Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 221 (2023) 450–457

Procedia Computer Science

www.elsevier.com/locate/procedia

10th International Conference on Information Technology and Quantitative Management

Predicting the Antecedents of Quality of Life from the Use of Smart Technologies in Supermarket Retail: An in-depth Investigation Using Artificial Neural Networks

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 article aims to identify the determining factors for advances in smart technologies in supermarket retail that influence citizens' quality of life in the context of the COVID-19 crisis. We developed a theoretical model using Artificial Neural Networks (ANN) from a sample of 469 users of smart technologies in supermarket retail. In contrast, a multivariate Exploratory Factor Analysis (EFA) approach organized the input data to an artificial neural network (ANN) model to predict factors of importance to the quality of life. Based on the results, this study revealed that the coexistence of the proposed predictive variables is analyzed to understand the quality of life using smart technologies and analyzing the users through generational classification. Subjective safety proved to be the construct with the most important predictive power of data analysis, and, at the same time, it is one of the main concerns of consumers.

Keywords: Artificial Neural Networks; quality of life; supermarket retail; smart technologies

1. Introduction

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 analysing 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

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

10.1016/j.procs.2023.07.060

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 [1].

Increased competitiveness is driven by innovation [2], as smart technologies can offer opportunities to facilitate entrepreneurship, creativity, and innovation to drive economic growth [3]. This type of initiative can also be seen from a strategic perspective, triggering the emergence of new value chains in companies and stakeholders involved in designing and executing smart city projects [4].

Most retail innovation approaches are typically focused on how to introduce new technologies aimed at increasing customer acceptance and business profitability [5]. Little research is directed at the concept of using smart technologies to improve the experience or quality of life in the customer purchase [6]. The point of concern in the application of smart retail is mainly associated with dependence, availability, risk, and obsolescence of technology. This is considered an essential pillar for obtaining the benefits of this business model [7]. The consumer's purchasing behaviour, habits, needs, and expectations of purchases have changed. The consumer journey is no longer predictable, and the retailer needs to respond to this reality [8].

This discussion is important, not only in the COVID-19 pandemic that puts society and cities in check, demanding immediate solutions with a transversal impact in its various domains, which must remain efficient. Supermarket consumers are changing their habits in response to the pandemic; they want more information about the product, touchless purchase availability, flexibility in the means of payment and delivery. The consumer's journey has been changing and is evident in behaviors such as staying at home for longer and interacting more frequently with mobile devices which inevitably leads to an online journey.

This article aims to identify the determining factors for advances in smart technologies (supermarket apps, assisted purchase, QR Code, Chatbots, and Self-checkout) in supermarket retail that influence citizens' quality of life in the context of the COVID-19 crisis.

2. Model construction and research hypotheses

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 [9], Perceived Usefulness [10,11], Perceived Convenience [12,13], Engagement [14], Subjective Security [15,16], and Quality of Life [17,18].

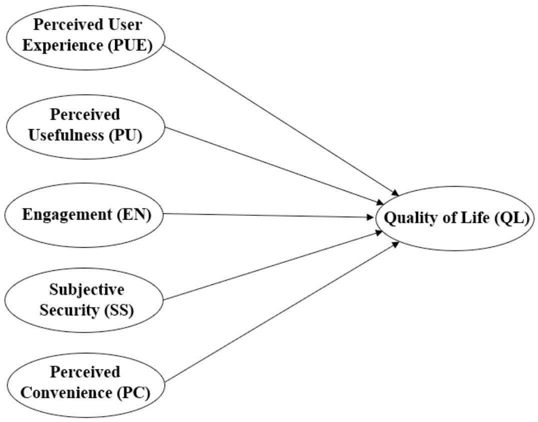

Fig 1. Research model of smart technologies

The structure of a neural network is composed of an input layer (independent variables) and an output layer (dependent variable). In this theoretical model, it was possible to find one artificial neural network (ANN). In the literature, 'Quality of Life' can often appear as a dependent variable in studies in smart cities. In this method, there are no pre-formulated hypotheses for causal relationships. As a result, to be verified measures of the level of importance of each independent variable. Therefore, it is a feature of the method [19,20].

3. Method

3.1. Method

The model was built with 24 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. 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. 526 participants completed the survey and, using the Mahalanobis distance criterion (D2) to identify outliers (n=57) for data purification, 469 valid responses remained. The Artificial Neural Network (ANN) does so for non-linear relationships between the identified factors influencing the variable of interest. Therefore, for the analysis, we employed an ANN approach [20–22].

