When Users Meet AI: Customer Acceptance of Recommendation Systems in Online Shopping

Vaida Kaduškeviit
Faculty of Economics and Business Administration, Vilnius University
Božena Mackevi?i?t?
Vilnius University

Cite as:
Kaduškeviit Vaida, Mackevi?i?t? Božena (2022), When Users Meet AI: Customer Acceptance of Recommendation Systems in Online Shopping. *Proceedings of the European Marketing Academy*, 50th, (111795)

Paper from the EMAC Regional 2022 Conference, Kaunas, Lithuania, September 21-23, 2022

When Users Meet AI: Customer Acceptance of Recommendation Systems in Online Shopping

Abstract

Study analyses how a set of factors influences intention to use recommendation. Based on theoretical analysis, Technology Acceptance Model and Theory of Planned Behaviour are employed while investigating this intention. Additionally, privacy risk and trust are chosen as important predictors. Survey revealed that perceived ease of use, perceived usefulness, trust and privacy risk has an impact on, while trust and privacy risks have an impact on perceived behavioural control. Finally, attitude was found out to have a strong impact on intention to use recommendation systems while perceived behavioural control did not have significant impact on intention to use recommendation systems.

Keywords: *Recommendation Systems, Trust, Privacy Risk*

Introduction

Rapidly evolving technology is opening up new opportunities for e-commerce users. E-commerce, in response to this technological phenomenon, promotes changes in consumer behaviour and habits and the performance of daily activities (Wu & Liao, 2011). With the popularity of online commerce and the number of technological tools being implemented in them, consumers can find more efficient and more affordable offers and prices (Nguyen et al., 2019). New technological solutions in commerce allow the consumer to shop faster and more conveniently, have a wider choice of products, find the information they need about the product they are looking for, reduce contact shopping, get personalized offers, and be the focus of salespeople (Macik, Mazurek, & Macik, 2012). As a result, innovative technological solutions are becoming integral to the consumer experience and decision-making processes in e-shops.

Technological advances have also accelerated e-commerce solutions to deploy artificial intelligence (AI), which facilitates the shopping process and seeks to meet consumer needs. Such solutions allow consumers to choose products and shop online in new ways (Lixandroiu, Cazan, & Maican, 2021). Improvements in innovative solutions are accelerating the change in e-commerce. With this change, consumer habits and experiences during shopping are also changing, as e-shop users use widespread chatbots, customized product recommendations, and customer feature recognition (Yin & Qiu, 2021). Such personalization of shopping improves and increases sales and changes the shopping experience. Artificial intelligence systems automatically analyse Big Data, interpret and shape user behaviour profiles, offering personalized products and services, thus improving their shopping experience (Nagy & Hadjú, 2021). Therefore, the introduction of technological tools in e-shops is no longer an indicator of advantage and competitiveness, but also e-commerce. part of the operation of marketplaces.

With a large amount of products and information about them, consumers face the problem of information overload. With large amounts of information in cyberspace, it is more difficult and longer for consumers to search for goods that interest them. In the e-commerce space, consumers also lack a contact with the seller who can offer quality recommendations, thus facilitating the product search process for the consumer. These difficulties and problems have led to the development of recommendation systems (RS).

1. Literature Review

1.1. Recommendation systems

Recommendation systems are the implementation of artificial intelligence that creates and provides users with personalized, high-quality recommendations in an e-shop. These systems create suggestions using user behavioural or customer-related information to process large amounts of data systematically and quickly. Often, in research, recommendation systems are identified as successful e-marketing tools to increase sales (Smith & Linden, 2017). Zhao et al. (2018) argue that recommendation systems create both short-term and long-term benefits for business. The first store to implement recommendation systems and successfully implement them are Amazon and Ebay, which have increased customer engagement, reduced product search time, and adopted a systematic approach to managing large amounts of consumer behaviour and product information (Smith & Linden, 2017).

