Data Protection as Predictor for the Acquisition of AI Devices

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Abstract
The significant development of AI has started to have an important impact on how people interact with robots and intelligent devices in the near future. Starting from the simplest AI forms, such as mobile applications for consumers' daily activities (example: e-commerce or health apps) to more complex forms of AI (example: robotic surgery), people represent its main beneficiary. Still, the consumers' acceptance and embracement of AI can depend on different factors. An important issue is represented by the collection of the individuals' private information, as mobile applications require different permissions in order to be installed and to be used. AI devices will also have the capacity to register private data, under specific forms. The main objective of this research is to analyze if the data protection associated with the AI usage directly influence the buying decision. The study was constructed using three pillars: willingness to buy an AI device, vulnerability of consumer related to data privacy concerns and the ability to control the private data used by AI devices. Using structural equation models in Smart-PLS3, it was shown that the vulnerability generated by the data accumulated by the AI does not influence the buying decision, while the ability to control the private data does play an important role for the willingness of consumers to buy AI devices. The practical implication of the research is given for the design of future AI devices as well as their future marketing and sales strategy. It should be taken into consideration the fact that for consumers it is important to control the availability of private data usage. Therefore AI devices should incorporate the possibility of consumers to switch-off the intelligent devices and enjoy their private life.

Keywords: Artificial intelligence, data protection, data privacy, consumer, buying decision, computer-human interaction.
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Introduction

The multifaceted applications and forms of artificial intelligence (AI) are manifested today by machines that are able to exhibit aspects of human intelligence, mimic human gestures and perform actions in the most accurate and human-like manner (Huang and Rust, 2018). It is no secret that data gathering, in-formation processing and problem solving are often achieved with the help of AI, in its many forms and different ways of working. Starting from simple mobile applications that help us achieve daily activities and going further to more complex tasks (e.g. consumer profiling or even social engagement), AI has become, without any doubt, an indispensable part of our daily life and routine.

Driven by data and information, AI-based software reach an out-standing performance by collecting, processing and analyzing consumers' data, whereby consumers' data protection becomes a more and more debated and researched subject nowadays. In many cases the need to protect personal data and the privacy associated with the use of AI devices comes to the fore and it is likely to be valued higher, sometimes even outweighing the benefits provided by the performance and accuracy of AI-systems (Kaplan and Haenlein, 2020). Moreover, theoretical research proves that privacy is sometimes to be defined context-specific as a *subtle good*, whereby it is about context-dependent economic properties of the related data (Farrell, 2012; Pelau, et al., 2019). In the digitalization era and the current AI context, the vulnerability of consumers related to privacy concerns and the ability to control the private data used by AI devices may become exchange goods in order to get the best of AI technologies. This interchange between data protection and the acquisition and further usage of AI came to be context-dependent and AI users may not always be aware of it.

To assess the influence of private data and the users' control ability over it on the willingness to buy an AI device, the present paper tries to examine if both data protection and the need for privacy influence the buying decision of consumers for such AI-devices. In the following sections of the present article, we review some existing applications and uses of AI. We then propose and empirically test an econometric model for private data as predictor for buying decision of AI devices. After conducting the quantitative research, we present and discuss the model results.

Literature review

The fabrication and usage of artificially intelligent devices has registered significant increase during the last period (Duan, et al., 2019). Starting from the robots used in factories for assembly lines to the ones used already in the hospitals for performing complex operations, AI is starting to be described as a necessary component in the production process. The increase of AI's abilities to replace human actions (Anthes, 2017; Anica-Popa, et al., 2021) like translating human language, conduction online search, can be only a part in the AI future evolution.

One of the primary lines in which people enter in contact with AI, are the smartphone mobile applications that perform a higher number of complex functions. The mobile applications represent a significant business sector as 1.85 million different apps are available for users to download from iOS App Store and 2.56 million available through the Google Play Store (Iqbal, 2020). Consumers are more familiar with the apps, due to the fast and easy access and use them in daily basis activities such as buying products, socialize with friends, sports activities being also more attracted by the brands that are offering mobile aps (Bellman, et al., 2011).

