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Neural network modeling of consumer satisfaction in mobile commerce: An empirical analysis☆

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ABSTRACT

The mobile commerce (m-commerce) industry has rapidly grown in value in recent years, as has the number of m-commerce service providers and interest in it from consumers and academia alike. In order to ensure customer loyalty, providers must determine which factors influence consumer satisfaction in m-commerce. Therefore, the objective of this study is to determine and rank the significant predictors of satisfaction in m-commerce. The paper also develops a procedure for artificial neural network model design and parameter setting in technology acceptance studies. Data was collected from 224 users of m-commerce services. The results presented are based on a combination of structural equation modeling (SEM) and artificial neural network (ANN) analyses. A multi-layer perceptron was used for ANN modeling. The results show that the optimal ANN model has one hidden layer and a sigmoid as an activation function in both layers, while the number of hidden nodes should be determined using a recommended rule-of-thumb. In addition, mobility and trust were found to be the most significant determinants of consumer satisfaction in m-commerce. The results of the study are significant as they have important implications for both academia and companies, due to the fact that some of the factors investigated in the study, such as mobility, have rarely been explored in previous consumer satisfaction studies, but were proved to be very significant. Another important result of the study is the proposal of a detailed procedure of ANN model design and the recommendations made for the selection of ANN model architecture and parameter settings.

1. Introduction

Mobile phones are nowadays the most popular devices used for communication among people (eMarketer, 2016), not only for conversation but also e-mail, text messaging and video calls. Increasingly mobile devices – particularly smartphones and tablets – are being used for many other activities, including purchases and payments. Gartner (2017) estimated that more than 3.5 billion new mobile devices were sold in 2018 and 2019, most of which were smartphones. Taking into consideration that in 2019, over 97% of the global population lived in areas covered by mobile telecommunication network signals and that at the same time, there are more mobile-cellular subscriptions than there are inhabitants of our planet (International Telecommunication Union (2019), 2019), the immense marketing and commercial potential of mobile phones is clear, with significant social influence.

Mobile commerce (m-commerce) refers to business activities conducted through Internet-enabled mobile devices (Chong, 2013a; Sarkar, Chauhan, & Khare, 2020) and such transactions have experienced very high growth rates in recent years. Mobile commerce is primarily driven by convenience and value. According to eCommerce research (2019) in the US, more than half of smartphone users and almost 70% of tablet users have purchased a product or service via mobile devices in the last year. During the 2017 Black Friday holiday in the US, purchases via mobile devices accounted for more than half of all online orders, thus exceeding computer orders for the first time in history (Business Insider, 2017). Finally, recent estimates predict that m-commerce sales will account for more than 70% of the US retail e-commerce market by 2021 (eMarketer, 2018), and it is clear that mobile commerce is becoming the

☆ The code (and data) in this article has been certified as Reproducible by the CodeOcean: https://codeocean.com/.

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dominant form of B2C e-commerce. In addition to the US, China, Japan, South Korea and the UK are the most significant m-commerce markets (eMarketer, 2019).

Due to the potential for growth of m-commerce and its significance, it is of crucial importance to examine the main factors that influence the adoption and continued use of m-commerce. Although a number of studies related to m-commerce adoption models and predictors exist (Agrebi & Jallais, 2015; Chong, 2013a, 2013b; Faqih & Jaradat, 2015; Kalinic & Marinkovic, 2016; Liébana-Cabanillas, Marinković, & Kalinić, 2017; Yadav, Sharma, & Tarhini, 2016), the number of studies on customer satisfaction and intention, regarding the future use of m-commerce is rather limited (Marinkovic & Kalinic, 2017; Marinković, Đorđević, & Kalinić, 2019; Kalinić, Marinković, Djordjevic, & Liebana-Cabanillas, 2019a). Therefore, the first objective of the research is to examine the factors which affect customer satisfaction in mobile commerce and to rank significant predictors of satisfaction by their influence.

One of the most important and well-known techniques for investigating dependencies in the social sciences is Structural Equation Modeling (SEM), and it has been successfully employed in a number of studies related to customer behavior in the m-commerce context (Gao, Waechter, & Bai, 2015; Lu, 2014; Kalinic & Marinkovic, 2016). Although SEM is a very efficient and reliable technique for hypothesis testing and examining causal relationships, being a linear technique, it can test only linear relationships among predictors and dependent variables. In many cases, especially in complex problems like the human decision-making process, SEM may over-simplify the problem (Liébana-Cabanillas et al., 2017; Tan, Ooi, Leong, & Lin, 2014). Conversely, artificial neural networks (ANNs) are not only capable of linear modeling, but also non-linear and non-compensatory relationships among predictors and dependent variables (Leong, Hew, Tan, & Ooi, 2013, Liébana-Cabanillas et al., 2017). However, due to their "black-box" nature, they are completely unsuitable for hypothesis testing (Chong, 2013b). Hence, an SEM-ANN hybrid approach perfectly balances both methods – it tests hypotheses in SEM analysis and uses significant determinants as inputs for ANN analysis to rank predictors by their degree of influence. The two-step approach presented was previously tested in the prediction of antecedents of the acceptance of various new technologies, including mobile commerce (Chong, 2013b; Hew, Leong, Tan, Ooi, & Lee, 2019; Kalinić et al., 2019a; Liébana-Cabanillas et al., 2017; Yadav et al., 2016), social commerce and media (Leong, Jaafar, & Ainin, 2018; Leong, Hew, Ooi, Lee, & Hew, 2019b; Leong, Hew, Ooi, & Chong, 2020; Li, Yang, Zhang, & Zhang, 2019), mobile payments and credit cards (Kalinic, Marinkovic, Molinillo, & Liébana-Cabanillas, 2019b; Lee, Hew, Leong, Tan, & Ooi, 2020; Ooi & Tan, 2016; Sharma, Sharma, & Dwivedi, 2019; Teo, Tan, Ooi, Hew, & Yew, 2015), cloud computing (Ooi, Lee, Tan, Hew, & Hew, 2019; Priyadarshinee, Raut, Jha, & Gardas, 2017; Qasem et al., 2020; Raut, Priyadarshinee, Gardas, & Jha, 2018), mobile learning (Tan et al., 2014), social CRM (Ahani, Rahim, & Nilasi, 2017), mobile government (Sharma et al., 2019), Facebook usage (Sharma, Joshi, & Sharma, 2016b), mobile banking (Sharma et al., 2019), and mobile entertainment (Hew, Leong, Ooi, & Chong, 2016). Although there are a number of studies which combine SEM and neural network analysis, many of them do not provide enough information related to the set-up of ANN and its parameters (a detailed analysis will be presented later, in Table 3). Therefore, the study will also use a hybrid, SEM-ANN approach: SEM being used to determine statistically significant antecedents of customer satisfaction in m-commerce, and neural network analysis being used to rank these parameters by their influence. In addition, the procedure of setting up the ANN model and its parameters will be presented. To the best of the authors' knowledge, this is the first study that performs a detailed analysis of ANN parameter selection in the area of technology adoption modeling and gives recommendations as to how to set these parameters. Therefore, the goal of this study, inspired by the research of Marinkovic and Kalinic (2017), can be summarized into two research objectives:

RO1: To determine and rank the most significant predictors of customer satisfaction in m-commerce.

RO2: To describe the procedure of setting up the ANN architecture which provides the best model of analyzed consumer behavior.

