage of iteration of the model adjustment, we excluded six variables: PU4, SS1, EN2, TR3, TR8, and QL7. According to the CFA results, the initial values of the model were adjusted by linking items with high covariance loads to avoid discarding items from the model, which is generally not recommended to ensure measurement reliability [32]. Thus, the model met the 'excellent' or 'acceptable' fit criteria for all items without the need to exclude variables. The adjustment indices were $\chi2$=1073.921; df=387.000; $\chi2$/df=2.777 (excellent); RMSEA=.062 [33]; SRMR=.082 [34]; GFI=.858 [35]; AGFI=.829; CFI=.933 [34]; IFI=.933 [35], and TLI=.925 [34]. We applied the strategy of correlating all exogenous and endogenous variables to test the convergent and discriminant validity. Maximum likelihood is the method used to estimate the parameters.

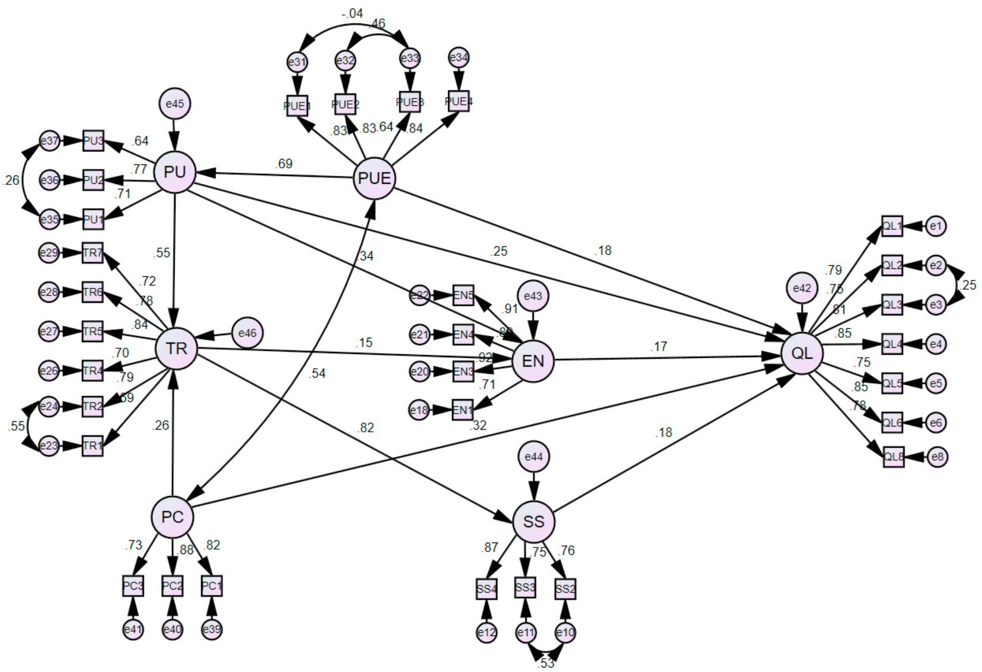

Fig 1. Results of the Structural Model

The reliability analysis results presented in Table 2 are as follows: the internal consistency of composite reliability (CR) was considered adequate, ranging from .800 to .930, with all variables above .7. The average variance extracted (AVE) value ranged between .572 and .739, indicating that all variables meet the criteria of being greater than .5 [36,37].

Table 2. Assessment of convergent and discriminant validity: Fornell-Larcker criterion (below the main diagonal) and HTMT (above the main diagonal)

Construct	CR	AVE	MSV	MaxR(H)	QL	SS	EN	TR	PUE	PU	PC
QL	.930	.655	.453	.933	.809	.630	.492	.634	.674	.674	.694
SS	.885	.720	.522	.895	.619	.848	.342	.766	.536	.488	.576
EN	.918	.739	.375	.936	.481	.297	.860	.373	.632	.313	.186
TR	.900	.600	.522	.907	.615	.722	.364	.775	.477	.636	.552
PUE	.886	.660	.417	.905	.646	.520	.612	.472	.813	.551	.463
PU	.800	.572	.467	.803	.673	.486	.315	.618	.546	.756	.695
PC	.852	.658	.467	.864	.668	.547	.183	.509	.435	.684	.811

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

We utilized the maximum shared quadratic variance (MSV) to test the discriminant validity of the measurement model. Discriminant validity is assessed by examining the indicator construct loads and the correlations between the constructs. They were first, comparing the square root of the AVE of each construct with all the correlations between it and other constructs [38], where all the square roots of the AVEs must be greater than any of the correlations between the constructs, corresponding, and other construction. In addition, the heterotrait-monotrait ratio (HTMT) criterion is added, which indicates that the values obtained must be less than .85 for conceptually different constructs [39].

