THE ATTITUDES TOWARD ARTIFICIAL INTELLIGENT APPLICATIONS: AN INVESTIGATION BASED ON INNOVATION RESISTANCE THEORY

Chia-Lun Lo, Department of Health- Business Administration, Fooyin University, Jinxue Rd., Daliao Dist., Kaohsiung City 83102, Taiwan (R.O.C.)

ABSTRACT

Artificial intelligence (AI) has been widely used by companies in their quest for digital transformation. Numerous low-level jobs have been replaced by AI because of its strong ability to handle repetitive tasks; however, this replacement process has increased new graduates' chance of unemployment. Based on the innovation resistance theory, we investigated new graduates' attitudes toward competition with AI in the job market. The findings of this study might serve as a reference for human resources staff in organizations that have implemented AI to determine whether new graduates are a good fit for the company.

Keywords: Artificial intelligence, Innovation resistance theory, Gadget lovers, Global innovativeness, Technological unemployment

INTRODUCTION

The maturing of artificial intelligence (AI) technology has increasingly widespread adoption and resulted in considerable changes in people's lives. Nilsson (2009) proposed the following useful and widely accepted definition of AI: "Artificial intelligence is that activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment." However, the rapid development of AI and automation technology might seriously harm the labor market.

Although the development of AI and automation might enhance worker productivity, AI might also replace some workers, thereby causing major changes in the workplace. Business leaders from diverse industries, including machinery, retail, and insurance, are concerned that AI might seriously harm their established lines of business and might lead to the loss of a considerable number of traditional jobs (Ulrich, 2018; Zhu et al., 2020). However, even strong proponents of AI admit that this technology has its limits. AI is unlikely to completely replace people's jobs in the near future (Ulrich, 2018; Zhu et al., 2020).

Two groups with strongly divergent views have thus emerged: One group is concerned that AI might replace humans, whereas the other group insists that human uniqueness cannot be replicated by AI. However, these perspectives are overly simplistic, with many additional factors requiring consideration. Consensus on this AI has remained elusive in academic research and general discussions. Some studies have indicated that even in creative jobs, AI might also do it better than humans. (Kolbjornsrud et al., 2016), whereas others believe that it is premature to make predictions regarding the scale of layoffs and the number of new jobs created by AI because of the relative immaturity of the technology (Winick, 2018).

We argue that the development of AI is both a threat and an opportunity for new graduates. When looking for a job, new graduates must consider what positions are still available if basic operational processes are handled by AI. A young person with insufficient professional skills or special expertise might face unemployment immediately after graduation, which is a phenomenon referred to as technological unemployment. However, those with irreplaceable skills and expertise who can create value by using AI can take advantage of the trend of AI development and position themselves favorably in the labor market. In general, it was thought that young people who have grown up in an information society are always more interested in computer use than older people. However, there is a difference between "playing on a computer or mobile phone" and "acceptable and skilled use of AI that possible replace themself". Therefore, even though young people are digital natives and comfortable with the integration of technology in their daily lives, whether their attitude toward AI would be changed when they found AI has the possibility of replaceability in their job are at play is yet to be examined.

In this study, we empirically examined new graduates' acceptance of AI on the basis of their degree of innovativeness and the affinity for information technology gadgets (so-called "gadget loving") and considered the moderating effects of the four innovation resistance factors, namely usage barrier, value barrier, risk barrier, and traditional barrier.

LITERATURE REVIEW

Artificial Intelligence

The concept of AI was proposed by John McCarthy, an emeritus professor at Stanford University, in 1955. He defined AI as "the science and engineering of making intelligent machines," where *intelligent* can be defined as having the ability to learn and having adequate skills for implementation to solve problems and achieve goals. AI plays a key role in several technologies, notably expert systems, machine learning, natural language processing, and deep learning. Specifically, deep learning can assist humans in decision-making (Chids. 2011)