The findings of this study, based on contemporary methodology such as ANNs, could prove significant for academia, when looking to better understand and predict consumer behavior in this emerging area. In addition, the results could prove to be of considerable interest to an increasing number of m-commerce providers, as they will be able to organize their operations and marketing campaigns in such a way to address the main drivers of satisfaction, increasing their customers' satisfaction and loyalty. Finally, customers and society will also benefit as a result of this study, as they will receive an improved, tailored and secure mobile service.

The paper is organized as follows: section two presents the literature review of previous studies of m-commerce acceptance predictors, as well as the research model and selected variables; section three details the research methodology used; section four presents a reliability and validity analysis and the SEM results; section five includes an introduction to ANN analysis and a literature review of previous ANN studies in technology acceptance is presented; in section six, a detailed procedure of ANN model design and setup is presented; in section seven an ANN-based sensitivity analysis and its results are presented; section eight contains a discussion of the study and explores its main implications; and finally, section nine includes the conclusion, a summary of the study's limitations and explores potential avenues for future research.

2. Literature review and research model

Attracting new customers is very important for all marketing managers. However, in many cases there is even more emphasis placed on ensuring they become regular, loyal customers, as the cost of acquiring new customers may be up to five times more than retaining existing ones (Bhattacherjee, 2001). In order to retain existing customers, m-commerce providers should put great emphasis on ensuring they are satisfied, as customer satisfaction has a positive impact on consumer loyalty and word-of-mouth (Marinkovic & Kalinic, 2017). Mobile commerce is still a novelty for many customers and as previously noted, studies on m-commerce satisfaction and continuance intention are rare (Lee, Tsao, & Chang, 2015a, 2015b; Shang & Wu, 2017).

The research model presented in this paper, is based on two important theories of behavior intention in technology acceptance: **the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which has been extended as UTAUT2.** TAM (Davis, 1989) and its variations, is one of the most common acceptance models **and perceived usefulness is one of the original TAM constructs, as well as being one of the most significant predictors of mobile technology acceptance** (Liu, Ben, & Zhang, 2019). UTAUT is based on several previously established theories, including TAM (Venkatesh, Morris, Davis, & Davis, 2003). It suggests, among other things, that performance expectancy (the equivalent of perceived usefulness) is a predictor of behavioral intentions and social influence, which considers the influence of peers on consumer decisions. Finally, UTAUT was extended to UTAUT2 (Venkatesh, Thong, & Xu, 2012) by three additional variables. One of the additional variables, hedonic motivation, represents pleasure derived from using a specific technology. It is also known as perceived enjoyment or perceived playfulness (Kalinić et al., 2019a). Although three suggested variables (perceived usefulness, social influence and perceived enjoyment) originate from technology acceptance theories, previous studies also reported these variables as important predictors of consumer satisfaction. Furthermore, trust is included due to the fact that it has been found to be one of the strongest predictors of m-commerce continuance intention (Chong, 2013c), as well as mobility – an inherently specific variable for mobile technologies acceptance (Marinkovic & Kalinic, 2017). Mobility is a variable rarely considered in technology acceptance studies, despite the fact that mobile devices enable consumers to use mobile services virtually "anywhere, anytime". This is a significant advantage of mobile technologies in several areas, such as medicine, particularly dermatology (Goceri, 2020), which is based on pattern recognition, and deep learning is efficient in skin lesion analysis (Goceri, 2019a; 2021). Therefore, it is believed that it will have significant impact of consumer satisfaction. The research model is presented in Fig. 1.

2.1. Perceived trust

In recent decades, research in marketing has brought to the forefront the impact of trust between the parties on the continuity of their partnership, which in turn is an especially significant factor in the business sector. In this sense, even though the concept of trust cannot be easily explained due to its complex nature, the vast majority of authors have approached this dimension through trustworthiness or security (Wang & Emurian, 2005).

Trust has been widely and thoroughly explored in many scientific disciplines from multiple perspectives (Kalinić, Liébana-Cabanillas, Muñoz-Leiva, & Marinković, 2019c; Sharma, 2019) by examining its cognitive and behavioral components.

The extant literature suggests three types of beliefs with regard to the cognitive component of trust: competence, benevolence and integrity, with fitting psychometric properties for the scale (McKnight, Choudhury, & Kacmar, 2002; Castañeda, 2005). In addition, Mayer, Davis, and Schoorman (1995) and McKnight et al. (1998) incorporate the concept of predictability as the ability of trust to predict behaviors in a wide range of situations (Muñoz, 2008).

If accounting for the behavioral component of trust, it can also be defined as "the predisposition of one party to be vulnerable to the actions of the other party based on the expectation that the other party will perform a particular action important to him or her, regardless of the ability to monitor or control the other" (Mayer et al., 1995) – that is the disposition to adopt a particular behavioral pattern. In this regard, trust dramatically affects the successful adoption of new technologies and services such as e-commerce (Yang, Lin, Chandlrees, & Chao, 2009).

Trust in online transactions and markets comes with the certainty that companies will honor their promises and obligations without manipulating or misleading the buying party (Wu and Chen, 2005). Each time clients trust service providers, they are generally assuming that their level of satisfaction will increase, resulting in enhanced loyalty over time (Yeh & Li, 2009; Artigas & Barajas-Portas, 2019). In this sense, clients are likely to generate positive word of mouth with regard to the companies involved in the commercial transaction (Deng, Lu, Wei, & Zhang, 2010). Kar (2020) explored and confirmed the significant impact of trust on consumer satisfaction in mobile payments. In their *meta*-analysis of antecedents and consequences of trust in mobile commerce Sarkar et al. (2020) found that trust was significantly related to all behavioral outcomes: attitude, user satisfaction, behavioral intention and loyalty. Hossain (2019) investigated the moderating influence of gender on consumer satisfaction in mobile payments and found that trust was an important predictor of satisfaction in the case of female consumers, while the same relationship with regards to male consumers was not significant. Trust was also reported as a significant antecedent of satisfaction within mobile banking services and applications (Poromatikul, De Maeyer, Leelapanyalert, & Zaby, 2020; Sharma & Sharma, 2019; Susanto, Chang, & Ha, 2016) and mobile applications in fashion sales (Aguilar-Illescas, Anaya-Sanchez, Alvarez-Frias, & Molinillo, 2020).

In light of the significant effect of trust in the context of m-commerce, the following hypothesis is proposed:

H1: Trust has a positive effect on mobile commerce customer satisfaction.

2.2. Social influence

Subjective norms are usually defined as the degree to which individuals perceive the beliefs of those people important to them with regard to the adequacy of using a particular technology or service or take some action, among other things. (Venkatesh & Bala, 2008). In this regard, social influence plays a significant role in the early stages of development and dissemination of new technology when most early adopters lack the experience and knowledge associated with it and turn to public opinion in the hope of filling in the gaps (Schierz, Schilke, & Wirtz, 2010). The impact of social influence on mobile phone user satisfaction was investigated and confirmed by Jahan, Rahman, Hossain, and Saiful (2019). San-Martín, Prodanova, and Jiménez (2015) investigated the impact of age on the influence of Subjective Norms on consumer satisfaction in mobile shopping. Significant impact of Subjective Norms on satisfaction in mobile shopping context was confirmed by San-Martín, Prodanova, and Lopez Catalan (2016). In addition, social influence was reported to be one of the most important predictors of consumer satisfaction in mobile payments (Kar, 2020).