The implementation of recommendation systems in e-shops depends primarily on consumers' choice to accept and use them. Consumer behaviour in e-shops is often determined by personal choices. These choices may be influenced by combinations of internal and external factors, with external factors independent of the individual and internal psychological and behavioural traits (Lixandroiu, Cazan, & Maican, 2021). Research analyses factors such as personal characteristics influencing behaviour, behavioural effects of product categories, or attitude-shaping variables that determine the intention to use innovative technological applications (Chen, Liang, Liao, & Kuo, 2020; Lu, Chang, & Chang, 2014; Lixandroiu, Cazan & Maican, 2021). In addition to the psychological aspects of research, technological factors related to consumer readiness, opportunity, innovation, security, privacy risks, and trust in technology are also explored (Hoyer et al., 2020, Lee, 2017; Wang, Yeh, & Liao, 2013; Elliot, Meng, & Hall, 2012; Lixandroiu, Cazan, & Maican, 2021; Bashir & Madhaviah, 2015). These research factors are often supported by theories of technology acceptance and planned behaviour that reveal the factors that determine the use of technology in e-commerce.

1.2. Theory of Planned Behaviour and Technology Acceptance Model

One of the most widely used models in the field of recommendation systems, is Technology Acceptance Model (TAM) (Davis, 1989). TAM incorporates perceived ease of use and perceived usefulness as attitude-shaping variables, which in turn defines the intention to use technology. This model explains users' perceptions of the characteristics of the technology under study and allows the analysis of what variables shape the intention to use.

The Planned Behaviour Theory (TPB) (Ajzen, 1991), which seeks to analyse and explain a person's behaviour in specific contexts, has laid the background for the development of the TAM. In this theory, behavioural intentions are determined by attitude, perceived behavioural control, and subjective norms. The use of the model in a variety of disciplines has demonstrated that the versatility, practicality, and meaningful results of the theory are indisputable (Chen et al., 2020).

When analysing behavioural factors using constructs of technology acceptance and planned behaviour models, researchers often supplement these models with external variables: confidence, risk, personal characteristics, and so on.

1.3. Perceived usefulness and perceived ease of use

TAM model distinguishes two factors that affect a person's intention to perform an action through their approach to technology, which is influenced by perceived ease of use and perceived usefulness. These beliefs make it possible to determine what factors shape attitudes towards information technology. Perceived ease of use for consumers is "the desired expectation that technology is as simple and clear as possible" (Ribokas & Burinskiene, 2019), and perceived usefulness of technology creates an attitude in the consumer that using technology will increase their productivity (Ribokas & Burinskiene, 2019). Under TAM model, perceived usefulness is affected by perceived ease of use.

1.4. Trust in recommendation systems

The concept of trust is widely discussed when analysing the use of technology in cyberspace. The choice to use technology is based on trust, so the construct of trust is approached with a technology acceptance model where trust is found to have a significant impact on attitudes towards the use of technological tools in e-commerce (Wu & Ke, 2015; Xie, Song, Peng & Shabbir, 2017; Yang, Lee & Zo, 2017).

1.5. Privacy risk

Many studies have revealed that perceived risks have a significant impact on the decision to use technological solutions in cyberspace, thereby also influencing consumer attitudes towards the use of a recommendation system (Zhou, 2010). Privacy risks also negatively affect perceived control, and loss of control negatively affects intentions (Bashir & Madhaviah, 2015). In the context of artificial intelligence-enabled tools, the assessment of privacy risks as part of the concept of perceived risk is complex but important. Due to the disclosure of personal data and the potential negative consequences, consumers feel at risk and reduce consumer confidence in the measures put in place (Hasan, Shams, & Rahman, 2020).

1.6. Attitude and perceived behavioural control

TPB argues that consumer attitudes directly define intention and thus influence behaviour. The more positive the attitude towards behaviour, the stronger the intention to use. A person's attitude can be determined by a variety of factors. Many studies incorporate elements that affect a situation and distinguish them from product type, trust and risk (Singh & Srivastava, 2018), product quality (Hendra & Lusiah, 2017; Haque et al., 2015), technology functionalities (Kim, Lee & Preis, 2020) as factors influencing consumer intentions.
Online channel is capable of placing great amount of information regarding product. As a consequence, this provides consumers with greater control over their behaviour because they have almost no limits to find all desired information about the product and place their order (Estrella-Ramon, Sanchez-Perez & Swinnen, 2016). As well, one of the biggest advantages of online channel is possibility to track delivery status which increases consumer’s perceived behavioural control over that purchase (Nguyen, de Leeuw & Dullaert, 2016).