The Internet and technologies with high data processing speeds have enabled the commercialization of AI (Grosz et al., 2016). AI has been applied in various fields, including manufacturing (Lu, 2017), agriculture (Patrício & Riedar, 2018), science (Li, Wang, Wang, Li., 2018; Lin, Wooder, Wang, Yang., 2018), education (Luo, 2018; Mcarthur, Lewis, Bishary., 2005), business (Bahrammirzaee, 2010; Fethi & Pasiouras, 2010), medicine (Lo & Tseng, 2017; Lo et al., 2021; Wu et al., 2020), government (Boyd & Holton, 2017; Viejo et al., 2018), retail (Grewal et al., 2017; Liu et al., 2018), and information security (Grzonka, Roggeveen, Nordfalt, 2018; Yan, Gong, Li., 2016). Self-deep-learning technologies based on AI have yielded excellent performance in various recognition systems. For example, AI has exhibited superior performance to conventional techniques in lesion tests and classification tasks. AI has the potential to generate revolutionary changes in medicine and health care. For example, it can assist doctors by increasing the accuracy and efficiency of various diagnoses and treatments (Lo & Tseng, 2017, Mao, et al., Wu, et al., 2020, Lo et al., 2021).

AI is incorporated into diverse software programs, products, and services. Many theories can be used to explain this phenomenon. Knight (2015) argued that AI has reached the organizational level and thus affects labor productivity and increases the speed of decision-making. Some studies have investigated factors affecting organizations' willingness to use AI (Zhu, et al., 2020); however, studies on information systems have not considered what types of people are willing to use AI. In the practical field, we also don't know if the new recruits cannot adapt to work with AI, not to mention that high-efficiency AI can replace workers who have limited experience in specific tasks producing some Human resource management issues. Thus, in this study, we investigated factors that affect an individual's viewpoint regarding AI adoption.

Innovativeness

Innovativeness is a key factor affecting the adoption of new products or services (Midglery, 1978). Studies have revealed that innovativeness in user habits affects the purchasing behavior for or adoption of innovative technology (Citrin et al., 2000; Lassar, Manolis, Lassar, 2005). Thus, users with a higher degree of innovativeness are more willing to accept new products and use the services that these products provide to achieve their goals (Bartels & Reinders, 2011).

Users with innovative personality traits might hold an innovative attitude in general or only toward specific items or purposes. Midgley and Dowling (1978) divided user innovativeness into global innovativeness and innovative habits in specific fields. Hlrunyawipada and Paswan (2006) expanded this concept into a hierarchical innovative structure that is described in the following text.

Global Innovativeness

According to Goldsmith and Hofacker (1991), innovativeness refers to the newness of a product or service. Global innovativeness refers to consumer innovativeness that is related to personal traits. The most abstract concept in hierarchical consumer innovativeness is called *innate innovativeness*. Global innovativeness is an innate trait (Boateng et al., 2016) and represents an individual's attitude toward innovativeness (Midgley & Dowling, 1978) and the tendency to be willing to accept new products. Those with the aforementioned trait are usually early adopters of new technologies. Thus, in studies addressing adaptation to technology, global innovativeness is considered an essential personality trait (Wu & Ke, 2016).

In general, neighbors, relatives, coworkers, and friends are parts of a person's social system, and they are potential critical sources of influence on the person's purchase behaviors (King & Summers, 1970). People regard information obtained from friends and relatives as more reliable and trustworthy than commercial information (Busch & Houston, 1985). In terms of exchanges in social systems, communication between communicators and acceptors is an effective factor for predicting consumer behaviors (Rogers & Cartano, 1962). Therefore, we adopted and modified the Revised Opinion Leadership Scale developed by King and Summers (1970) in this study. During exchanges in a social system, communicators who can understand crucial information are considered more innovative than those who do not.

Technological Innovativeness

Innovation acceptance in a given field represents people's acceptance of innovation in a specific category of products and services (Chao et al., 2016), which affects their willingness to accept innovations and changes in the category (Gatignon & Roberson, 1985). Innovation acceptance is therefore defined as the tendency to learn about and adopt specific products or services. In this study, we measured the degree of acceptance of AI in a field in which participants were going to provide services. People inclined toward technological innovativeness adopt and accept new technologies earlier than do other people, and they are more motivated than others are to learn about and accept new technology. That is the concept of hierarchical innovation degree (Hur et al., 2017).

Overall, the hierarchical innovation is based on the degree of abstraction in relation to innovative concepts. Innovativeness in specific fields refers to the innovativeness of people in fields that they are interested in or in fields that they specialize in. In this study, we evaluated whether graduating students accepted the adoption of innovative AI applications in workplaces related to their fields. Thus, *global innovativeness* and *innovativeness in specific fields* were the two concepts included in the research framework of this study.