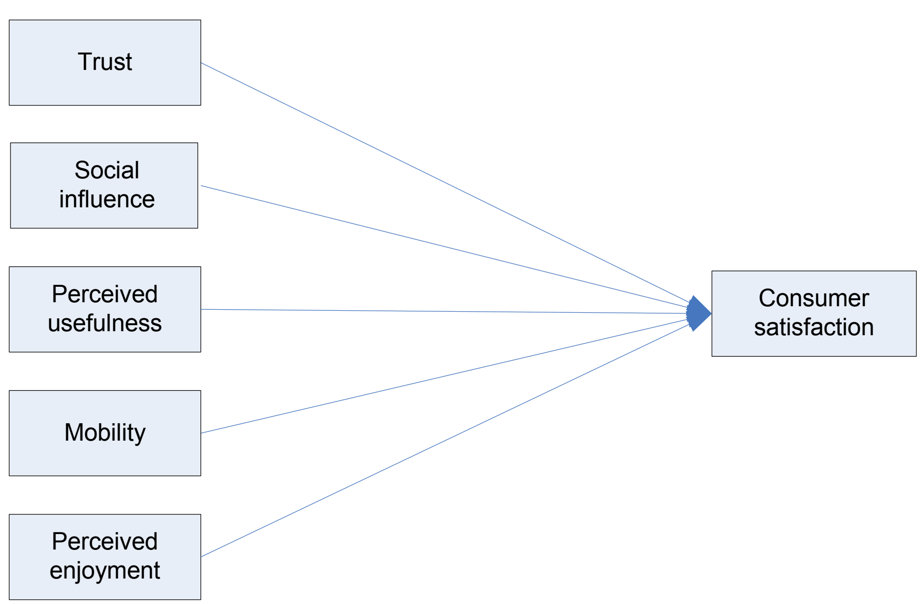

Fig. 1. The Research Model.

As social influence is instrumental to consumers' successful adoption of m-commerce, the following hypothesis is suggested:

H2: Social influence positively impacts customer satisfaction in mobile commerce.

2.3. Perceived usefulness

Perceived usefulness is generally defined as "the potential user's subjective probability that using a specific system will improve work performance in an organizational context" (Davis, 1989). This variable has often been approached as a perceived advantage.

In an online context, perceived utility will usually identify particular technologies and services that may be useful to accomplish specific results (Munoz-Leiva, Climent-Climent, & Liébana-Cabanillas, 2017). In this regard, Vijayasarathy (2004) defines it as "the degree to which the consumer believes that online shopping will provide access to useful information, facilitate comparison of offers and enable faster purchase".

Many authors approach perceived usefulness as a strong predictor of the level of satisfaction of consumers adopting new technology. In addition, perceived usefulness is generally considered the most reliable predictor of consumer satisfaction with regard to online banking services (Liébana-Cabanillas et al., 2016), with a remarkable influence on the level of satisfaction with mobile websites (Zhou, 2011). Mohd Thas Thaker (2019) found usability to be an important predictor of customer satisfaction in Islamic mobile banking. Perceived usefulness was reported as a significant antecedent of satisfaction with mobile branded apps (Li & Fang, 2019), mobile payments (Kar, 2020) and mobile apps in fashion sales (Aguilar-Illescas et al., 2020). In addition, performance expectancy, as a UTAUT equivalent to perceived usefulness in TAM, was found to be an important determinant of consumer satisfaction with mobile learning (Cao, 2018) and mobile food ordering applications (Alalwan, 2020).

Perceived usefulness could therefore be considered a reliable predictor of intention to use m-commerce and to frequently impact customer satisfaction. In view of these findings, the following hypothesis is put forward:

H3: Perceived usefulness has a positive impact on customer satisfaction in mobile commerce.

2.4. Mobility

As a significant factor driving the acceptance of electronic commerce (Schierz et al., 2010), *mobility* can be defined as "the benefits of access and use of services independent of time and place" (Mallat, Rossi, Tuunainen, & Öörni, 2009, p. 58). In this regard, the advantage of mobile technologies is twofold: improved consumer mobility allows "anytime, anywhere" access, while mitigating the need to move about in order to purchase goods or services (Mallat et al., 2009).

Schierz et al. (2010) identified mobility as a strong antecedent of an individual's intention to use, attitudes and perceived utility in the context of m-payment services. Kim (2010) also found that mobility affects the perceived utility of m-payment services. However, a significant influence of mobility on perceived ease of use could not be identified. Mallat et al. (2009) discovered the dramatic impact of mobility on consumer adoption of a particular mobile ticketing service. In addition, the study also found a significant effect on mobile services adoption compared with perceived utility. Perceived mobility has also been considered instrumental to the perceived usefulness of 4G mobile services in the long term (Park & Kim, 2013). The influence of mobility (direct and indirect) on consumer intentions was investigated in the context of m-commerce (Kalinic & Marinkovic, 2016; Liébana-Cabanillas et al., 2017) and m-payment ((Liébana-Cabanillas, Marinković, Ramos de Luna, & Kalinić, 2018). The notable impact of mobility on satisfaction in the m-commerce context was reported by Marinkovic and Kalinic (2017). Finally, Aguilar-Illescas et al. (2020) investigated and confirmed mobility as a significant predictor of consumer satisfaction with C2C mobile applications in fashion sales.

Cobos (2017) found that perceived mobility positively impacted user 's satisfaction with hotel branded mobile apps.

This research assumes that mobility leads to improved intention to use and level of satisfaction. Therefore, the following hypothesis is suggested:

H4: Mobility positively influences customer satisfaction in mobile commerce.

2.5. Perceived enjoyment

Perceived enjoyment can be defined as "the degree to which the activity of using technology is perceived to be enjoyable in its own right, excluding any performance consequences that may be anticipated" (Manis & Choi, 2019). In line with Kim and Nam (2019), in the present research, perceived enjoyment is defined as "an intrinsic motivation, as opposed to perceived usefulness, which is extrinsic motivation". Many authors have proposed in numerous investigations that enjoyment has a positive relationship with intention to use (Armenteros, Liaw, Sánchez-Franco, Fernández, & Sánchez, 2017; Köse, Morschheuser, & Hamari, 2019) and many others have defined a positive relationship with satisfaction (Amoroso & Chen, 2017; Casalo, Flavián, & Ibáñez-Sánchez, 2017; Cheung, Zheng, & Lee, 2015; Kim, 2010; Oghuma, Chang, Libaque-Saenz, Park, & Rho, 2015; Oghuma, Libaque-Saenz, Wong, & Chang, 2016; Natarajan et al., 2017). Chao (2019) found perceived enjoyment to be the most significant predictor of satisfaction in the mobile learning context. Hedonic motivation – the UTAUT2 variable which is very similar to perceived enjoyment (Kalinić et al., 2019a) – had a significant impact on consumer satisfaction with mobile food ordering applications (Alalwan, 2020).

In this sense, perceived enjoyment significantly affects the adoption of mobile commerce as well as its continuance intention. Therefore, the following hypothesis is put forward:

H5: Perceived enjoyment positively impacts customer satisfaction in mobile commerce.

3. Research methodology

3.1. Sample and data collection

An empirical study was conducted on a convenience sample of 224 clients of three mobile vendors which operate in the Republic of Serbia. Although small, the sample size is large enough for the implementation of SEM analysis (Myers, Ahn, & Jin, 2011). In addition, the sample also meets the requirement of the 10:1 ratio between the number of participants and the number of items in the survey, as recommended by Bentler and Chou (1987). The respondents were approached by the interviewers when leaving mobile operator stores after conducting a certain transaction. The sample included only those users who have realized a commercial transaction via mobile phone in the last twelve months.