2. Methodology
2.1. Hypotheses

Empirical studies in different contexts show that the relationship between perceived ease of use and perceived usefulness is positive. The easier it is for consumers to use information technology, the more likely they are to use it and to see its benefits (Wei, Lee & Shen, 2018; Nguyen et al., 2019; Dachyar & Banjarnahor, 2017; Abbas, 2014). This allows to raise following hypotheses:
H1. Perceived ease of use has a direct and positive impact on attitude towards using recommendation systems.
H2. Perceived usefulness has a direct and positive impact on attitude towards using recommendation systems.
Although many studies have revealed a relationship between trust and attitude, only a few studies have examined the impact of trust on perceived behavioural control (Xie, Song, & Peng, 2016; Hansen, Saridakis, & Benson, 2018; Yang, Lee, & Zo, 2017). High confidence in technology can increase a person’s perceived control over using a technological tool. Therefore, the following hypotheses are being raised:
H3. Trust has a direct and positive impact on attitude towards using recommendation systems.

H4. Trust has a direct and positive impact on perceived behavioural control towards using recommendation systems.

Concerns about the disclosure of personal data to websites negatively affect consumers 'perceptions of an efficient and secure way to perform daily activities in the online space with the help of technological tools (Nguyen & Khoa, 2019). Also, distrust of a recommendation system that uses personal user data when creating proposals can be negatively affected by a privacy risk factor (Pappas, 2018).

H5. Privacy risk has a direct and negative impact on attitude towards using recommendation systems.

H6. Privacy risk has a direct and negative impact on perceived behavioural control towards using recommendation systems.

TPB is a common ground in researching purchase online behaviour and intention related with it. Attitude and perceived behavioural control are proved to have impact on purchase intention online in numerous studies (Hansen, Jensen & Solgaard, 2004; George, 2004; Hsu et al., 2006). This allows to raise following hypotheses:

H7. Attitude has a direct and positive impact on intention to use recommendations systems.

H8. Perceived behavioural control has a direct and positive impact on intention to use recommendation systems.

2.2. Measurement

Constructs of perceived ease of use and perceived utility consist of 6 statements adapted from Martínez-López et al. (2015). The trust scale construct consists of 3 statements according to the technology confidence scale developed by Gulati, Souda & Lamas (2019). The scale of the privacy risk construct was adapted from Xu, Michael, and Chen (2013) study and consists of 3 items. The construct of the attitude consists of 3 statements based on Hernández, Jiménez, and Martin (2010). 3 perceived behavioural control statements adapted and constructed according to Peña-Garcia et al. (2020) study. The intention to use a recommendation system is based on Shen and Zolfagharian (2014) and this construct consists of 3 statements. Measurements for all variables will be measured using the Likert scale, where respondents select one point from 1 to 7 that best reflects their choice. These scales use definitions to measure each point, from strongly disagree to strongly agree. Also, the reliability of each selected construct is assessed as valid and suitable for use in the study.

2.4. Results

To test hypotheses, SPSS 23 software was employed. Performed exploratory factor analysis and subsequent testing of hypotheses on the basis of correlation analysis. Extraction method of maximum likelihood and Promax rotation with Kaiser Normalization have been applied. KMO and Bartlett's test high significance ($p=0.000$), Kaiser-Meyer-Olkin measure of sampling adequacy = 0.830; approx. chi-square = 8388.589; df=595. Together, the five considered factors explain 28.74% of the variance.

For all scales reliability analysis was implemented. Perceived ease of use was investigated with 3 items, resulting in high reliability ($\alpha=0.769$). For perceived usefulness were used 3 high reliability ($\alpha=0.827$) items. Trust was measured with 3 high reliability ($\alpha=0.817$) items. Further, privacy risk was tested with 3 high reliability ($\alpha=0.780$) items. Scale measuring attitude consisted of 4 highly reliable items ($\alpha=0.859$). Moreover, perceived behavioural control, which was measured with 3

items showed high reliability as well (α=0.780). Finally, intention to use recommendation systems was measured with 3 high reliability (α=0.832) items.
Hypotheses were tested on the basis of regression model.
First of all, analysis of how perceived ease of use, perceived usefulness, trust and privacy risk has an impact on attitude towards using recommendation systems.
The linear regression showed F=84.052, p=0.000 for ANOVA, adjusted R^2=0.496. Table 1 summarizes the model.