The MSV results are less than the AVE values, which means the discriminant values are valid. Furthermore, the measurement model follows the assumptions initially made [37]. The maximum reliability [MaxR(H)] of the seven factors was considered satisfactory indices must be greater than .7. The standard factor loading of all items was above the recommended level (≥.50), and, based on the analysis results, the measurement model was accepted and is reliable.

The R^2 value measures the model's predictive accuracy, representing the combined effects of endogenous variables on exogenous variables [37]. The research brought interesting data that revealed that the measure of adjustment of the model - the coefficient of determination - for the smart technologies' effects 'PU' was R^2=.482, 'TR' was R^2=.471, 'EN' was R^2=.207, 'SS' was R^2=.677, and 'QL' was R^2=.665. As shown in Table 3, all direct paths in the research model were positive and statistically significant.

Table 3. Confirmation of hypotheses

H#	Path	Standardized estimates	Unstandardized estimates	S.E.	t-test	p-value	Confirm
H1a	PUE → PU	.695	.452	.039	11.482	***	Yes
H1b	PUE → QL	.181	.144	.050	2.900	.004	Yes
H2a	PU → TR	.547	.637	.074	8.576	***	Yes
H2b	PU → EN	.343	.561	.125	4.494	***	Yes
H2c	PU → QL	.255	.312	.088	3.552	***	Yes
H3a	TR → EN	.150	.211	.096	2.186	.029	Yes
H3b	TR → SS	.823	.898	.071	12.714	***	Yes
H4a	PC → TR	.257	.238	.046	5.160	***	Yes
H4b	PC → QL	.320	.310	.045	6.927	***	Yes
H5	EN → QL	.165	.124	.029	4.243	***	Yes
H6	SS → QL	.181	.174	.045	3.916	***	Yes

5. Discussion

When analyzing the results of the hypotheses in Table 3, we observed that all were accepted. We presented those with greater relevance in the general theoretical context in terms of standardized estimators.

H3b (β=0.823; TR→SS) had the highest standardized estimator. The perception of trust is related to subjective security due to the context of new smart technologies that create risks and insecurities 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, the website ReclameAQUI (a Brazilian company that mediates the interaction between company and customer or videos made available on YouTube).

The leading platforms that provide these services available in the city of São Paulo usually guide consumers on how the services operate, providing explanations on how the applications work. If this service is not offered by service providers, consumers will perceive a greater risk when adopting this technology [15]. Especially in the case of ‘assisted shopping’ or ‘supermarket apps’ where there is the possibility of distributing more information to customers.

To maintain the users’ trust and maintain a good reputation, the institutions that provide the technologies need to be aware of their individual and societal needs. This can favor a positive perception of safety [23]. Thus, subjective security for users who live in a technological context builds layers with the insertion of new threats, such as cyber-attacks and information theft, in addition to the main traditional issues such as physical and psychological attacks, which can be exacerbated or helped by technology. Furthermore, the relationship with data privacy also changes, as it is easier to lose control over it, as it is more vulnerable due to several factors, such as lack of care on the part of individuals (by not reading consent terms), lack of barriers (which allow easy access by malicious third parties), and lack of choice (as it is a basic requirement for the use of certain services or applications), among others [16].

Significant changes in digital relationships are expected going forward and there have been some advances by government institutions over the years. In Brazil, the government recently implemented the new General Data Protection Law [40], which aims to remedy related issues, such as the power of the processing agents (controllers and information operators) over the individual’s data. Subjective safety is seen from the individual’s point of view, leaving his/her comfort zone, and launching into a risky activity which, is characterized using smart technologies for consumption in supermarket retail. Therefore, the trust construct is essential for the user to gain self-confidence from experience and thus contribute to subjective security, although there may be risks in the activity [22].

Generation Z and the Millennials exhibited the highest frequency of use in all smart technologies - frequent (39.4%) or occasionally (32.2%). When analyzing which technologies were most used, the data revealed that ‘assisted purchase’ is used more, with Generation Z with 43.4% and Millennials with 33.5%. This technology gained strength during the pandemic period due to the applications that mediate between supermarkets and customers. For consumers to trust these digital platforms, they must convey credibility to citizens, mainly when the concern lies in the information sent (e.g., personal data, credit cards, access codes, etc.).