An analysis of respondents' profiles indicates that there are more women in the sample (55.8%) compared to men (44.2%). Regarding age, the sample had the following structure: 18–24 (26.3%), 25–34 (30.4%), 35–44 (22.8%), 45 or more (20.5%). For level of education, respondents with a high school diploma accounted 45.1% of the whole sample, followed by those with a university diploma (42.0%), while the remaining 12.9% of respondents possessed a college degree. Since m-commerce studies in Serbia are rare, there are no official or reliable socio-demographic data on the m-commerce consumer profile. However, the sample structure is similar to the official governmental statistics on e-commerce and mobile phone users (Statistical Office of the Republic of Serbia (2018), 2018), and therefore it can be concluded that the sample represents the analyzed population in Serbia to a satisfactory level.

3.2. Measurement of variables

The proposed model consists of five independent variables and one dependent variable (Fig. 1). All latent constructs were measured by means of several items based on the review of relevant studies. The respondents expressed their attitudes on a seven-point Likert scale. Four items per one construct were used to measure trust, social influence and mobility (Trust: Chong, Chan, & Ooi, 2012; Social influence: Chong et al., 2012; Chan & Chong, 2012; Mobility: Kim et al., 2009), while perceived usefulness, perceived enjoyment and satisfaction were each measured by three items (Chan & Chong, 2012).

3.3. Statistical analysis

For data analysis, a quantitative approach was decided upon. IBM SPSS 20 and Amos 18 software was used. Firstly, the reliability of each latent construct in the research model was tested by calculating the alpha values. Secondly, confirmative factor analysis was implemented to determine the fit and validity of the proposed model. Thirdly, the research hypotheses were tested by using SEM. Fourthly, by conducting neural network analysis, the strength of the hypothesized relationships whose significance was previously confirmed by SEM was verified.

4. Empirical findings

4.1. Reliability and validity analysis

In the first step, the internal consistency of the items which were used for measuring the latent variables was estimated. In all cases, the alpha values are higher than threshold of 0.7 (Trust: 0.93; Social influence: 0.80; Perceived usefulness: 0.94; Mobility: 0.92; Perceived enjoyment: 0.92; Consumer satisfaction: 0.91). Thus, the reliability criteria, suggested by Verkijika (2018), were met. In addition, the model showed an adequate fit (χ^2/df = 1.66; Goodness-of-fit index = 0.91; Normed fit index = 0.93; Comparative goodness of fit = 0.97; Tucker-Lewis Index = 0.96; Root mean square error of approximation = 0.05; Standardized root mean square residual = 0.04).

All factor loadings are greater than 0.6. The results from Table 1 indicate that the model is characterized by convergent and discriminant validity. For all variables AVE values are higher than 0.5, assuring convergent validity (Hair, Black, Babin, & Anderson, 2014). Also, for each construct, AVE is greater than MSV and ASV. Thus, discriminant validity is satisfied. Finally, in all cases, CR values are higher than 0.7.

4.2. SEM results

In the research model, the effects of trust, social influence, perceived usefulness, mobility and perceived enjoyment on consumer satisfaction were tested (Marinkovic & Kalinic, 2017). For the purpose of this analysis, SEM was used. Four out of five relationships were statistically significant. It is important to note that research model describes 69.5% of variance in consumer satisfaction. The SEM results are presented in Table 2.

Mobility emerges as a main driver of consumer satisfaction in the model (estimate = 0.368, p < 0.01). Thus, hypothesis H4 is confirmed.

Table 1
Average variance extracted (AVE), composite reliability (CR), maximum shared squared variance (MSV) and average shared squared variance (ASV).

	CR	AVE	MSV	ASV
Trust	0.927	0.762	0.460	0.269
Social influence	0.801	0.579	0.230	0.141
Perceived usefulness	0.942	0.844	0.401	0.251
Mobility	0.925	0.756	0.391	0.167
Perceived enjoyment	0.924	0.802	0.315	0.184
Consumer satisfaction	0.913	0.779	0.460	0.340

Table 2
Results of SEM analysis.

Hypotheses	Estimates	Conclusion
H1: Trust → Consumer satisfaction	0.241*	Supported
H2: Social influence → Consumer satisfaction	0.022 ns	Not supported
H3: Perceived usefulness → Consumer satisfaction	0.213*	Supported
H4: Mobility → Consumer satisfaction	0.368*	Supported
H5: Perceived enjoyment → Consumer satisfaction	0.223*	Supported

* Significant at 0.01 level.
ns Not significant

Obviously, a key advantage of using mobile services is the ability to make purchases from anywhere at any time. The impacts of trust, perceived usefulness and perceived enjoyment on consumer satisfaction have similiar strength and all are significant at a level of 0.01. Hence, hypotheses H1, H3 and H5 are supported. However, trust is a slightly stronger predictor of satisfaction than the remaining two variables. Results indicate that users perceive mobile commerce as useful and fun, and security and personal data protection are of great importance to them. On the other hand, the impact of social influence on consumer satisfaction is not significant. Therefore, hypothesis H2 is not supported.

5. ANNs

ANNs are a widely-used artificial intelligence technique that is sophisticated, robust and very efficient in modelling complex relationships among inputs and outputs (Chong, 2013b; Sharma, Al-Badi, Govindaluri, & Al-Kharusi, 2016a; Sharma et al., 2019). ANN has a higher prediction accuracy in comparison to conventional linear techniques such as Multiple Linear Regression (MLR), SEM, Binary Logistics Regression and Multiple Discriminant Analysis (Chong, 2013b; Leong et al., 2013; Priyadarshinee et al., 2017). Another advantage of the ANN approach is that it requires no multivariate assumptions (e.g. linearity, normality, and homoscedasticity) to be fulfilled (Chong, 2013a; Lee, Cho, Seo, Shon, & Won, 2013; Leong, Hew, Lee, & Ooi, 2015).

ANN is built as a simplified model of the human brain. It consists of a number of simple and interconnected neurons (Negnevitsky, 2011), which are analogous to the biological neurons in the human brain. In addition, as in the human brain, the knowledge stored in interneuron-weighted links (synaptic weights) is acquired through the learning process – network training (Liébana-Cabanillas et al., 2017; SPSS, 2012). The architecture of a basic ANN model is presented in Fig. 2.

A typical neural network consists of several hierarchical layers – one input layer, one or more hidden layers and one output layer. There are numerous types of ANN, which can be broadly divided into four sets:

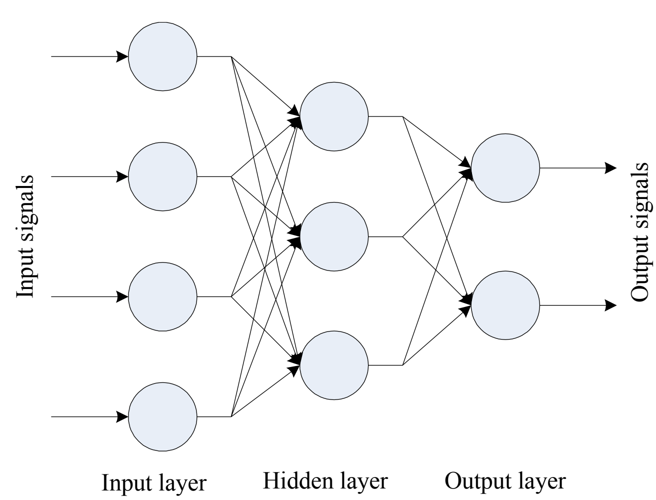

Fig. 2. Basic ANN model.

feedforward neural networks; radial basis function networks; recurrent networks; and multi-layer perceptron networks (Sim, Tan, Wong, Ooi, & Hew, 2014; Sharma et al., 2019). The common choice in technology adoption studies is a multi-layer perceptron (MLP), as it has several advantages (Sim et al., 2014):

1. MLP has the ability to adapt without input from the user.
2. It enables the modeling of non-linear relationships, as it is non-linear itself.
3. The MLP neural network is able to learn by adapting weight coefficients and constructing an input–output mapping.
4. MLP neural networks are highly robust in the presence of noisy data.