Table 1. Linear regression coefficients (attitude)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.177	.287		11.072	.000
	Perceived ease of use	0.149	0.039	0.168	3.851	0.000
	Perceived usefulness	0.166	0.035	0.223	4.754	0.000
	Trust	0.309	0.034	0.401	8.991	0.000
	Privacy risk	-0.169	0.030	-0.228	-5.663	0.000
a. Dependent Variable: Attitude						

First of all, perceived ease of use has statistically significant (p=0.000) and positive impact (β =0.168, t=3.851) impact on attitude towards using recommendation systems. This allows to confirm H1. Secondly, perceived usefulness has a significant (p=0.000) and positive impact (β=0.223, t=4.754) on attitude towards using recommendation systems. Therefore, hypothesis H2 is confirmed. Trust also has a significant (p=0.000) and positive impact (β=0.401, t=8.991) on attitude towards using recommendation systems. Thus, H3 is confirmed. Finally, privacy risk has statistically significant (p=0.000) and negative impact (β=-0.228, t=-5.663) on attitude towards using recommendation systems. This allows to confirm H5.
Second step is to analyse how trust and privacy risk influence perceived behavioural control. The linear regression showed F=21.457, p=0.000 for ANOVA, adjusted R^2=0.108. Table 2 summarizes the model.

Table 2. Linear regression coefficients (perceived behavioural control)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	5.103	0.311		16.391	0.000
	Trust	0.225	0.043	0.272	5.172	0.000
	Privacy risk	-0.118	0.042	-0.148	-2.816	0.005
a. Dependent Variable: Perceived behavioural control						

As seen from results in the table, trust has statistically significant (p=0.000) and positive impact (β=0.272, t=5.172) on perceived behavioural control towards using recommendation systems which allows to confirm H4. On the other hand, privacy risk has a significant (p=0.000) and negative impact (β=-0.148, t=-2.816) on perceived behavioural control. H6 is confirmed.
Finally, analysis of how attitude and perceived behavioural control towards using recommendation systems has an influence on intention to use those systems is implemented.

The linear regression showed F=145.558, p=0.000 for ANOVA, adjusted R^2=0.461. Table 3 summarizes the model.

Table 3. Linear regression coefficients (perceived behavioural control)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	0.421	0.305		1.379	0.169
	Attitude	0.225	0.043	0.272	5.172	0.000
	Perceived behavioural control	0.092	0.048	0.083	1.902	0.058
a. Dependent Variable: Intention to use recommendation systems						

Results reveal that attitude has a significant (p=0.000) and positive impact (β=0.272, t=5.172) on intention to use recommendation systems. Thus, H7 is confirmed. On the other hand, impact of perceived behavioural control does not have an impact (p=0.058) on intention to use recommendation systems. As a result, H8 is not confirmed.

3. Discussion, Limitations and Further Research

The study revealed that perceived ease of use and perceived usefulness are important technological features that positively shape consumer attitudes. It is suggested that RS developers take these results into account and provide users with a simple RS design that does not require much effort or knowledge to operate. Moreover, it can be concluded that trust is the most important factor shaping consumer attitudes towards the use of RS, thus determining the intention to use it. Merchants must ensure that consumers are informed about the usefulness of the RS system and its desire to best meet the needs of the user, to improve the e-commerce experience and strengthen confidence in the technological tool.
Summarizing the results of the empirical study, it can be stated that e-retail website visitors to use the recommendation system are encouraged by the overall positive attitude, which is defined by strong trust, simple and clear use. Also, the ability to control the choice to use the system independently positively encourages the user to use the recommendation system.

References

1. Abbas, A. (2014). An empirical investigation to validate the technology acceptance model (TAM) in explaining intentions to shop online in Saudi Arabia using SEM. Jordan Journal of Business Administration, 10(2), 317-332.
2. Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179-211.
3. Bashir, I., Madhavaiah, C. (2015). Trust, social influence, self-efficacy, perceived risk and internet banking acceptance: an extension of technology acceptance model in Indian context. Metamophosis, 14(1), 25-38.
4. Chen, H. S., Liang, C. H., Liao, S.Y., Kuo, H.Y. (2020). Consumer attitudes and purchase intentions toward food delivery platform services. Sustainability, 12(23), 1-18.