Another relationship to highlight is the H1a (β=0.695; PUE→PU) since the perceived usage experience is a factor that influences the perceived usefulness at the time of purchase, bringing prior knowledge related to convenience, speed, ease of handling, range of product and service options, and ability to compare products. These characteristics make the consumer perceive the environment in which he is inserted, thus measuring his level of motivation, based on the experience acquired with smart technologies, in addition to the companies he relates to virtually [41]. Perceived use experience will enable better conditions to follow the different technologies of competing companies and, soon, will develop a critical sense concerning the service based on previous learnings [14].

Finally, H2a (PU→TR; β=.547) provided indications that the use of smart technologies, specifically ‘assisted shopping’ or ‘supermarket apps’, is a way to acquire products from services that bring innovative technology and enable consumers convenience. Technologies provide instrumental value and production guidance to users at a time when this practice can become a habit [42]. As in several acceptance models, we observe that perceived usefulness is a fundamental variable to analyze the impact of trust [15].

Although all paths of causal relationships are accepted, a hypothesis that deserves more attention is H3a (TR→EN; β=.150). This may be due to the change in attitudes individuals have towards human contact, especially when there is a belief that individuals are becoming more engaged in using smart technologies [43,44]. These companies could reinforce their attention-grabbing strategies using their innovations and the lessons that can be acquired from the intensification of use for a better quality of life [18]. While chatbot technology has been the smallest consumer presence, chatbots bring a revolution to perceived convenience service with systems embedded in websites or within major messaging applications, e.g., WhatsApp, Facebook Messenger, and Apple Business Chat. This type of technology makes it possible to transform the supermarket into an interactive recipe concierge, ordering meals, party item entries, and the products being delivered to the home or the store.

6. Conclusion

The study provided support to observe that, in a way, a large part of the respondents felt good, and their expectations were met when assessing smart technology services in supermarket retail and will continue using them, even after the pandemic. Therefore, the effect of acceleration on the adoption of e-commerce is noticeable. Added to this is the likely change in the profile of consumers who, after the COVID-19 pandemic, will have a different view on quality of life. Respondents categorized as Generation Z and Millennials demonstrated their involvement with the majority of the smart technologies proposed in this study. However, the natural evolution for this type of service is likely personalization for each consumer and, for that, technologies arising from Industry 4.0 such as Big Data, Artificial Intelligence, Internet of Things, among others, will bring dynamism and personalization of content consistently in the customers' unique view. In addition to an evident concern with information security aspects.

As a result, consumers have changed and adapted to new ways of buying their daily groceries. '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 created with companies through digital channels favors a satisfaction that is materialized in the quality of life present in everyday attitudinal actions in purchasing behavior [24,25,45]. Despite not being born immersed in smart technologies, Generations X and Baby Boomers are adapting, but at a slower pace. Older generations worry about different sectors that try to create solutions from this opportunity to include them in new technologies. Consequently, this segment of society could benefit from technologies that help them have a better quality of life when interacting with them.

Retailers create a sense of community or ecosystem that is an innovative experience with their smart technologies changing the shopping routine. Supermarket retailers try to differentiate themselves, offering their brands and building stronger relationships with their consumers, reflecting an increase in sales and loyalty. Confidence in technologies such as 'assisted purchase' and 'supermarket app' is expressed with the construction of a strong social presence among its target audience due to the ease that exists for consumers to give their opinion about the service. Buying behavior tends to change, and it is precisely this change in mentality that represents the new within the concept of adaptive resilience. To meet the high demand during the pandemic, many retailers also adapted to operations, directing efforts towards delivery using their workforce and partnering for a complete service. Many companies are struggling to keep up with the demand for media to the critical challenges of their operations. Finally, the proposed model showed consistency and can be applied for future research.

References

[1] Chanias S, Myers MD, Hess T. Digital transformation strategy making in pre-digital organizations: The case of a financial services provider. The Journal of Strategic Information Systems 2019;28:17–33. https://doi.org/10.1016/j.jsis.2018.11.003.

[2] Grewal D, Hulland J, Kopalle PK, Karahanna E. The future of technology and marketing: a multidisciplinary perspective. J of the Acad Mark Sci 2020;48:1–8. https://doi.org/10.1007/s11747-019-00711-4.

[3] Vial G. Understanding digital transformation: A review and a research agenda. The Journal of Strategic Information Systems 2019;28:118–44. https://doi.org/10.1016/j.jsis.2019.01.003.

[4] Orji CI. Digital Business Transformation: Towards and Integrated Capability Framework for Digitalization and Business Value Generation. Journal of Global Business and Technology 2019;15:12.