Innovation Resistance

Ram (1987) proposed the concept of innovation resistance, which refers to a user's resistance toward the changes induced by innovation. Notably, innovation resistance is not the opposite of innovation adoption. Adoption occurs only when a user's initial resistance is overcome. Thus, if the innovation resistance is high in the early stage of an innovation, the innovation might not be adopted. Furthermore, innovation adoption and innovation resistance can coexist. Sheth (1982) indicated that when users face barriers in using an innovation, they resist using or become unwilling to use the innovation. Ram and Sheth (1989) divided the barriers faced by users when using innovations into functional barriers and psychological barriers. Functional barriers are related to usage, value, and risk, whereas psychological barriers are related to tradition and image.

Affinity for Information Technology Devices

McLuhan (1964) proposed the notion of information technology tendency. However, they only considered hardware products with relevant software, such as computers, tablets, and cellphones, as information technology. Bruner and Kumar (2007) defined information technology lovers (gadget lovers) as consumers with a high degree of willingness to use high-tech products and services autonomously. Gadget lovers are a unique user type: they are more willing than the general public to use advanced technology early, and compared with people with other personality traits, gadget lovers are more likely to affect others' views on innovation. Studies have indicated that people with the aforementioned trait enjoy learning how to operate high-tech products and are highly willing to understand the operational theories of such products.

Attitudes Toward AI

New employees generally accumulate work skills by learning from their mentors under the mentor–apprentice system and through practical experience. Initially, new employees must spend some time to accumulate sufficient capabilities and work experience. If employees believe that they can use AI-based technologies to increase their work efficiency and productivity and reduce the need for daily repetitive tasks, they would hold a positive rational attitude toward the incorporation of AI in the workplace. By contrast, if employees believe that AI-based technologies would prevent them from fully understanding their work, prevent them from performing tasks appropriately, generate various risks, and affect their employment, they would hold a negative rational attitude toward the incorporation of AI in the workplace. If employees believe that AI is complex but can assist them in upgrading their skills, generating revolutionary innovations, and achieving rapid professional growth, they would have a positive emotional attitudes toward AI adoption in the workplace. However, if the incorporation of AI in the workplace induces negative emotions in employees and prompts concern about job security, they would have a negative emotional attitude toward AI adoption in the workplace (Zhu et al., 2020)

In summary, employees' attitudes toward AI can change in the rational and emotional dimensions. Rational attitudes are based on logical assessments of the function and potential of AI, whereas emotional attitudes are based on emotions, not deep and careful thinking. Typically, people with a rational attitude consider the incorporation of AI in the workplace as a means to create professional and commercial value, whereas those with an emotional attitude hold a humanistic concern regarding the replacement of human labor by AI.

METHODS

Conceptual Framework

On the basis of our literature review and following the definition by Zue et al.(2020). we designated attitudes toward AI as the dependent variable and categorized this attitude from the definition by Zue et al.to simply concentrate on rationality and sensibility. The degree of global innovation and gadget loving served as the independent variables in this study, and the four innovation resistance barriers served as the moderating variables. We propose the following hypotheses:

H1: *Global innovativeness has a significant influence on gadget loving.*
H2: *Gadget loving has a significant positive influence on attitudes toward AI.*
H3: *Global innovativeness has a significant positive influence on attitudes toward AI.*
H4: *Innovation resistance has a significant moderating effect on the relationship between gadget loving and attitudes toward AI.*
H5: *Innovation resistance has a significant moderating effect on the relationship between global innovativeness and attitudes toward AI.*

Data Collection

By conducting a survey, we collected data from a university with nearly 2000 fresh graduates a year in southern Taiwan. The surveyed individuals comprised graduates from 4-year undergraduate programs, 2-year undergraduate programs, and master programs. Before the survey, we conducted a pretest with 50 current students to verify the reliability and validity of the questionnaire. Based on the pretest results, some items were deleted to produce the final questionnaire. A link to the questionnaire on Google Forms was sent to the registered email addresses of new graduates in June 2022 in batches.