5. Cho, Y.C., Sagynov, E. (2015). Exploring factors that affect usefulness, ease of use, trust, and purchase intention in the online environment. International Journal of Management & Information Systems, 19(1), 21-36.
6. Dachyar, M., Banjarnahor, L. (2017). Factors influencing purchase intention towards consumer-to-consumer e-commerce. Intagible Capital, 13(5), 948.
7. Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319-340.
8. Elliott, K., Meng, G., Hall, M. (2012). The influence of technology readiness on the evaluation of self-service technology attributes and resulting attitude toward technology usage. Services Marketing Quarterly, 33(4), 311-329.
9. Estrella-Ramon, A., Sanchez-Perez, M. & Swinnen, G. (2016). How customers' offline experience affects the adoption of online banking. Internet Research, 26(5), 1072-1092.
10. George, J.F. (2004). The Theory of Planned behavior and Internet Purchasing. Internet Research, 14(3), 198-212.
11. Gulati, S., Souda, S., Lamas, D. (2019). Design, development and evaluation of a human-computer trust scale. Behaviour and Information Technology, 38(3), 1-12.
12. Hansen, J.M., Saridakis, G., Benson, V. (2018). Risk, trust, and the interaction of perceived ease of use and behavioral control in predicting consumers' use of social media for transactions. Computers in Human Behavior, 80(1), 197-206.
13. Hansen, T., Jensen, J.M. & Solgaard, H.S. (2004). Predicting Online Grocery Buying Intention: A Comparison of the Theory of Reasoned Action and The Theory of Planned Behavior. International Journal of Information, 24(6), 539-550.
14. Haque, A., Anwar, N., Yasmin, F., Sarwar, A., Ibrahim, Z., Momen, A. (2015). Purchase intention of foreign products: A study on Bangladeshi consumer perspective. SAGE Open, 5(2), 1-12.
15. Hendra, Lusiah (2017). Impact of brand image, product quality and self-efficacy on purchase decisions on private label rights products. Expert Journal of Business and Management, 5(2), 74-82.
16. Hernández, B., Jiménez, J., Martin, M.J. (2010). Customer behavior in electronic commerce: The moderating effect of e-purchasing experience, Journal of Business Research, 63(9), 964-971.
17. Hoyer, W.D., Kroschke, M., Schmitt, B., Kraume, K., Shankar, V. (2020). Transforming the customer experience through new technologies. Journal of Interactive Marketing, 51(1), 57-71.
18. Hsu, M.-H., Yen, C.-H., Chiu, C.-M. & Chang, C.-M. (2006). A longitudinal investigation of continued online shopping behavior: An extension of the theory of planned behavior. International Journal of Human-Computer Studies, 64, 889-904.
19. Kim, J. B. (2012). An empirical study on consumer first purchase intention in online shopping: integrating initial trust and TAM. Electron Commer Res, 12(1), 125-150.
20. Kim, M.J., Lee, Ch.K., Preis, M.W. (2020). The impact of innovation and gratification on authentic experience, subjective well-being, and behavioral intention in tourism virtual reality: The moderating role of technology readiness. Telematics and Informatics, 49, 101349.
21. Lee, H.J. (2017). Personality determinants of need for interaction with a retail employee and its impact on self-service technology (SST) usage intentions. Journal of Research in Interactive Marketing, 11(3), 214-231.