3.2. Exploratory Factor Analysis (EFA)

EFA was employed to examine the data set to identify interrelationships between group items that form part of integrated concepts. In addition, this step verified the variables that make up the selected scales. Each item underwent analysis with its respective variables, in which the interest was mainly focused on common factors interpreted about the observed variables [23]. We employ varimax rotation as a statistical technique used at a factor analysis level to clarify the relationship between the factors (constructs of the model proposed in Fig. 1), where the process involves adjusting the coordinates of the data resulting from the principal component analysis. The Kaiser-Meyer-Olkin (KMO) criterion and Bartlett's Test of Sphericity were used for this analysis ($p<.001$). KMO values showed adequate results for all scales, where KMO>0.8 is considered excellent, according to Hutcheson [24].

After these procedures, we observed the cross factor loading and excluded some variables by the extraction value (h2) to minimize complex factors and maximize the variance of the factor loadings. Subsequently, the results detected unidimensionality (score>.5 in the factor) and low cross-load (score <.4 in the other factors). All variables had adjustments due to commonality (h2<0.5) and weak coefficients (<.4). In the end, the factor loadings of the scale items were adjusted to just one factor, for each of the observed scales, with adequate values to explain the total variance of the sample, as well as the reliability, confirmed with Cronbach's alpha (Table 1). All factor loadings were ⩾ 70, considered excellent by Comrey [25]. Finally, the seven factors presented an acceptable total explained variance above 60%, as shown in Table 1.

Table 1. Results obtained by EFA

Factors	number of items	KMO	Sphericity Test	% total variance	α
Perceived usefulness (PU)	3	.706	p<.001	71.43%	.800
Perceived user experience (PUE)	7	.796	p<.001	74.08%	.878
Engagement (EN)	4	.836	p<.001	77.42%	.902
Perceived convenience (PC)	3	.794	p<.001	76.31%	.844
Subjective Security (SS)	3	.719	p<.001	80.60%	.879
Quality of live (QL)	7	.937	p<.001	70.34%	.928

3.3. Artificial Neural Network (ANN)

In analogy to biological neural networks, an artificial neural network is an aggregate of computational units known as artificial neurons. Each neuron has input terminals similar to the dendrites of biological neurons, where information is inserted and subsequently computed, resulting in an output value that will be propagated to other units until the last layer provides the network response.

The Strucutural Equation Modeling (SEM) likely oversimplifies the complexity of decisions since it can only detect linear relationships. Therefore, this study adopted ANN approach to resolve this gap, as ANN does not require multivariate assumptions (e.g., linearity, normality, or homoscedasticity) and can identify non-linear relationships [26]. The variables determined by the Exploratory Factor Analysis (EFA) as input units for the ANN solve this limitation, which will provide greater prediction accuracy than linear models [27]. Therefore, these methods can be complementary in a data analytical process.

Haykin (1998) defines an ANN as a massively parallel distributed processor composed of simple processing units, which have a neural propensity to store experimental knowledge and make it available for use for a specific purpose. In this study, we proposed a multilayer perceptron (MLP) with the feedforward propagation back-propagation multilayer perceptron (FFBP) algorithm [29]. MLP had five input layers (independent variables) PUE, UP, EN, SS, and PC, automatically calculating the hidden layers that resulted in three depending on the complexity of the problem to be solved observed by Negnevtsky [30], and an output layer (the dependent variable) QL. From the means of the items of each variable ($\bar{V}_i$), the items were normalized [0, 1] from the following expression:

$$\bar{X}_i = \frac{\bar{V}_i - 1}{6} \tag{1}$$

Training refers to the supervised learning process during which training cases are presented to the neural network, and the connection weights are modified. Selecting an appropriate set of training cases and the training protocol. The training cases must implicitly contain the essential knowledge that describes the material behaviour if the neural network is to be able to predict that full range of behaviour; that is, the set of training cases should constitute a comprehensive set. A neural network trained with a comprehensive data set can use its generalization capability and respond appropriately when queried about stress paths not explicitly included in the training data set. Unfortunately, there are no rigorous methods for testing a priori whether a training set is comprehensive; this is currently done by testing the trained neural network against a variety of novel training cases to which it has not been exposed during training. However, this has apparent shortcomings as a true test of the trained neural network [31].