[5] Shankar K, Phelan D, Suri VR, Watermeyer R, Knight C, Crick T. 'The COVID-19 crisis is not the core problem': experiences, challenges, and concerns of Irish academia during the pandemic. Irish Educational Studies 2021;40:169–75. https://doi.org/10.1080/03323315.2021.1932550.

[6] Konopik J, Jahn C, Schuster T, Hoßbach N, Pflaum A. Mastering the digital transformation through organizational capabilities: A conceptual framework. Digital Business 2022;2:100019. https://doi.org/10.1016/j.digbus.2021.100019.

[7] Marsal-Llacuna M-L, Colomer-Llinàs J, Meléndez-Frigola J. Lessons in urban monitoring taken from sustainable and livable cities to better address the Smart Cities initiative. Technological Forecasting and Social Change 2015;90:611–22. https://doi.org/10.1016/j.techfore.2014.01.012.

[8] Bartoli A, Hernandez-Serrano J, Soriano M, Dohler M, Kountouris A, Barthel D. Security and Privacy in your Smart City. Barcelona Smart Cities Congress, Barcelona (Spain): 2011, p. 1–6.

[9] Elmaghraby AS, Losavio MM. Cyber security challenges in Smart Cities: Safety, security and privacy. Journal of Advanced Research 2014;5:491–7. https://doi.org/10.1016/j.jare.2014.02.006.

[10] Pantano E, Priporas CV, Dennis C. A new approach to retailing for successful competition in the new smart scenario. IJRDM 2018;46:264–82. https://doi.org/10.1108/IJRDM-04-2017-0080.

[11] Demirkan H, Spohrer J. Developing a framework to improve virtual shopping in digital malls with intelligent self-service systems. Journal of Retailing and Consumer Services 2014;21:860–8. https://doi.org/10.1016/j.jretconser.2014.02.012.

[12] Vrontis D, Thrassou A, Amirkhanpour M. B2C smart retailing: A consumer-focused value-based analysis of interactions and synergies. Technological Forecasting and Social Change 2017;124:271–82. https://doi.org/10.1016/j.techfore.2016.10.064.

[13] Pantano E, Timmermans H. What is Smart for Retailing? Procedia Environmental Sciences 2014;22:101–7. https://doi.org/10.1016/j.proenv.2014.11.010.

[14] Soto-Acosta P, Jose Molina-Castillo F, Lopez-Nicolas C, Colomo-Palacios R. The effect of information overload and disorganisation on intention to purchase online: The role of perceived risk and internet experience. Online Information Review 2014;38:543–61. https://doi.org/10.1108/OIR-01-2014-0008.

[15] Abu-Shanab EA. E-government familiarity influence on Jordanians' perceptions. Telematics and Informatics 2017;34:103–13. https://doi.org/10.1016/j.tele.2016.05.001.

[16] Sepasgozar SME, Hawken S, Sargolzaei S, Foroozanfa M. Implementing citizen centric technology in developing smart cities: A model for predicting the acceptance of urban technologies. Technological Forecasting and Social Change 2019;142:105–16. https://doi.org/10.1016/j.techfore.2018.09.012.