22. Lixandroiu, R., Cazan, A.M., Maican, C.I. (2021) An Analysis of the Impact of Personality Traits towards Augmented Reality in Online Shopping. Symmetry, 13(1),
23. Macik, R., Mazurek, G., Macik, D. (2012). Channel characteristics' influence on physical vs. virtual channel choice for information search and purchase – the case of Polish young consumers. International Journal of Cyber Society and Education, 5(1), 35-54.
24. Martínez-López, F.J., Esteban-Millat, I., Cabal, C.C., Gengler, C. (2015). Psychological factors explaining consumer adoption of an e-vendor's recommender. Industrial Management and Data Systems, 115(2), 284-310.
25. Moslehpour, M., Thanh, H.L.T., Kien, P.V. (2018). Technology perception, personality traits and online purchase intention of Taiwanese consumers. Predictive Econometrics and Big Data, 392-407.
26. Nagy, S., Hajdu, N. (2021). Consumer Acceptance of the Use of Artificial Intelligence in Online Shopping: Evidence from Hungary. Amfiteatru Economic, 23(56), 155-173.
27. Nguyen, D.H., de Leeuw, S. & Dullaert, W.E.H. (2016). Consumer Behaviour and Order Fulfilment in Online Retailing: A Systematic Review. International Journal of Management Reviews, 00, 1-22.
28. Nguyen, H.M., Khoa, B.T. (2019). The relationship between the perceived mental benefits, online trust, and personal information disclosure in online shopping. Journal of Asian Finance, Economics and Business, 6(4), 261-270.
29. Nguyen, T. T. H., Nguyen, N., Nguyen, T. B. L., Phan, T. T. H., Bui, L. P., Moon, H. C. (2019). Investigating consumer attitude and intention towards online food purchasing in an emerging economy: an extended TAM approach. Foods, 8(11), 576.
30. Pappas, I.O. (2018). User experience in personalized online shopping: a fuzzy-set analysis. European Journal of Marketing, 52(7/8), 1679-1703.
31. Peña-Garcia, N., Gil-Saura, I., Rodriguez-Orejuela, A., Siqueira-Junior, J. R. (2020). Purchase intention and purchase behavior online: a cross cultural approach. Heliyon, 6(6), 1-11.
32. Ribokas, P., Burinskienė, A. (2019). Technologijų priėmimo modeliai elektroninėje komercijoje. In: 22-osios Lietuvos jaunųjų mokslininkų konferencijos „Mokslas – Lietuvos ateitis“ teminė konferencija "Ekonomika ir vadyba", Vilnius
33. Singh, S., Srivastava, R.K. (2018). Predicting the intention to use mobile banking in India. International Journal of Bank Marketing, 36(2), 357-378.
34. Smith, B., Linden, G. (2017). Two decades of recommender systems at Amazon.com. IEEE Internet Computing, 21(3), 12-18.
35. Wang, Y. S., Yeh, C. H., Liao, Y. W. (2013). What drives purchase intention in the context of online content services? The moderating role of ethical self-efficacy for online piracy. International Journal of Information Management, 33(1), 199-208.
36. Wei, Z., Lee, M.Y., Shen, H. (2018). What drives consumers in China to buy clothing online? Application of the technology acceptance model. Journal of Textiles and Fibrous Materials, 1(1), 1-10.
37. Wu, W.Y., Ke, C.C. (2015). An online shopping behavior model integrating personality traits, perceived risk, and technology acceptance. Social Behavior and Personality, 43(1), 85-98.
38. Wu, M.Y., Liao, S.C. (2011). Consumers' behavioral intention to use internet shopping: an integrated model of TAM and TRA. Journal of Statistics and Management Systems, 14(2), 375-392.

39. Xie, Q., Song, W., Peng, X., Shabbir, M. (2017). Predictors for e-government adoption: integrating TAM, TPB, trust and perceived risk. The Electronic Library, 35(1), 2-20.
40. Xu, F., Michael, K., Chen, X. (2013). Factors affecting privacy disclosure on social network sites: An integrated model. Electronic Commerce Research, 13(2), 151-168.
41. Yang, H., Lee, H. Zo, H. (2017). User acceptance of smart home services: an extension of the theory of planned behavior. Industrial Management & Data Systems, 117(1), 68-89.
42. Yin, J., Qiu, X. (2021). AI Technology and Online Purchase Intention: Structural Equation Model Based on Perceived Value. Sustainability, 13(10), 5671.
43. Zhao, X., Zhang, L., Ding, Z., Xia, L., Tang, J., Yin, D. (2018). Recommendations with negative feedback via pairwise deep reinforcement learning. In: Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, Association for Computing Machinery, London, United Kingdom.
44. Zhou, T. (2010). The impact of privacy concern on user adoption of location-based services. Industrial Management and Data Systems, 111(2), 212-226.