Because the research targets were new graduates who planned to find a job, those who were planning to pursue further study, delay graduation, or serve in the army were excluded from the mailing list. Before completing the questionnaire, the respondents watched a 3-min video on how the broad application of AI in various industries might cause technological unemployment. A total of 950 emails with the survey link were sent, and 230 questionnaires were retrieved; thus, the response rate was 24%. After item missing, incomplete and invalid questionnaires were excluded, 201 questionnaires remained for analysis.

Of the respondents, 66 were men and 135 were women. Most of the respondents were students from the 4-year undergraduate program of the School of Nursing. Most of the respondents spent over 8 hr a day using computer, communication, and consumer electronics (3C) products. Most of the respondents obtained information on innovative technology from the news. Regarding the respondents' willingness to use innovative gadgets, most of them based their decisions on other users' comments.

Questionnaire design

We adopted a structured questionnaire for data collection. The reliability and validity of the questionnaire were reviewed by three experts in information management. The questionnaire contained two parts. The first part consisted of items measuring demographic information (sex, age, education, time spent using 3C products, source of technology information, and willingness to use innovative gadgets). The second part focused on the measurement of the main variables: the four types of innovation resistance—namely usage barrier, value barrier, risk barrier, and traditional barrier—as well as global innovativeness and gadget loving (comprising two constructs: gadget loving and technological innovation). Finally, the respondents' attitudes toward AI were surveyed using two scales: the rationality scale and sensibility scale. The respondents used a 5-point Likert scale to rate each item, with 1 indicating *strongly agree* and 5 indicating *strongly disagree*.

Research Tool

The scales used in this study were based on relevant scales with favorable reliability and validity, which were modified according to the findings of our literature review and our research goals. The scales used to measure the main constructs in this study are described in the following sections.

Innovation resistance

The Innovation Resistance scale was based on the scales developed by Laukkanen and Kiviniemi (2010) and Rammile and Nel (2012). On the basis of the purpose of this study, the factor titled *the resistance to mobile banks* in these scales was changed to *the resistance to AI*. The Innovation Resistance scale consisted of four constructs, namely usage barrier, value barrier, risk barrier, and traditional barrier. A higher score on this scale represents stronger resistance and thus greater barriers.

Global innovativeness

The Global Innovativeness scale contained seven items and was based on the Revised Opinion Leadership Scale developed by King and Summers (1970). We changed the factor titled the understanding of TV to the grasp of information related to AI applications to determine whether the respondents could obtain more information on AI applications in the workplace than from exchanges in social systems to express their degree of innovation of mindset. we also explore the respondents' personal traits, being open to new things, and if the respondents can be early adopters of innovative technology.

Gadget loving

The Gadget Loving scale was based on the Gadget Lover scale developed by Bruner and Kumar (2007). The Gadget Loving scale was used to measure the respondents' preference for technology through two constructs, namely gadget loving and technological innovation. Following the pretest and a consistency evaluation, we excluded two items that did not meet the reliability criterion. A higher score on this scale indicates a higher motivation to try new products or services.

Attitudes toward AI

The Attitudes Toward AI scale consisted of seven items based on the rationality–sensibility scales developed by Ratchford (1987) and expanded by Putrevu and Lord (1994). The Attitudes Toward AI scale was used to measure the respondents' knowledge of AI through two constructs: rationality and sensibility. A lower score for rationality or sensibility suggests a more rational or sensible attitude towards AI, respectively.

DATA ANALYSIS

Results of Measurement Model Analysis

To assess whether our questionnaire could accurately investigate the relationship between the considered constructs, we used three indicators, namely Cronbach's α, construct reliability (CR), and average variance extracted (AVE). In this study, the CR and Cronbach's α values for all constructs were greater than 0.7 (consistent with the criteria of Hair et al. [2010]), which indicated that all the latent variables met the consistency standard. AVE is used to identify the percentage of variation that is measurable for each latent variable. AVE represents not only the reliability of judgments but also the discriminant validity of latent variables. Regarding the criterion for discriminant validity, the AVE value should be greater than 0.5 (Fornell & Lacker, 1981), and all the construct loadings should be greater than 0.7. In this study, all the AVE values were between 0.712 and 0.893, and all the construct CR values were greater than 0.7. The analysis results indicated that the measurement model used in this study was acceptable because the convergent validity criterion was met. To avoid non-response bias and ensure the representation of samples to support the use of the samples, the non-response bias test are also implement in the study. The samples were tested for evidence of non-response bias by applying the technique proposed by Armstrong and Overton (1977). According to this method, the 201 responses were dived into two groups: those received early (junior college program and 4-year undergraduate program) and those received late (2-year program and graduate program. The Chisquare test showed that there were no significant differences between two groups in terms of source of technology information and 3C product's experience of respondents.