Therefore, for the purposes of the study, a feedforward back-propagation multilayer perceptron was adopted as a base ANN model, as a result of the fact that it was present in all the adoption studies presented in Table 2. Each network layer consists of nodes (neurons), connected with the neurons of subsequent layers via adaptable synaptic weights. The number of nodes in the input layer corresponds to the number of inputs – predictors, while the number of nodes in the output layer corresponds to the number of outputs – dependent variables. In feed-forward networks, the input data is fed forward through the network, from the input via hidden layers, to the output layer (Liébana-Cabanillas et al., 2017). The knowledge acquisition in supervised learning ANNs, such as MLP, is performed by training the network with known inputs and outputs. The estimation error, calculated as the difference between the known and predicted output, is fed back through the network and used to reduce and minimize errors in estimation by adjusting synaptic weights.

The ANN model is complex and there are several parameters which must be set in order to obtain an accurate model. The vital element involves determining how many hidden layers will be used in the ANN model, how many neurons will be set in the hidden layers, and finally, which activation functions will be used in hidden and output layers. There are several recent studies that employ ANN models to quantify and rank the influence of predictors on dependent variables. The overview of these studies, with the selected network parameters, is presented in Table 3.

Generally, there are no strict rules as to how to best determine and set ANN model parameters. In addition, as can be seen from the information in Table 3, some of the model parameters are unavailable for a number of the studies. One of the main objectives of the paper is to present the detailed process of the selection of neural network parameters for such studies and to give some recommendations regarding these factors. In line with the research model presented in Fig. 1 and the SEM findings that social influence does not have significant influence on consumer satisfaction, the ANN model will have four inputs – trust, perceived usefulness, mobility and perceived enjoyment. This means that there will be four neurons in the input layer and one output – consumer satisfaction – and therefore, one neuron in the output layer.

6. The selection of ANN parameters

Constructing an ANN involves setting parameters, which can be divided into those that specify ANN structure itself and those that determine how the ANN is trained (Yoo, 2019). The main parameters of the ANN structure are the number of hidden layers and hidden neurons, as well as activation functions in hidden and output layers. The options for choosing them, as well as how they were chosen for this study, are analyzed in detail later in the paper.

6.1. The number of hidden layers

The number of hidden layers is dependent on the complexity of the problem to be solved. More complex neural networks enable the modeling of more complex problems, but also bring a higher computational load and request more data for training and testing. Depending on the number of hidden layers, ANNs are either 'shallow' – with one hidden layer – or 'deep' – with two or more hidden layers (Orimoloye, Sung, Tiejun Ma, & Johnson, 2020). Deep neural networks are particularly useful for more complex problems, based on the high quantities of unstructured, complex data. Types of deep neural networks include Convolutional Neural Networks (CNNs) (which is most commonly used for image processing and computer vision) and Recurrent Neural Networks (RNNs) (most frequently used for natural language processing). However, Negnevitsky (2011) stated that any continuous function can be represented with just one hidden layer, and that using two hidden layers enables the modeling of even discontinuous functions. As a general rule, for standard structured data sets (excluding Big data) in marketing research and technology acceptance studies, neural networks based on MLP with more than two hidden layers are rarely used, because more complex models require more data for training and testing and do not necessarily lead to better results. As demonstrated by the review presented in Table 3, all of the documented prior studies, with the exception of one, used only one hidden layer.

For the purposes of the study and the analysis of the selection of the number of hidden layers, two ANN models were created using IBM SPSS 20 software – one with one hidden layer and another with two hidden layers. Other parameters (the number of hidden neurons and activation functions in the hidden and output layers) were set at the same level for both models. In order to increase the effectiveness of training (Liébana-Cabanillas et al., 2017; Negnevitsky, 2011), all inputs and outputs were normalized in the range [0, 1]. To avoid possible problems with overfitting, a ten-fold cross validation procedure was performed, with a training set consisting of 90% of sampled data and a testing set, with the remaining 10% being the sampled data (Leong et al., 2013; Ooi & Tan, 2016; Tan et al., 2014). In order to evaluate the efficiency of the network models (Chong, 2013a, 2013b; Leong et al., 2013; Liébana-Cabanillas et al., 2017; Ooi & Tan, 2016; Sharma, Govindaluri, & Al-Kharusi, 2015; Sim et al., 2014; Yadav et al., 2016), average Root Mean Square Error (RMSE) was computed and is presented in Table 4, with the average training time for each model.

As can be readily observed, the model with one hidden layer has lower RMSE values for both training and testing, as well as lower training time. Consistent with previous assumptions and these results, it can be concluded that in the case of technology adoption and similar studies based on limited sample size and not too complex a research model, the use of one hidden layer leads to better performance and is therefore recommended.

6.2. The number of hidden neurons

The selection of the number of neurons in the input and output layers is a simple process as these values correspond to the number of independent and dependent variables (predictors and outputs). However, the selection of the number of neurons in the hidden layer can prove to be challenging, as there may be several influential factors, such as the neural network architecture (including the number of hidden layers), the size of the sample, ANN training algorithms or selected activation function (Gnana Sheela & Deepa, 2013; Liébana-Cabanillas et al., 2017). Since there is no standard (heuristic) approach to determine this parameter, the frequent method employed to test network performance is to change the hidden neuron number on a trial and error basis (Table 3). In some studies, the number of hidden neurons is suggested by the software used for ANN modeling or a rule-of-thumb is applied (Kalinic et al., 2019b; Liébana-Cabanillas et al., 2017). The number of neurons in the hidden layer generally affects the predictive accuracy of the ANN model, but also the speed of ANN model training: a higher number of hidden neurons should give more accurate models, but only to a certain point, after which computational load can increase dramatically (Negnevitsky, 2011). Another important issue is overfitting. In the case of a too high number of hidden neurons, the ANN

Table 3
Literature review of the studies employing ANN models, with model parameters.