Following the chosen training algorithm, the connection weights will be adjusted. It is important to consider, at this stage, some aspects such as network initialization, training mode and training time. A good choice of the initial values of the network weights can decrease the time needed for training. Typically, the initial values of the network weights are uniformly distributed random numbers within a defined range. The wrong choice of these weights can lead to premature saturation. As for the training time, several factors can influence its duration, but it will always be necessary to use some stopping criterion. The stopping criterion of the backpropagation algorithm is not well defined, and a maximum number of cycles is usually used. However, the average error rate per cycle and the generalization capacity of the network must be considered. It may happen that at a certain moment of training the generalization starts to degenerate, causing the problem of over-training, that is, the network specializes in the training data set and loses its generalization capacity. Training should be stopped when the network has a good generalization ability and when the error rate is small enough, that is, less than an admissible error. Thus, an optimal stopping point with minimum error and maximum generalizability must be found [32].

The test set is used to determine network performance with previously unused data. Network performance, measured at this stage, is a good indication of its actual performance. Other tests should also be considered, such as analysis of the network behaviour using special inputs and analysis of the current weights of the network, because if there are very small values, the associated connections can be considered insignificant and thus eliminated (pruning, the practice of removing parameters). Conversely, values substantially larger than the others could indicate that there was over-training of the network.

This research process utilized the sigmoid function to activate neurons for hidden and output layers [19]. The basic ANN model uses a supervised learning process in which the outputs are known and used in training (with descending gradient optimization algorithm). The FFBP algorithm for prediction and classification was assumed to be an advanced multiple regression analysis (MRA) capable of dealing with complex and nonlinear relationships. We conducted cross-validation with 90:10 data partition for training and testing, respectively. The number of hidden units was automatically generated, and the root means square of errors (RMSE) was calculated along with the normalized importance in the sensitivity analysis. The RMSE of training and testing datasets for all ten neural networks and the means and standard deviations were calculated and presented in Table 2.

Table 2. RMSE values for the Neural Networks

Network	Training			Testing			RMSE(Training)-RMSE (Testing)
	n	SSE	RMSE	n	SSE	RMSE	
1	409	3.201	.088	60	.518	.093	.004
2	417	2.393	.076	52	.268	.072	.004
3	422	2.789	.081	47	.276	.077	.005
4	414	2.402	.076	55	.316	.076	.000
5	418	2.665	.080	51	.253	.070	.009
6	421	2.267	.073	48	.262	.074	.000
7	420	2.372	.075	49	.243	.070	.005
8	421	2.989	.084	48	.495	.102	.017
9	428	2.276	.073	41	.241	.077	.004
10	422	2.516	.077	47	.261	.075	.003

mean	2.587	.078	mean	.313	.078	.005
sd	.318	.005	sd	.104	.010	.005

Note: SSE= Sum Squares of Error, RMSE=Root Mean Square Error, sd=standard deviation.

Definitions of these criteria are given as follows:

$$\mathrm{SSE} = \sum_{t=1}^{n}\left(\mathrm{Q_t} - \widehat{\mathrm{Q}}_{\mathrm{t}}\right) \tag{2}$$

$$\mathrm{RMSE} = \sqrt{\frac{\mathrm{SSE}}{\mathrm{n}}} \tag{3}$$

$\mathrm{Q_t}$ is the observed data (Q) at time t, $\widehat{\mathrm{Q}}_{\mathrm{t}}$ is the predicted value at time t.

3.4. Validating the ANN model

In this study, an Artificial Neural Network (ANN) model contains five input neurons, three hidden neurons (automatically calculated by SPSS software – usually, the number of hidden neurons is around 2/3 the size of the input layer), and one neuron output (Fig. 2). In addition, bias is a cell that issues a fixed value to contemplate 'start values' that are ≠0 when all inputs are 0. Based on the RMSE values of the Neural Network (Table 2), we conclude that the ANN model has high precision in the means for training ($\bar{x}_{training} = .078$) and testing ($\bar{x}_{testing} = .078$) respectively. Training determines weights and values for each bias to minimize forecast error and is used to estimate the network parameters. Testing feeds the network already trained with different data, to verify if the network 'understands' the phenomenon and it's used to prevent overtraining. Therefore, the models can provide a very accurate prediction based on RMSE values that should be relatively small (around 0.10) indicating a quite accurate prediction [19,27].