Measurement Results

Table 1 presents the relationships of attitudes toward AI with the other main factors. Age had a significant negative relationship only with global innovativeness, which indicated that the higher the age, the lower was the global innovativeness score. All four innovation resistance subconstructs were negatively related to global innovativeness, gadget loving, technological innovation, and attitudes toward AI, which indicated that the stronger the resistance, the more negative was the (rational and sensible) perception of innovation and attitudes toward AI.

Table 1
Results of Correlation Analysis Between the Constructs

Variables	age	a	b	c	d	e	f	g
Usage barrier(a)	0.037	1						
Value barrier(b)	-0.004	.607**	1					
Risk barrier€	-0.032	.171*	.231**	1				
Traditional barrier (d)	0.035	.296**	.492**	-.204**	1			
Global innovativen€(e)	-.210**	-0.074	0.060	0.101	0.021	1		
Gadget loving(f)	-0.040	-.494**	-.516**	-.197**	-.304**	.236**	1	
Technological innovation(g)	0.011	-.314**	-.186**	-0.004	-0.100	.363**	.477**	1
Attitudes toward AI	-0.090	-.447**	-.463**	-.280**	-.243**	0.103	.632**	.326**

*$p < .05$, **$p < .01$

Next, significant different were observed between the sexes in terms of their global innovativeness, gadget loving, and technological innovation scores. The male graduates had higher scores for global innovativeness, gadget loving, and technological innovation, whereas the female graduates had higher scores for value barrier. The scores of traditional barrier, global innovativeness, and gadget loving differed significantly by study program. The post hoc test results indicated that the traditional barrier scores of the students of the 2-year undergraduate program were higher than those of the students of the graduate program and 4-year undergraduate program. The gadget loving scores of the students of the 4-year undergraduate program were higher than those of the students of the 2-year undergraduate program. The global innovativeness scores of the students of the junior college program, 4-year undergraduate program, and 2-year undergraduate program were higher than those of the students of the graduate program. Graduates of different ages, from different schools, and with different 3C habits did not exhibit significant differences in their independent variable scores

We subsequently applied hierarchical regression for hypothesis testing. the independent variable is global innovativeness, whereas the dependent variable is gadget loving (with two constructs, namely gadget loving and technological innovation). The only control variable in the aforementioned analysis information is sex because the dependent variable only differed significantly by sex. Model 2 indicated that the differences in global innovativeness and gadget loving were significant ($F = 5.971$, $p < .000$); therefore, H1 is supported.

The only control variable included is sex. The independent variable in this table is gadget loving, whereas the dependent variable is attitudes toward AI. Model 4 revealed that attitudes toward AI was significantly different among graduates with different degrees of gadget loving ($F = 14.551$, $p < .000$). We examined the moderating effect of innovation resistance (i.e., usage barrier, value barrier, risk barrier, and traditional barrier) on the relationship between gadget loving and attitudes toward AI. According to Model 5, this effect was significant ($F = 20.075$, $p < .000$). The aforementioned results support H2 and H4.

Finally, consistent with our procedure in the preceding two analyses, we performed another analysis with sex as the control variable, global innovativeness as the independent variable, attitudes toward AI as the dependent variable, and innovation resistance as the moderating variable. Model 7 revealed that attitudes toward AI was not significantly different between different levels of global innovativeness. However, Model 8 indicated that if the moderating effect of innovation resistance was considered, the model and interaction term were statistically significant ($F = 9.878$, $p < .000$), which confirmed that innovation resistance had a significant moderating effect on the relationship between global innovativeness and attitudes toward AI. Therefore, H3 and H5 are supported. All of the hypothesis test results are summarized in Table 2.