Source	Area	Methods	Number of hidden layers	How was the number of hidden neurons determined?	Network structure	Activation function	
						Hidden layer	Output layer
Ahani et al., 2017	Social CRM adoption	SEM + ANN	1	Testing 1 to 10	9-8-1	N/A	N/A
Al-Shihi, Sharma, & Sarrab, 2018	Mobile learning acceptance	ANN	1	Automatically by software	6-5-1	Hyperbolic Tangent	Identity
Anouze & Alamro, 2020	E-banking adoption	SEM + ANN	1	Automatically by software	6-N/A-1 2-N/A-1	Sigmoid	Sigmoid
Asadi, Abdullah, Safaei, & Nazir, 2019	Wearable healthcare devices adoption	SEM + ANN	1	Testing 1 to 10	5-10-1	N/A	N/A
Bhuian, Sharma, Butt, & Ahmed, 2018	Pro-environmental consumer behavior	MRA*+ANN	1	Testing 1 to 10	10-3-1	N/A	Hyperbolic Tangent
Binsawad, 2020	University competitiveness	PLS-SEM + ANN	1	Automatically by software	3-2-1	Sigmoid	Sigmoid
Chan & Chong, 2012	Standard adoption	SEM + ANN	1	Testing 2 to 20, step 2	9-10-1	Sigmoid	Sigmoid
Chong, 2013a	Mobile commerce adoption	MRA*+ANN	1	Testing 1 to 10	11-5-1	N/A	N/A
Chong, 2013b	Mobile commerce adoption	SEM + ANN	1	Testing 1 to 10	6-10-1	N/A	N/A
Chong and Bai, 2014	IOS adoption in SMEs	SEM + ANN	1	Testing 1 to 10	6-6-1	N/A	N/A
Chong et al., 2015	RFID adoption	ANN	1	Testing 1 to 10	11-6-1	N/A	N/A
Ding, Yang, Chen, Long, & Wei, 2019	Mobile government services adoption	SEM + ANN	1	Testing 1 to 10	2-N/A-1 2-N/A-1 2-N/A-1 3-N/A-1 3-N/A-1	N/A	N/A
Foo, Lee, Tan, & Ooi, 2018	Sustainability performance	PLS-SEM + ANN	1	N/A	5-3-1	Sigmoid	Sigmoid
Gbongli, Xu, & Amedjonekou, 2019	Mobile-based money acceptance	SEM + ANN	1	Automatically by software	2-2-1 2-2-1 3-2-1 2-2-1	Sigmoid	Sigmoid
Hew et al., 2016	Mobile entertainment adoption	SEM + ANN	1	Automatically by software	3-2-1 3-2-1 3-2-1	Sigmoid	Sigmoid
Hew, Leong, Tan, Lee, & Ooi, 2018	Mobile social tourism shopping adoption	SEM + ANN	1	Automatically by software	3-2-1 3-2-1 5-3-1	Sigmoid	Sigmoid
Hew et al., 2019	Mobile social commerce adoption	ANN	1	Automatically by software	6-4-1	Sigmoid	Sigmoid
Higueras-Castillo et al., 2020	Electric and hybrid vehicles adoption	SEM + ANN	1	Automatically by software	3-2-1 4-3-1	Sigmoid	Sigmoid
Kalinić et al., 2019a	Customer satisfaction in m-commerce	SEM + ANN	1	Automatically by software	3-2-1 3-2-1 3-2-1	Sigmoid	Sigmoid
Kalinic et al., 2019b	Mobile payment adoption	SEM + ANN	1	Automatically by software	2-2-1 5-3-1	Sigmoid	Sigmoid
Kardan et al., 2013	Student course selection prediction	ANN	1	Testing 20, 30, 40 nodes	8-20-1 9-20-1	Sigmoid	Linear
Khan & Ali, 2018	Mobile payment adoption	SEM + ANN	1	N/A	8-N/A-1	Sigmoid	Sigmoid
Lee et al., 2020	Wearable payment adoption	PLS-SEM + ANN	2	Automatically by software	3-2-2-1 2-2-2-1 2-2-2-1	Sigmoid	Sigmoid
Leong et al., 2013	Mobile credit card acceptance	SEM + ANN	1	Automatically by software	2-2-1 3-2-1 2-2-1	Sigmoid	Sigmoid
Leong et al., 2015	Satisfaction with airliners	SEM + ANN	1	Automatically by software	3-N/A-1	Sigmoid	Sigmoid
Leong et al., 2018	Facebook commerce actual purchase	ANN	1	Automatically by software	11-7-1	Sigmoid	Sigmoid
Leong, Hew, Ooi, & Tan, 2019a	Spending in online group buying	ANN	1	N/A	6-4-1	Sigmoid	Sigmoid
Leong et al., 2019b	Social media addiction	SEM + ANN	1	N/A	5-3-1	Sigmoid	Sigmoid
Leong et al., 2020	Social commerce	SEM + ANN	1	Automatically by software	4-3-1	Sigmoid	Sigmoid
Li et al., 2019	Mobile social media adoption	SEM + ANN	1	Automatically by software	4-3-1 2-2-1	Sigmoid	Sigmoid
Liébana-Cabanillas et al., 2017	Mobile commerce adoption	SEM + ANN	1	Recommendations-best practice	4-2-1	Sigmoid	Sigmoid
Liébana-Cabanillas et al., 2018	Mobile payment adoption	SEM + ANN	1	Automatically by software	4-3-1 4-3-1 2-2-1	Sigmoid	Sigmoid
		MRA*+ANN	1	Testing 1 to 10	5-4-1	N/A	N/A

(continued on next page)

Table 3 (*continued*)

Source	Area	Methods	Number of hidden layers	How was the number of hidden neurons determined?	Network structure	Activation function Hidden layer	Output layer
Moosmayer, Chong, Liu, & Schuppar, 2013	Price negotiation outcome prediction						
Ooi & Tan, 2016	Smartphone credit card acceptance	PLS-SEM + ANN	1	Automatically by software	2-2-1 1-1-1 3-2-1	Sigmoid	Sigmoid
Ooi et al., 2019	Cloud computing in manufacturing	PLS-SEM + ANN	1	Automatically by software	3-2-1 2-2-1	Sigmoid	Sigmoid
Priyadarshinee et al., 2017	Cloud computing adoption	SEM + ANN	1	Automatically by software	5-N/A-1	Sigmoid	Sigmoid
Pozón-López, Kalinic, Higueras-Castillo, & Liébana-Cabanillas, 2020	Satisfaction with massive open online courses	SEM + ANN	1	Automatically by software	3-2-1 3-2-1	Sigmoid	Sigmoid
Qasem et al., 2020	Cloud computing adoption	PLS-SEM + ANN	1	N/A	7-10-1	N/A	N/A
Raut et al., 2018	Cloud computing adoption	SEM + ANN + ISM**	1	Testing 1 to 10	5-N/A-1	Sigmoid	Sigmoid
Raut et al., 2019	Big data analytics	SEM + ANN	1	Testing 1 to 10	5-10-1	Sigmoid	Sigmoid
Sharma et al., 2018	Mobile banking adoption	SEM + ANN	1	Testing 1 to 10	5-2-1	Hyperbolic Tangent	Identity
Sharma et al., 2015	Internet banking adoption	MRA*+ANN	1	Testing 1 to 10	10-4-1	Hyperbolic Tangent	N/A
Sharma et al., 2016a	Cloud computing adoption	MRA*+ANN	1	Testing 1 to 10	5-5-1	Hyperbolic Tangent	Identity
Sharma et al., 2016b	Facebook usage prediction	SEM + ANN	1	Testing 1 to 10	5-N/A-1	Hyperbolic Tangent	N/A
Sharma, Govindaluri, Al-Muharrami, & Tarhini, 2017a	Mobile banking adoption	MRA*+ANN	1	Testing 1 to 10	8-3-1	N/A	Hyperbolic Tangent
Sharma, Gaur, Saddikuti, & Rastogi, 2017b	E-learning management system acceptance	SEM + ANN	1	Testing 1 to 10	5-3-1	Hyperbolic Tangent	Identity
Sharma, Al-Badi, Rana, & Al-Azizi, 2018	Mobile government adoption	SEM + ANN	1	Testing 1 to 10	5-2-1	Hyperbolic Tangent	Identity
Sharma & Sharma, 2019	Mobile banking actual usage	SEM + ANN	1	N/A	3-2-1 3-2-1 2-2-1	Hyperbolic Tangent	Identity
Sharma et al., 2019	Mobile payment acceptance	SEM + ANN	1	Automatically by software	2-2-1 3-3-1 4-4-1	Hyperbolic Tangent	Identity
Singh, Singh, Kalinić, & Liébana-Cabanillas, 2020	Continued use of live streaming services	SEM + ANN	1	Automatically by software	2-2-1 4-3-1 4-3-1	Sigmoid	Sigmoid
Sim et al., 2014	Mobile music acceptance	MRA*+ANN	1	N/A	1-1-1 2-2-1 4-3-1 4-3-1	Sigmoid	Sigmoid
Sternad Zabukovšek, Kalinic, Bobek, & Tominc, 2019	Extended use of ERP software	SEM + ANN	1	Automatically by software	4-3-1	Sigmoid	Sigmoid
Tan et al., 2014	Mobile learning acceptance	SEM + ANN	1	Automatically by software	1-1-1 2-2-1 3-2-1	Sigmoid	Sigmoid
Teo et al., 2015	Mobile payment adoption	PLS-SEM + ANN	1	Automatically by software	3-2-1 2-2-1 2-2-1	Sigmoid	Sigmoid
Wong, Leong, Hew, Tan, & Ooi, 2020	Blockchain adoption in operations and SCM	PLS-SEM + ANN	1	N/A	4-3-1 2-2-1	Sigmoid	Sigmoid
Yadav et al., 2016	Mobile commerce adoption	SEM + ANN	1	Testing 1 to 10	6-4-1	Hyperbolic Tangent	N/A