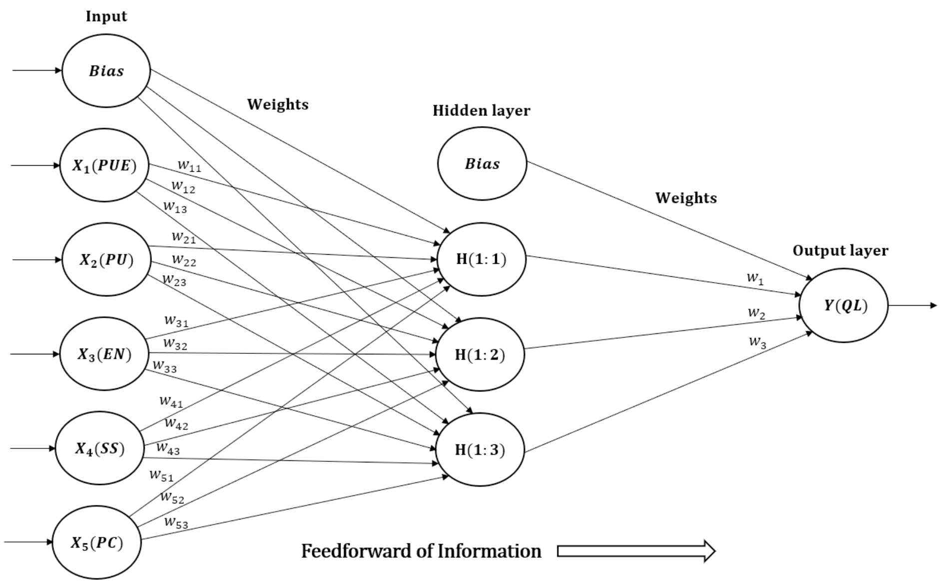

Fig. 2. The Proposed Artificial Neural Network Architecture.

According to Fig. 2, the results validated the predictive relevance of the weight resistances (w_{ij}), as each input neuron is connected to the three hidden neurons through synaptic weights different from zero. To validate an ANN model, we cannot fix the threshold value for RMSE. We must look at the comparison of RMSE of both test and train datasets. If the model is good, then the RMSE of test data is quite similar to the train dataset. Otherwise, we can identify the following conditions: RMSE of test > RMSE of train overfitting the data or RMSE of test < RMSE of train ⟹ underfitting the data. Fig. 3 shows the comparison between the RMSE values, showing that the occurrences of over and under fittings in this research were similar.

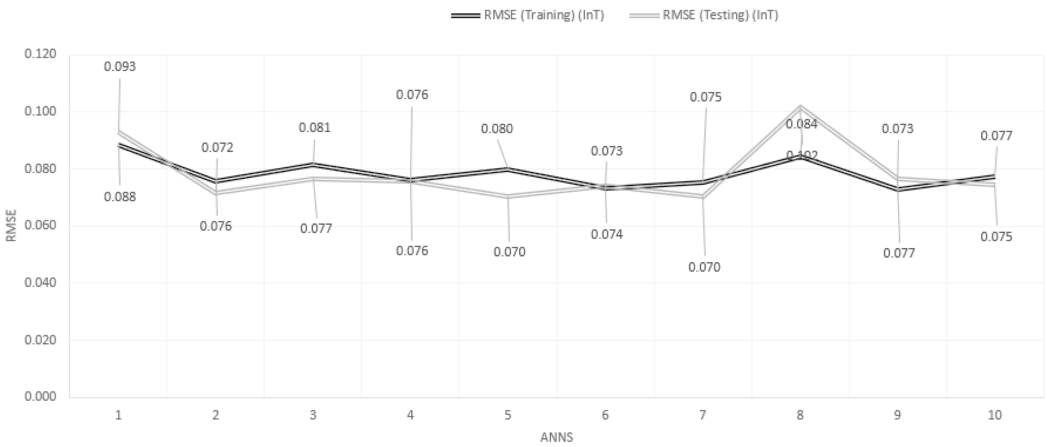

Fig. 3. Comparation of RMSE of both test and train datasets

4. Sensitivity analysis

We conducted the sensitivity analysis to measure the strength of the weight resistances by calculating the normalized importance of the resistances from the ten ANN simulations. Normalized importance is the ratio of relative importance to greater relative importance and is indicated as a percentage. Table 3 shows that the security subjective is the most significant predictor in the sensitivity analysis, showing 100% normalized importance and 25.9% of the average overall importance among the predictors of quality of life. Next, we have engagement ($\bar{x}_{EN} = 19.9\%$), perceived usefulness ($\bar{x}_{PU} = 19.6\%$), perceived user experience ($\bar{x}_{PUE} = 16.1\%$), and perceived convenience ($\bar{x}_{PC} = 16.8\%$), respectively by the degree of importance. It is possible to observe that all predictors had high relative mean values of importance.