[17] Mittendorf C. What Trust means in the Sharing Economy: A provider perspective on Airbnb.com. Twenty-Second Americas Conference on Information Systems 2016:10.
[18] Chang SE, Liu AY, Shen WC. User trust in social networking services: A comparison of Facebook and LinkedIn. Computers in Human Behavior 2017;69:207–17. https://doi.org/10.1016/j.chb.2016.12.013.
[19] Chang K, Chen M, Hsu C, Kuo N. The effect of service convenience on post-purchasing behaviours. Industr Mngmnt & Data Systems 2010;110:1420–43. https://doi.org/10.1108/02635571011087464.
[20] Morganosky MA. Cost- versus convenience-oriented consumers: Demographic, lifestyle, and value perspectives. Psychology & Marketing 1986;3:35–46. https://doi.org/10.1002/mar.4220030104.
[21] Vivek SD, Beatty SE, Dalela V, Morgan RM. A generalized multidimensional scale for measuring customer engagement. Journal of Marketing Theory and Practice 2014;22:401–20. https://doi.org/10.2753/MTP1069-6679220404.
[22] Cui F, Lin D, Qu H. The impact of perceived security and consumer innovativeness on e-loyalty in online travel shopping. Journal of Travel & Tourism Marketing 2018;35:819–34. https://doi.org/10.1080/10548408.2017.1422452.
[23] Urmetzer F, Walinski I. User Acceptance and Mobile Payment Security. International Journal of E-Services and Mobile Applications 2014;6:37–66.
[24] Ejdys J, Halicka K. Sustainable Adaptation of New Technology—The Case of Humanoids Used for the Care of Older Adults. Sustainability 2018;10:3770. https://doi.org/10.3390/su10103770.
[25] De Guimarães JCF, Severo EA, Felix Júnior LA, Da Costa WPLB, Salmoria FT. Governance and quality of life in smart cities: Towards sustainable development goals. Journal of Cleaner Production 2020;253:119926. https://doi.org/10.1016/j.jclepro.2019.119926.
[26] Urban Systems. Ranking Connected Smart Cities. Urban Systems 2021. https://www.urbansystems.com.br (accessed November 14, 2021).
[27] Global Power City Index 2020. The Mori Memorial Foundation 2020. https://www.mori-m-foundation.or.jp/english/ius2/gpci2/2020.shtml (accessed November 14, 2021).
[28] Podsakoff PM, Organ DW. Self-Reports in Organizational Research: Problems and Prospects. Journal of Management 1986;12:531–44. https://doi.org/10.1177/014920638601200408.
[29] Armstrong JS, Overton TS. Estimating Nonresponse Bias in Mail Surveys. Journal of Marketing Research 1977;14:396–402. https://doi.org/10.1177/002224377701400320.
[30] Kock N. Common Method Bias in PLS-SEM: A Full Collinearity Assessment Approach. Int J e-Collab 2015;11:1–10. https://doi.org/10.4018/ijec.2015100101.
[31] Pew Research Center. Generations & Age 2021. https://www.pewresearch.org/topic/generations-age/ (accessed November 14, 2021).
[32] Brown TA. Confirmatory Factor Analysis for Applied Research, Second Edition. 2ª edição. New York ; London: Guilford Publications; 2015.
[33] Steiger JH. Understanding the limitations of global fit assessment in structural equation modeling. Personality and Individual Differences 2007;42:893–8. https://doi.org/10.1016/j.paid.2006.09.017.
[34] Hu L, Bentler PM. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling: A Multidisciplinary Journal 1999;6:1–55. https://doi.org/10.1080/10705519909540118.
[35] Miles J, Shevlin M. A time and a place for incremental fit indices. Personality and Individual Differences 2007;42:869–74. https://doi.org/10.1016/j.paid.2006.09.022.
[36] Bagozzi RP, Yi Y. On the evaluation of structural equation models. JAMS 1988;16:74–94. https://doi.org/10.1007/BF02723327.
[37] Hair J, Anderson R, Babin B. Multivariate Data Analysis. 7th Edition. Upper Saddle River, NJ: Prentice Hall; 2009.
[38] Fornell C, Larcker DF. Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. Journal of Marketing Research 1981;18:39–50. https://doi.org/10.2307/3151312.
[39] Franke G, Sarstedt M. Heuristics versus statistics in discriminant validity testing: a comparison of four procedures. INTR 2019;29:430–47. https://doi.org/10.1108/IntR-12-2017-0515.
[40] BRASIL. Lei Geral de Proteção de Dados Pessoais, no 13.709 2018. http://www.planalto.gov.br/ccivil_03/_ato2015-2018/2018/lei/l13709.htm (accessed November 14, 2021).
[41] Nysveen H, Pedersen PE. An exploratory study of customers' perception of company web sites offering various interactive applications: moderating effects of customers' Internet experience. Decision Support Systems 2004;37:137–50. https://doi.org/10.1016/S0167-9236(02)00212-9.
[42] Dogruel L, Joeckel S, Bowman ND. The use and acceptance of new media entertainment technology by elderly users: development of an expanded technology acceptance model. Behaviour & Information Technology 2015;34:1052–63. https://doi.org/10.1080/0144929X.2015.1077890.
[43] Söllner M, Benbasat I, Gefen D, Leimeister JM, Pavlou PA. MIS Quarterly Research Curation on Trust. MIS Quarterly 2016:1–9. https://doi.org/10.25300/10312016.
[44] Coombs C. Will COVID-19 be the tipping point for the Intelligent Automation of work? A review of the debate and implications for research. International Journal of Information Management 2020;55:102182. https://doi.org/10.1016/j.ijinfomgt.2020.102182.
[45] Khan Z, Pervez Z, Abbasi AG. Towards a secure service provisioning framework in a Smart city environment. Future Generation Computer Systems 2017;77:112–35. https://doi.org/10.1016/j.future.2017.06.031.