Note: N/A = not available, i.e. the information is not presented in the paper
* MRA – Multiple Regression Analysis
** ISM – Interpretive Structural Modeling

Table 4
RMSE values for the neural networks with one and two hidden layers.

ANN model	RMSE_training	RMSE_testing	Training_time
One hidden layer	0.0966	0.0848	1.7
Two hidden layers	0.0973	0.0908	2.6

model simply memorizes all training examples, losing the ability to generalize and give a valid prediction when using data not used in the training set.

In the research presented, the number of hidden neurons was varied from one to 50, while keeping other neural network parameters the same. For each ANN model, ten runs were made, with a training set consisting of 90% of sampled data and a testing set (the remaining 10% being sampled data). The average values of RMSEs as well as average training times are presented in Table 5.

Table 5
RMSE values for the neural networks with variation of hidden neurons.

Number of hidden neurons	RMSE_training	RMSE_testing	Training_time
1	0.0973	0.0985	1.0
2	0.0958	0.0885	1.6
3	**0.0966**	**0.0848**	**1.7**
4	0.0976	0.0859	1.8
5	0.0960	0.0868	1.8
6	0.0966	0.0860	2.2
8	0.0978	0.0882	2.5
10	0.0971	0.0922	2.5
15	0.0975	0.0922	3.5
20	0.0988	0.0918	3.8
30	0.0970	0.0924	5.2
50	0.0967	0.0922	7.5
Average	0.0971	0.0900	2.93
St. dev.	0.0008	0.0040	1.85

As shown in Fig. 3, RMSE for the testing set has a minimal value for three hidden neurons, so therefore this value was set as the final parameter. In addition, it can be seen that as the number of hidden neurons, and hence, the complexity of the model increases, the training time also increases (Fig. 4).

Finally, based on the research for this paper and previous research on technology acceptance and related studies, presented in Table 3, the following rule-of-thumb is recommended for determining the number of hidden neurons in the case of one hidden layer and one output:

$$\text{Numberofhiddenneurons} = \text{INT}\left(\frac{\text{Numberofinputneurons}}{2}\right) + 1$$

where INT represents the integer part function.

6.3. Activation functions

Each neuron computes the weighted sum of the input signals and this sum is transformed to the usually limited output signal by activation function. Although in theory, there are many kinds of activation functions, only a few of them have practical applicability (Negnevitsky, 2011). The simplest of these, step and sign activation functions (also known as hard-limit functions) are not applicable to the problems such as those studied in this research, as they are generally used in classification and pattern recognition problems.

One of the most frequently used activation functions in feed-forward networks is the sigmoid function (Table 6), but in the research, two other activation functions present in used simulation software were also tested and compared: identity and hyperbolic tangent, both of which have also been used in some other prior studies (see Table 3).

It is worthy of mentioning that besides three analyzed activation functions, there are many others, such as Softmax, Rectified Linear Unit (ReLU), Leaky ReLU, and Scaled Exponential Linear Unit (SELU) (which outperforms ReLU in validation accuracy in image classification tasks (Goceri, 2019b)) which are particularly useful in complex deep neural networks, such as CNNs and RNNs. Unfortunately, some of these activation functions are not suitable for analyzing this problem (for example, Softmax can be used only if all dependent variables are categorical), while others are not supported by IBM SPSS – the most frequently used simulation software in social science studies. Finally, as presented in Table 3, none of the existing studies used an activation function other than those analyzed in this study, but this could be an avenue to explore in a future line of research.

Since there are two computing levels of neurons (hidden and output), it is necessary to set two activation functions, one on each level and for all neurons within them. Since it is only possible to set hyperbolic tangent and sigmoid functions in the hidden layer, there were six combinations of training and testing sets. Again, there were ten runs for each combination, using 90% of the sampled data for training of the ANN model and the remaining 10% for testing. The average RMSEs for the various combinations of activation functions in hidden and output layers are presented in Tables 7 and 8. The training time for each combination is presented in Table 9.

In line with the figures, although the training time is a bit higher, the minimum value of RMSE for the testing set for the sigmoid activation function in both hidden and output layers, is more than two times lower