Table 3. Sensitivity analysis

	Relative importance				
Neural Network	PUE	PU	PC	EN	SS
ANN (1)	.129	.238	.140	.227	.267
ANN (2)	.140	.145	.221	.211	.282
ANN (3)	.205	.246	.159	.101	.289
ANN (4)	.111	.136	.224	.255	.273
ANN (5)	.315	.128	.104	.172	.281
ANN (6)	.110	.244	.196	.179	.270
ANN (7)	.241	.160	.123	.244	.231
ANN (8)	.177	.226	.207	.160	.230
ANN (9)	.181	.214	.125	.234	.247
ANN (10)	.174	.221	.178	.202	.224
Average relative importance	.178	.196	.168	.199	.259
Normalized relative importance (%)	68.8	76.9	65.4	77.6	100.0

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. Respondents generally seek in these digital channels an immediate environment for payments and receipt of goods. 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.

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

The digitization of the city and the companies that provide essential services (supermarket retail) need to open a dialogue of what must be built (direct channels or even with intermediaries such as 'assisted shopping'), as it becomes critical to gain insight into consumer preferences. This is related to the relationship process between companies and consumers, having as intelligent intermediary technologies, which the bias of service marketing can manage, a branch of the various marketing strategies [33]. These are used by organizations to deliver value to their consumers in the process of exchange, or value co-creation to create and develop long-term relationships with their customers and add value in the exchange process, always with synergy between those involved, since the interrelationship between the parties becomes a fundamental component in the process of developing, creating, and delivering value in a service, in the case of this study, retail supermarket.

As it emerged together with technologies and is strongly related to them, the concept of the smart city is constantly being updated. The technological component is one of the main factors' researchers from all over the world in the fields of the scientific community are increasingly addressing this factor to encompass the most diverse aspects of life, society, information, among others.

One of the questions that will remain after the COVID-19 pandemic is how to make the different agents that participate in the economic development of a city (in this case São Paulo with its supermarket retail) contribute to the development of a smart city that also meet citizens' expectations. This process should leave only the issue of communications and accountability; moving towards the empowerment of groups in society to make decisions and formulate public policies, improvements, and actions for development and innovation. The governance of how the situation was handled and the civic engagement of the citizen protagonist is what will make a difference as future learning for the next emergency as well as make a city smart and resilient. 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.

5. Conclusion

Applying deep learning with ANN analysis becomes a robust methodological approach, detecting non-linear associations between the constructs. From the data analysis, subjective security has proven to be the construct with greater predictive power and, simultaneously, of greatest concern to consumers. 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.

The limitations of this study are mainly related to its external validity. Respondents from the city of São Paulo participated in the study. Although these respondents manage to bring the essence of the study, the extension of the study to other cities and states in Brazil can be considered for future studies. This is in addition, to performing a comparative study with other smart cities worldwide.

Due to the global conditions of the pandemic (COVID-19), the sample was mostly obtained via social networks and communication applications, which can create, a priori, a bias in collecting respondents with greater familiarity with the technology. The transversal nature of the collection instrument used limits the research since this approach is based on a single moment analysis (seeking to circumvent this situation, we used the ANN method for simulation).

Furthermore, depending on the moment of the pandemic, one possibility would be to include the construct 'resilience' or 'adaptive resilience' to better understand the effect on which companies seek to create online experiences by putting customers at the center of the strategy and think of new ways to connect customers with digital channels that are effective for support [34].

References

[1] 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.

[2] Appio FP, Lima M, Paroutis S. Understanding Smart Cities: Innovation ecosystems, technological advancements, and societal challenges. Technological Forecasting and Social Change 2019;142:1–14. https://doi.org/10.1016/j.techfore.2018.12.018.

[3] Kraus S, Richter C, Papagiannidis S, Durst S. Innovating and Exploiting Entrepreneurial Opportunities in Smart Cities: Evidence from Germany: Entrepreneurial Opportunities in Smart Cities. Creativity and Innovation Management 2015;24:601–16. https://doi.org/10.1111/caim.12154.

[4] Paroutis S, Bennett M, Heracleous L. A strategic view on smart city technology: The case of IBM Smarter Cities during a recession. Technological Forecasting and Social Change 2014;89:262–72. https://doi.org/10.1016/j.techfore.2013.08.041.