Table 2

Results of Hypothesis Testing

	Research hypotheses	Results
H1	Global innovativeness has a significant influence on gadget loving	Supported
H2	Gadget love has a significant positive influence on attitudes toward AI	Supported
H3	Global innovativeness has a significant positive influence on attitudes toward AI	Supported
H4	Innovation resistance has a significant moderating effect on the relationship between gadget-loving and attitudes toward AI	Supported
H5	Innovation resistance has a significant moderating effect on the relationship between global innovativeness and attitudes toward AI	Supported

CONCLUSION AND IMPLICATIONS

AI is a business application with considerable potential, and it has demonstrated its value in various industries. Through the analysis of big data and the use of dynamic self-improving algorithms, AI can handle numerous repetitive tasks rapidly and thus help organizations reduce costs and increase productivity. However, AI might also represent a threat to organizations because of passive employee resistance, thus negating the benefits of AI and reducing team cohesiveness. Because people are key components of organizations, people's differences and uniqueness of humans sets them apart from AI. Rationalizing the combination of AI and human characteristics is the key factor for industrial development in the future.

Due to the training resources limited and the rising turnover rate of the employee, human resource managers often feel reluctant to spend more time developing employees, and instead, they hope can find "ready-to-play anytime" employees in each recruitment. Therefore, artificial intelligence is bound to become a trend in the occupation market, managers must understand candidates' attitudes toward artificial intelligence earlier, and listen carefully to whether they feel irrational concerns about artificial intelligence in order to find suitable employees.

For existing employees, after understanding the mentality of employees, managers can also take the initiative to hold some discussion meetings to understand the concerns or joys of employees after the introduction of artificial intelligence into business processes, and to understand their future of artificial intelligence. Imagine that when employees respond to some questions from Bubukou, it can also reveal employees' rational or emotional attitudes towards artificial intelligence. With these data, managers can introduce different education and training according to different objects.

To sum up, this study extent the scope of application of innovation resistance theory. Through the results of the study, we revealed that new graduates' characteristics in terms of innovation and gadget loving can help them develop a positive and fearless attitude. However, new graduates' resistance to innovation might also influence their attitudes toward AI because they might have doubts and thus oppose AI. Our findings have some management implications. Managers should pay attention to relevant AI applications, and how to make use of them to improve the business quality and raise income. Meanwhile, it is also very important to improve current employees' understanding of AI and strengthen current employees' ability to apply AI.

New employees play can play crucial roles in organizations. Their positive attitudes can be a catalyst for the future development of the organization. Organizations that wish to excel in the present high-tech environment will have to apply AI broadly to replace repetitive and basic tasks. New employees in such organizations must know how to coexist with AI to increase their competitive advantage and survive in their workplaces. Thus, the present findings can also serve as a reference for human resources personnel to evaluate new employees.

This study has some limitations that represent opportunities for future research. All the respondents of this study were new graduates from the same university, and the link to the online questionnaire was sent to their email addresses; however, their participation was voluntary. Consequently, the response rate was relatively low. Future research can explore differences among students of different backgrounds or differences caused by other factors. For example, urban schools might have more resources for AI applications than do rural schools. The influence of such resource allocation on graduates' attitudes toward AI merits examination. Moreover, studies can examine whether graduates with different majors have different perceptions of AI. Finally, by using the data of graduates from alumni employment surveys, researchers can compare graduates' acceptance and knowledge of AI immediately following graduation with those 3–5 years after graduation.

Acknowledgement

This work was supported by the Ministry of Science and Technology of Taiwan under project number MOST 109-2637-H-242 -001, and MOST 110-2410-H-242 -001 -MY2. Thanks for all our research assistant team members (Shao-Xuan, Li, Pei-Ying, Su, Xiao-Ting, Hong, Meng-Hua-Xie) from department of Health-Business Administration, Fooyin University for forming the research process.

References

Bahrammirzaee, A. A comparative survey of artificial intelligence applications in finance: Artificial neural networks, expert system and hybrid intelligent systems. Neural Computing and Applications, 2010, 19(8), 1165–1195.

Bartels, J., and Reinders, M. J. Consumer innovativeness and its correlates: A Propositional inventory for future research. *Journal of Business Research*, 2011, 64(6), 601-609.

Bruner, G. C., and Kumar, A. Gadget lovers. Journal of the Academy of Marketing Science, 2007, 35(3), 329-339.