A large number of apps are using information received from the users. Therefore, they adapt constantly to the user behavior in terms of preferences, historical searches, GPS location. There is a permanent "learning process", based on which applications personalize consumers' information (Vesanen, 2007). The most common example in this sense is Nike + Run Club or Samsung Health that creates users collectivities in which information can be shared through the users. Mobile applications are also used by the brands in advertising campaigns, in order to increase brand loyalty (Wang, et al., 2015). They are developed for an easier communication with the users (Pantano and Priporas, 2016) or as support for the experience in the shopping environment (Albastroiu, et al., 2018; Dabija and Babut, 2019) During COVID pandemic lockdown, more and more brands convergence to the digital environment by creating apps or associating with existing apps in order to sell their products.

Another form of AI interaction with consumers are the chatbots used by companies in order to transform the customer service perspective (Cath, et al., 2018; Wirtz, et al., 2018). They represent automated programs that can communicate with the consumers by text (Przegalinska, et al., 2019; Radziwill and Benton, 2017; Sivaramakrishnan, et al., 2007). Consumers are open to this kind of communication that provides various services from food delivery to bank information (Sivaramakrishnan, et al., 2007; Luo, et al., 2019). The main benefit of chatbots is that they are easy to use and assures low cost services for companies (Przegalinska, et al., 2019; Radziwill and Benton, 2017). Based on PointSource estimation, by the end of 2020, chatbots will provide 85% from the total customer services area (PointSource, 2018). Another important element is that consumers can interact with chatbots on all available platforms like tablets, desktop or mobile devices (Araujo, 2018; Luo, et al., 2019). The major advantage of chatbots is that they can offer assistance to consumers at any given time and place (Chung, et al., 2018; Holzwarth, et al., 2006). The chatbots can also help increasing customer satisfaction by offering permanent assistance services (Radziwill and Benton, 2017). The AI presented above can be seen as a basic interaction form with AI, with which users are nowadays familiar and that can be used and implemented in day by day life. Another AI area is represented by robots that are used in hospitality and tourism sectors. With the help of IBM, Hilton Worldwide created a robot concierge named “Connie”. Residence Inn by Marriott and Aloft Hotels use robots for delivering room services called “Relay” and “Wally” (Crook, 2014; Silva and DeSocio, 2016; Marin-Pantelescu et al., 2019). In Amsterdam, KLM has “Spencer”, a robot for customer services to guide passengers (KLM, 2016) and Royal Caribbean’s Quantum of the Seas use robots at the bar (Majendie, 2015).

Due to the increased development of AI, its adoption is on an increasing curve. Besides, AI devices and robots are constantly improved in order to deliver higher quality services based on an increased data storage and processing speed (West et al., 2018). From the company’s perspective, this can lead also to operational cost decrease by reducing human workload (Cobos, et al., 2016; Marinova, et al., 2017; West, et al., 2018; Busu and Gyorgy, 2020; Or, et al., 2021).

During the last years, a large number of studies have been developed in order to test people willingness to accept and interact with AI. For example Niemel et al., (2017) discovered that hedonic motivation is the main premise that directly influence customers’ intention to use AI in retail stores. Other findings are related to the usefulness and ease to use characteristic of AI (Davis, et al., 1989; Hsiao and Yang, 2011; Ozturk, et al., 2016; Wang, et al., 2018b), previous experiences (Morgan-Thomas and Veloutsou, 2013), social influence (Pelau, et al., 2021) or cognitive process (Venkatesh and Davis, 2000). Lu, et al. (2019) has highlighted six factors for using AI devices and robots in service delivery: performance efficacy, hedonic motivation, anthropomorphism, social influence, facilitating condition, and emotion. In the last period, social robots have been used in various services (Kuo, et al., 2017), from tourism to medical areas.