[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] Pantano E, Viassone M. Engaging consumers on new integrated multichannel retail settings: Challenges for retailers. Journal of Retailing and Consumer Services 2015;25:106–14. https://doi.org/10.1016/j.jretconser.2015.04.003.
[7] 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.
[8] Vader R. Global retail trends 2020 - KPMG Global. KPMG 2021. https://home.kpmg/xx/en/home/insights/2020/05/global-retail-trends-2020-preparing-for-new-reality.html (accessed November 14, 2021).
[9] 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.
[10] 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.
[11] 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.
[12] 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.
[13] 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.
[14] 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.
[15] 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.
[16] Urmetzer F, Walinski I. User Acceptance and Mobile Payment Security. International Journal of E-Services and Mobile Applications 2014;6:37–66.
[17] 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.
[18] 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.
[19] Leong L-Y, Hew T-S, Tan GW-H, Ooi K-B. Predicting the determinants of the NFC-enabled mobile credit card acceptance: A neural networks approach. Expert Systems with Applications 2013;40:5604–20. https://doi.org/10.1016/j.eswa.2013.04.018.
[20] Liébana-Cabanillas F, Marinković V, Kalinić Z. A SEM-neural network approach for predicting antecedents of m-commerce acceptance. International Journal of Information Management 2017;37:14–24. https://doi.org/10.1016/j.ijinfomgt.2016.10.008.
[21] Alam MZ, Hu W, Kaium MA, Hoque MR, Alam MMD. Understanding the determinants of mHealth apps adoption in Bangladesh: A SEM-Neural network approach. Technology in Society 2020;61:101255. https://doi.org/10.1016/j.techsoc.2020.101255.
[22] Raut RD, Priyadarshinee P, Gardas BB, Jha MK. Analyzing the factors influencing cloud computing adoption using three stage hybrid SEM-ANN-ISM (SEANIS) approach. Technological Forecasting and Social Change 2018;134:98–123. https://doi.org/10.1016/j.techfore.2018.05.020.
[23] Hair J, Babin B, Anderson R, Black W. Multivariate Data Analysis. 8a ed. Intl Thomson Business Pre, Andover, Hampshire: 2018.
[24] Hutcheson G. The Multivariate Social Scientist: Introductory Statistics Using Generalized Linear Models. 6 Bonhill Street, London EC2A 4PU: SAGE Publications, Ltd.; 1999. https://doi.org/10.4135/9780857028075.
[25] Comrey AL, Lee HB. A First Course in Factor Analysis, Psychology Press. 2013.
[26] Lee V-H, Leong L-Y, Hew T-S, Ooi K-B. Knowledge management: A key determinant in advancing technological innovation? Journal of Knowledge Management 2013;17:848–72. https://doi.org/10.1108/JKM-08-2013-0315.
[27] Tan GW-H, Ooi K-B, Leong L-Y, Lin B. Predicting the drivers of behavioral intention to use mobile learning: A hybrid SEM-Neural Networks approach. Computers in Human Behavior 2014;36:198–213. https://doi.org/10.1016/j.chb.2014.03.052.
[28] Haykin S. Neural Networks: A Comprehensive Foundation. Subsequent edition. Upper Saddle River, N.J: Prentice Hall; 1998.
[29] Yee-Loong Chong A, Liu MJ, Luo J, Keng-Boon O. Predicting RFID adoption in healthcare supply chain from the perspectives of users. International Journal of Production Economics 2015;159:66–75.
[30] Negnevitsky M. Artificial Intelligence: A Guide to Intelligent Systems. 3rd Edition; 2011.
[31] Ghaboussi J, Pecknold DA, Zhang M, Haj-Ali RM. Autoprogressive training of neural network constitutive models. International Journal for Numerical Methods in Engineering 1998;42:105–26. https://doi.org/10.1002/(SICI)1097-0207(19980515)42:1<105::AID-NME356>3.0.CO;2-V.
[32] Rosmaliati, Setiawati NE, Purnomo MH, Priyadi A. Nguyen-Widrow Neural Network for Distribution Transformer Lifetime Prediction. 2018 International Conference on Computer Engineering, Network and Intelligent Multimedia (CENIM), 2018, p. 305–10. https://doi.org/10.1109/CENIM.2018.8710815.
[33] 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.
[34] Komninos N, Kakderi C, Panori A, Tsarchopoulos P. Smart City Planning from an Evolutionary Perspective. Journal of Urban Technology 2019;26:3–20. https://doi.org/10.1080/10630732.2018.1485368.