Boateng, H., Okoe, A.F., and Omane, A. B. Does personal innovativeness moderate the effect of irritation onf consumers' attitudes towards mobile advertising? *Journal of Direct, Data and Digital Marketing Practice,* 2016, 17(3), 201-210.

Boyd, R., & Holton, R. J. Technology, innovation, employment and power: Does robotics and artificial intelligence really mean social transformation? Journal of Sociology, 2017, 54(3), 331–345

Busch, P.S., Houston, M.J., Irwin, R.D. Marketing: Strategic Foundations Irwin Series in Management and the Behavioral Sciences Irwin series in marketing, 1985.

Chao, C. W., Reid, M., and Hung, Y. C. Vicarious innovativeness or vicarious learning: the role of existing vicarious innovativeness in new product purchase intentions. *Australasian Marketing Journal*, 2016, 24(1), 87-92.

Childs, M., John McCarthy: Computer scientist known as the father of AI. [online] The Independent, 2011. Available at: <http://www.independent.co.uk/news/obituaries/john-mccarthy-computer-scientist-known-as-thefather-of-ai-6255307.html>

Fethi, M. D., & Pasiouras, F. Assessing bank efficiency and performance with operational research and artificial intelligence techniques: A survey. *European Journal of Operational Research*, 2010, 204(2), 189–198

Fornell, C. D., and Lacker, D. F., "Evaluating Structural Equation models with Unobservable Variables and Measurement Error," *Journal of Marketing Research*,1981, 18: 39-50.

Citrin, V. A., Sprott, D. E., Silverman, S. N., and Stem Jr, D. E. Adoption of Internet shopping: The role of consumer innovativeness. *Industrial Management and Data Systems*, 2000, 100(7), 294-300.

Gatignon, H., and Robertson, T. S. A Propositional inventory for new diffusion research. *Journal of Consumer Research*, 1985, 11(4), 849-867.

Goldsmith, R. E., and Hofacker, C. F. Measuring consumer innovativeness. *Journal of the Academy of Marketing Science*, 1991, 19(3), 209-221.

Grewal, D., Roggeveen, A. L., & Nordfält, J. The future of retailing. Journal of Retailing, 2017, 93(1), 1–6.

Grosz, B.J., Altman, R., Horvitz, E., Mackworth, A., Mitchell, T., Mulligan, D. and Shoham, Y., Artifical Inelligence and Life in 2030- One Hundred Year Study of Artificial Intelligence, 2016.

Grzonka, D., Jakobik, A., Kołodziej, J., & Pllana, S. Using a multi-agent system and artificial intelligence for monitoring and improving the cloud performance and security. Future Generation Computer Systems, 2018, 86, 1106–1117.

Hair, J.F., Black, W.C., Babin, B.J. and Anderson, R.E. Multivariate Data Analysis. 7th Edition, Pearson, New York. 2010.

Hirunyawipada, T. and Paswan, A.K., Consumer innovativeness and perceived risk: implications for high technology product adoption, *Journal of Consumer Marketing*, 2006, 23(4), 182-198.

Hur, H. J., Lee, H. K., and Choo, H. J. Understanding usage intention in innovative mobile App service: Comparison between millennial and mature consumers. *Computers in Human Behavior*, 2017, 73, 353-361.

King and Summers The King and Summers opinion leadership scale: Revision and refinement, *Journal of Business Research,* 1970, 31(1), 55-64.

Kolbjornsrud, V., Amico, R., and Thomas, R. J. . How artificial intelligence will redefine management. Harvard Business Review, November 2. 2016.

Lassar, W. M., Manolis, C., and Lassar, S. S. The relationship between consumer innovativeness, personal characteristics, and online banking adoption. *International Journal of Bank Marketing*, 2005, 23(2), 176-199.

Laukkanen, T., and Kiviniemi, V. The role of information in mobile banking resistance. International Journal of Bank Marketing, 2010, 28(5), 372-388.

Li, J., Wang, R., Wang, J., & Li, Y. Analysis and forecasting of the oil consumption in China based on combination models optimized by artificial intelligence algorithms. Energy, 2018, 144, 243–264.

Lin, P. H., Wooders, A., Wang, J. T. Y., & Yuan, W. M. Artificial intelligence, the missing piece of online education? *IEEE Engineering Management Review*, 2018, 46(3), 25–28.