One of the customers’ main concerns is related to the fact that robots can in a near future replace a serial of human jobs, some researchers even think that a total replacement of humans is possible (Ivanov and Webster, 2018; Microsoft, 2018; Banacu, et al., 2019; Li, et al., 2019). Still, people are becoming more familiar with AI and with the benefits provided by it. It is possible that a step by step transition will conduct to high benefits in the near future.

Research methodology and data collection

The objective of our research is to determine if the protection of data and privacy associated with the use of AI devices has an impact on the buying decision of consumers for such devices. Data collection took place based on an online survey, which has been carried out in September 2020 on a pilot sample of 76 respondents. The questionnaire contained several items for the following constructs: willingness to buy an AI device (4 items self-determined and adapted after Bruner (2019); Kumar and Pansari (2016)), vulnerability of consumer relate to data privacy concerns (5 items adapted after Bruner (2019); Kelly, et al. (2018)) and the ability to control the private data used by AI devices (4 items adapted after Bruner (2019); Kelly, et al. (2018)). The data has been analyzed with the help of SPSS 20.0 for the confirmatory factor analysis and with Smart-PLS3 for determining the relation between the variables.

Results of the factor analysis

In order to test the reliability of the data a confirmatory hierarchical factor analysis with varimax rotation has been performed in SPSS20. The Kaiser-Mayer-Olkin criterion of 0.803 (Chi=898.7, p=0.000) indicates a good fit of the data for the factor analysis. The result of the three determined factors have a cumulated variance of 81.597. The loadings of each of the items can be observed in table no. 1.

The item loadings with values higher than 0.7 indicate a good fit for the determined constructs. Only the item info6 had a loading of 0.634 but has been kept for the further analysis. It can be observed that the items related to the private data have been split among two factors.

Table no. 1. Results of the confirmatory factor analysis with varimax rotation in SPSS20

Var	Item	Buy	Data1	Data2	Cronbach-Alpha
Buy1	I wish I had a robot to help me with my daily activities	.858			0.934
Buy2	I am willing to buy a robot to help me with my daily activities	.935			
Buy3	I will continue my interaction with the robot in the near future	.910			
Buy4	The purchase and usage of a robot make me content	.871			
Info1	Personal information used by robot makes me insecure		.884		0.947
Info2	Personal information used by robot makes me exposed		.936		
Info3	Personal information used by robot makes me threatened		.861		
Info4	Personal information used by robot makes me vulnerable		.903		
Info5	Personal information used by robot makes me susceptible		.930		
Info6	I believe I have a control over what happens to my personal information in relation to the robot			.634	0.889
Info7	It is up to me how much the robot uses my information			.860	
Info8	I have a say in how my information is used by the robot			.936	
Info9	I have a say in whether my information is shared with others			.898	

Source: Own research results.

The first factor contains the items about the perceived vulnerability of exposing private information. These are associated with feelings such as insecurity (0.884), exposure (0.936), threat (0.861), vulnerability (0.903) and susceptibility (0.930). The second factor contains items about the consumers' perception to have a control over the data provided to the robot or AI device. It contains items about the belief of having control over the provided private data (0.634), the amount of the provided data (0.860), the way in which the information is used (0.936) and if it is visible to others (0.898).

Results and discussion

In order to test the impact of the consumers' perception of private data use by AI on the buying decision a structural equation model in SmartPLS3 has been tested. For this model, there have been used the previously determined independent variables related to the perceived vulnerability of consumers by exposing the private data (private data 1) and the consumers' ability to control the exposed private data (private data 2). The dependent variable is the consumers' willingness to buy AI devices, as it has been previously determined in the confirmatory factor analysis. In order to test the relations, a two-tailed bootstrapping method based on 500 subsamples has been performed by applying a partial least square structural equation model. The results of SEM can be observed in table no. 2, while the graphical representation of the model can be observed in figure no. 1.