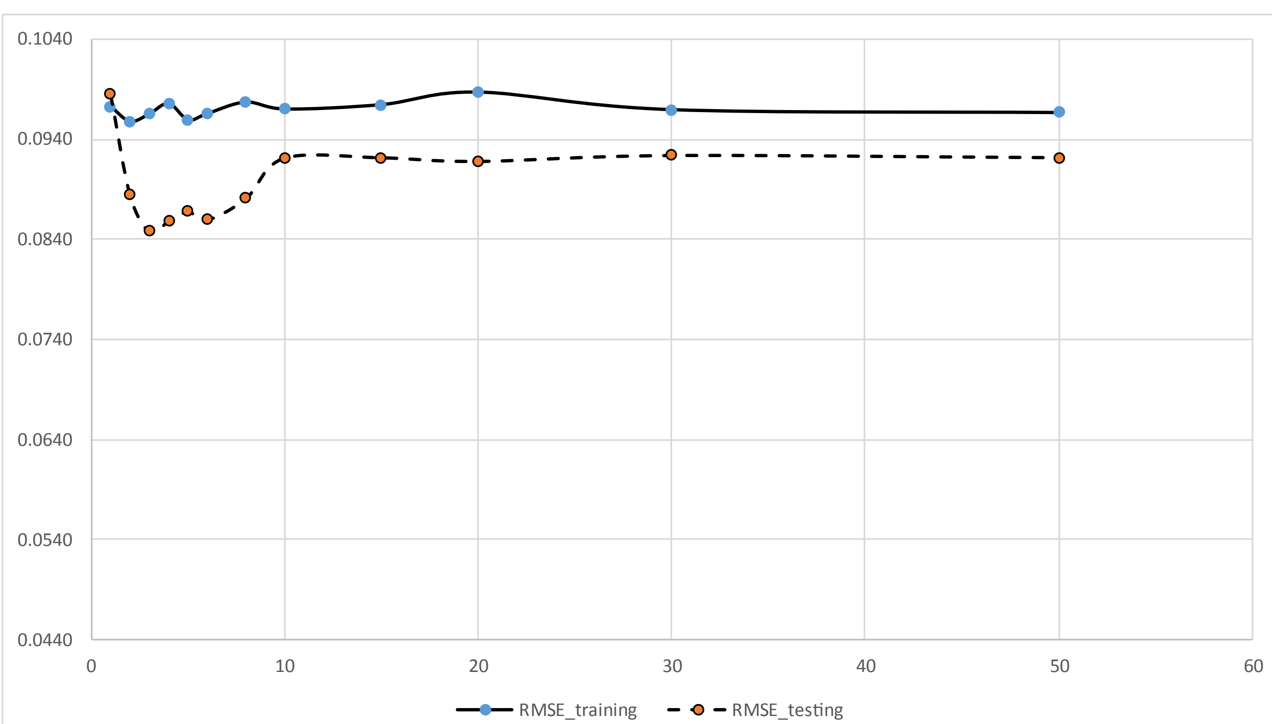

Fig. 3. RMSEs for training and testing sets for various values of the number of hidden neurons.

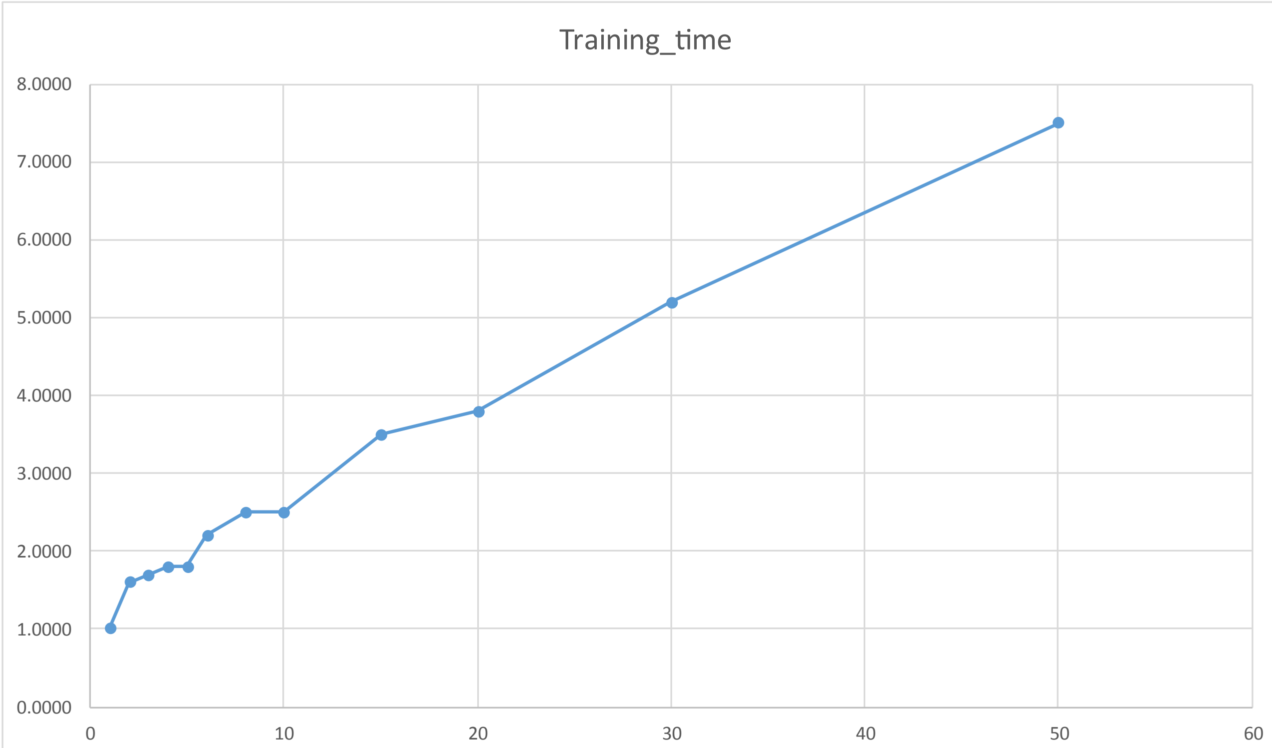

Fig. 4. Training time for different number of hidden neurons.

Table 6
Activation functions.

Activation function	Equation
Identity (Linear)	$f(x) = x$
Hyperbolic Tangent	$f(x) = \tanh(x) = \frac{2}{1+e^{-2x}} - 1$
Sigmoid (Logistic or Soft step)	$f(x) = \frac{1}{1+e^{-x}}$

Table 7
RMSE for the training set, for different combinations of activation functions.

RMSE_training	Output layer		
Hidden layer	**Identity**	**Hyperbolic Tangent**	**Sigmoid**
Hyperbolic Tangent	0.0957	0.1926	0.0970
Sigmoid	0.0967	0.1939	0.0966

Table 8
RMSE for the testing set, for different combinations of activation functions.

RMSE_testing Hidden layer	Output layer Identity	Hyperbolic Tangent	Sigmoid
Hyperbolic Tangent	0.0935	0.1817	0.0860
Sigmoid	0.0897	0.1854	0.0848

Table 9
Training time for different combinations of activation functions.

Training_time	Output layer		
Hidden layer	**Identity**	**Hyperbolic Tangent**	**Sigmoid**
Hyperbolic Tangent	1	1.3	1.7
Sigmoid	1.3	1.5	1.7

than RMSE for the testing set for the hyperbolic tangent activation function in both layers. Therefore, it is suggested that the sigmoid is set as an activation function in both layers.

6.4. Other ANN parameters

The ANN training process also requires several parameters to be set, which can significantly influence training speed and accuracy. These parameters include batch size, optimization method, loss function, learning rate, momentum, and the number of training iterations (epochs) (Yoo, 2019).

There are three main types of ANN training, based on the number of training records (examples) passed through the ANN before synaptic weights update (IBM SPSS, 2019):

- Batch. Synaptic weights are updated only after passing all training records. On the positive side, this approach directly minimizes the total error, but it might require many data passes before some of the stopping rules are met. Generally, it is used for smaller datasets.
- Online (opposite of Batch type). Synaptic weights are updated after every single training record. This approach can more quickly converge to a final solution and is superior for larger datasets.
- Mini-batch. This training dataset is divided into groups of approximately equal size, and the synaptic weights are updated after passing each group. This approach offers a compromise between batch and online training, and is usually applied to medium-size datasets. The size of a mini-batch significantly influences training performances (Goceri & Gooya, 2018; Yoo, 2019).

Another important parameter of ANN training is optimization algorithm, used to change ANN attributes (such as synaptic weights and learning rates), in order to minimize losses. There are several options: gradient descent, with several variations (a very popular algorithm, suitable for all three types of training); scaled conjugate gradient (suitable only for batch training); Adam; Sobolev gradient-based

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Further reading

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