Lo, C.L., Tseng, H. T. A Study of Stroke Patients' Rehabilitation Treatment Effectiveness: A supervised learning approach. *Artificial Intelligence Research***,** 2017, 6(2), 1-9.

Lo, C.L., Yang, Y.H., Tseng, H.T. A fact-finding procedure integrating Machine learning & AHP technique to predict delayed diagnosis of bladder patients with hematuria, *Journal of Healthcare Engineering*, 2021, 32(1), 20-31

Luo, D. Guide teaching system based on artificial intelligence. International Journal of Emerging Technologies in Learning, 2018, 13(08), 90–102.

Liu, L., Zhou, B., Zou, Z., Yeh, S. C., & Zheng, L. A smart unstaffed retail shop based on artificial intelligence and IoT. In 2018 IEEE 23rd International workshop on computer aided modeling and design of communication links and networks (CAMAD) (pp. 1–4). Barcelona: IEEE. 2018.

Lu, Y. Industry 4.0: A survey on technologies, applications and open research issues. *Journal of Industrial Information Integration*, 2017, 6, 1–10.

McArthur, D., Lewis, M., & Bishary, M. The roles of artificial intelligence in education: Current progress and future prospects. *Journal of Educational Technology,* 2005, 1(4), 42–80.

McLuhan, M. *Understanding medial: The Extensions of Man*. London: Routledge Publications.1964.

Mao, T.C., Hu, Y.H., Lo, C. L. Predicting the Prolonged Length of Stay of General Surgery Patients: A Supervised Learning Approach; *International Transactions in Operational Research*; 2018, 25(1), 75-90.

Midgley, D. F. and Dowling, G.R. Innovativeness, The concept and its measurement. *Journal of Consumer Research*, 1978, 4(4), 229-242.

Patrício, D. I., & Rieder, R. Computer vision and artificial intelligence in precision agriculture for grain crops: A systematic review. *Computers and Electronics in Agriculture*, 2018, 153, 69–81.

Putrevu,S.,& Lord,R.K.Comparative and noncomparative advertising: Attitudinal effects under cognitive and affective involvement conditions. Journal of Advertising, 1994, 23(2),77-90.

Ratchford,B.T. New Insights about the FCB Grid. *Journal of Advertising Research*, 1987, 27(4),24-38.

Ram, S. A model of innovation resistance. *Advances in Consumer Research*, 1987, 14, 208-212.

Rammile, N., and Nel, J. Understanding resistance to cell phone banking adoption through the application of the technology acceptance model (TAM). *African Journal of Business Management*, 2012, 6(1), 86-97.

Rogers, E.M., Gartano, D.G., Methods of Measuring Opinion leadership, *Public Opinion Quarterly,* 1962, 26(3), 435-441.

Sheth, J. N. An integrative theory of patronage, preference, and behavior. In Darden, W. and Lusch, R. (Eds.), *Patronage Behavior and Retail Management* (pp. 9-28). Elsevier: North Holland, 1982.

Viejo, C. G., Fuentes, S., Howell, K., Torrico, D., & Dunshea, F. R. Robotics and computer vision techniques combined with non-invasive consumer biometrics to assess quality traits from beer foamability using machine learning: A potential for artificial intelligence applications. *Food Control*, 2018, 92, 72–79.

Winick, E. Every study we could find on what automation will do to jobs, in one chart. *MIT Technology Review*, January 25.2018.

Wu, C.T., Lo, C.L., Hsueh, T.C., Cheng, H.L. Applying Data Mining Techniques for Predicting Prognosis in Patients with Rheumatoid Arthritis, *Healthcare***,** 2020, 8,85

Wu, W. Y., and Ke, C. C. An online shopping behavior model integrating personality traits, perceived risk, and technology acceptance. *Social Behavior and Personality*, 2016, 44(3), 85-97.

Yan, Q., Yu, F. R., Gong, Q., & Li, J. Software-defined networking (SDN) and distributed denial of service (DDoS) attacks in cloud computing environments: A survey, some research issues, and challenges. *IEEE Communications Surveys & Tutorials,* 2015, 18(1), 602–622

Zhu, Y. Q., Corbett, J.U., Chiu, Y.T. Understanding employees' responses to artificial intelligence, *Organizational Dynamics,* 2020, 50(2), 100786.

.