Table no. 2. PLS-SEM results about private data as a predictor of the buying decision of AI devices

Path	Coefficient (original sample)	Coefficient (Sample mean)	t	p	CI
Private data 1 → Buy	0.357	0.092	1.562	0.119	[-0.324; 0.417]
Private data 2 → Buy	0.426	0.431	4.188	0.000	[0.204; 0.621]

Source: Own research results.

The results of PLS-SEM show that only the variable private data 2, about the perceived control of the exposure of private data through AI devices has a significant influence on the buying decision of AI devices. The bootstrapping coefficient mean has a value of 0.431 (t=4.188, p=0.000) and a confidence interval with positive values CI=[0.204; 0.621]. This shows that the ability to control the exposed private data influences in a positive way the buying decision of AI devices. On the other hand the vulnerability created by the exposure of data does not influence in a significant way the buying decision of

AI devices. In spite of the positive value of the coefficient for the original sample of 0.357, the bootstrapping coefficient mean of samples has a lower value of 0.092. This is also confirmed by the t-value t=0.119 (p=0.119) and the CI=[-0.324; 0.417] containing the value 0. Probably it depends on each consumer how he/she perceives his/her vulnerability by the exposure of private data and information. It is not the vulnerability that predicts the buying decision, but the ability to control the exposed private data and information.

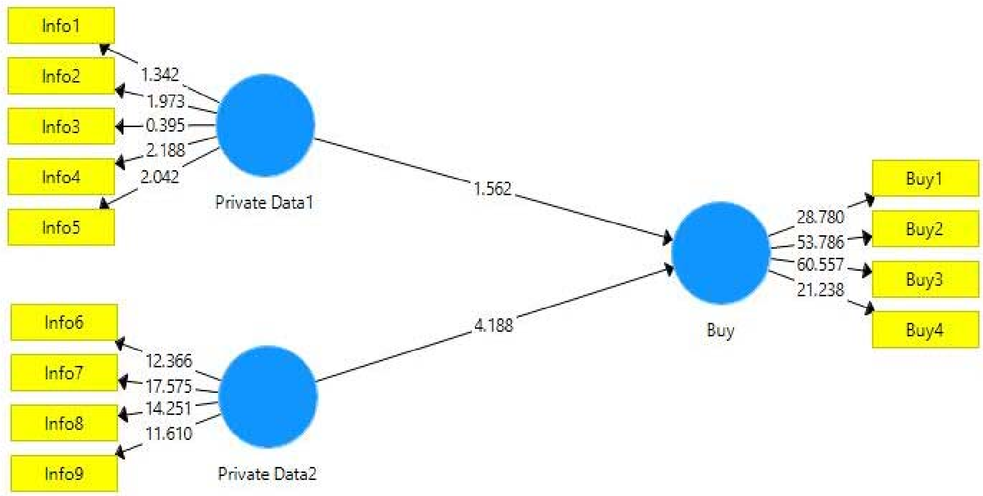

Figure no. 1. Econometric model for private data as predictor for buying decision of AI devices – Results from SmartPLS3

Source: Own research results.

Conclusion

The results of our research show that the buying decision of AI devices is influenced by their ability to collect private information. Based on the study, it is not the collection of private data gather by AI that have a direct impact on the buying decision, but the important factor that counts for the consumers is their ability to control the private data collected by AI.

Nowadays the development of AI plays an important role in almost all the fields. Due to the COVID pandemic, people were forced to embrace rapidly new forms of AI, starting from mobile apps (e-commerce, grocery delivery apps, food delivery apps) to more elaborated forms (online meetings, doctor online appointments). A change has been made in this direction and after half year of COVID pandemic, people are more willing to use and interact with AI, for their own benefit. Still, the problem of private data is a concern, but apparently this influences less the buying decision. Consumers understand their privacy vulnerability but they also consider that they can manage it by the ability to control how much information they are sharing.

In the near future, probably the human civilization is going to relay more on AI, starting from simple tasks that can improve an individual activity to more complex one. The most important factor will be to find a balance between the private data that consumers are sharing and the benefits that results from it.

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