FACTORS THAT INFLUENCE ADOPTION OF AI IN ORGANIZATIONS

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Abstract: *In the last few years, the rapid development of Artificial Intelligence (AI) has created the conditions for its increasing use in various organizations, in order to achieve the well-known goals of increasing productivity, efficiency, effectiveness and more rational use of resources. However, most companies have difficulties in implementing artificial intelligence and realizing the benefits it brings. Most of the researchers in this field, in order to examine in more detail which factors influence the adoption of new technologies in the organization and what their mutual relationship is, uses previously well-developed models such as TAM (Technology acceptance Model), UTAUT (The Unified Theory of Acceptance and Use of Technology) and TOE (Technology-Organization-Environment). Through a more detailed review of the literature, this paper provides a framework overview of the factors. The article highlights the insufficient focus of previous studies on the factors related to the intention of employees to use artificial intelligence in everyday business tasks, that is, it proposes a framework for further research in this area with special attention to the intention of employees to use AI. Our results can help scholars and practitioners to include those factors in further theory development.*

Key words: *Artificial Intelligence, Intention to use, Adoption of AI, Organizations*

1. INTRODUCTION

Artificial Intelligence is a term that has long been recognized within academic circles. It was initially coined by John McCarthy in the mid 50's during a scientific conference aimed at establishing standard methods for this new field (Smith et al., 2006). Since then, the development of AI has closely followed advancements in computer technologies, including the storage and processing of vast amounts of data, faster data access, handling different types of data, and other related areas (Venkatesh, 2021). The availability of such technologies and access to large data sets have fueled the rapid progress of AI over the past decade, enabling its widespread application in various organizational contexts. As noted by (Hal Varian, 2018), significant progress has been made in areas like image recognition, speech recognition, and machine translation, allowing AI, as a general-purpose technology, to make a profound impact across numerous industries. This impact, as noted by (Dwivedi et al., 2021), can also be seen through a numerous research papers published in the field of various application of AI in education (Zawacki-Richter, Marín, Bond, & Gouverneur, 2019), healthcare (Rong, Mendez, Bou Assi, Zhao, & Sawan, 2020), agriculture (Misra et al., 2022), business and finance (L. Cao, 2020), robotics (Vrontis et al., 2022), marketing (Vlačić, Corbo, e Silva, & Dabić, 2021), transportation (Vlačić et al., 2021), day life, etc.

In order to enhance competitiveness, reduce costs and harness the various benefits offered by this innovative technology, organizations strive to integrate AI into their operational units. However, a question arises: Have innovative technologies always been readily adopted and swiftly implemented throughout organizations? Regarding intention to use AI and its adoption, scientists are often engaged in exploring factors at various levels, including individual, organizational, and contextual. At the individual level, factors such as perceived usefulness, perceived ease of use, attitudes, and individual characteristics may play a role in shaping the intention to use and accept AI. Organizational factors can encompass aspects such as organizational culture, leadership support, resources, and training (Lecic, Milic, Visnjic, & Culibrk, 2023). Contextual factors consider external influences, such as industry characteristics, regulatory frameworks, and societal norms. Different theories, which are used to explain technology adaption in general, are also used to explain adaption of AI as an innovative IT technology on individual or organizational level. The most common theories used on individual level are Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), Theory of Planned Behavior (TPB) (Ajzen, 1985), Technology Acceptance

Model (TAM) (Davis, 1989), Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003), etc. On the organizational level, the two most common used are Technology-Organization-Environment (TOE) model proposed by (Tornatzky & Fleischer, 1990) and Diffusion of Innovations theory (DOI) proposed by (Rogers, 1995). All the above theories are also combined in the literature in an attempt of authors to predict more percentage of cases of acceptance of any technology.

Throughout history, humans have consistently pursued the adoption of new technologies to improve work efficiency, productivity, and overall system success by achieving faster results with fewer resources (Dwivedi et al., 2021). However, according to (Venkatesh, 2021), just like many times before, organizations today are facing with problems regarding adaption and use of innovative technologies which is influenced by many factors, and AI is not an exception. These problems are very often the result of employees' reluctance to accept and use new technologies, because AI can be seen as a technology which has a potential to replace their work (Burgess, 2018). Consider the steam engine revolution, where physical labor was gradually replaced by machines. Similarly, contemporary efforts today are focused on perfecting technologies that facilitate cognitive tasks. However, historical evidence indicates that every form of automation led to the fear of job displacement, alongside other accompanying obstacles, and this fear is even more justified considering estimation that job displacement due to automation could lead to up to a third of current working activities being impacted by 2030 (Manyika et al., 2017). While AI may be perceived as a potential threat that could replace human jobs, on the other hand it also offers opportunities for job performance improvement. AI systems can provide timely and accurate information, facilitate data analysis (Dabbous, Aoun Barakat, & Merhej Sayegh, 2022), and assist in the decision-making process (Bader & Kaiser, 2019), which is one of its most significant applications (G. Cao, Duan, Edwards, & Dwivedi, 2021). Therefore, it becomes crucial to focus on employees and explore the factors that influence the likelihood of organizations intending to adopt AI and those that may hinder such intentions.

2. FACTORS INFLUENCING INTENTION TO USE AI

Absence of grounded theory in research on information systems caused scientists to relay on theories from the field of social psychology in order to provide an explanation on factors that can predict Individuals' acceptance behaviour (Venkatesh, James, & Xu, 2012) (Kaur & Arora, 2021). Those theories mentioned earlier, TRA, TPB, TAM and UTAUT are based on the reasoned and planned individual behavior resulting from and consistent with people's conscious intentions regarding that behaviour (Fishbein & Ajzen, 1975).

TRA (Fishbein & Ajzen, 1975) is among the core and influential theories that profoundly shape human behavior and is used to predict behavioral intention or behaviour. It aims to explain how attitudes and behaviors in human actions are related. The theory suggests that behavioral intention, as a direct precursor to behavior, is determined by prominent information or beliefs regarding the probability that engaging in a specific behavior will result in a specific outcome (Dwivedi et al., 2017).

TPB (Ajzen, 1985) is an attempt to deal with limitations of TRA theory and represents its extended version. It introduced perceived behavioral control as a new construct which pertains to individuals' perception of the level of ease or difficulty related to engaging in a specific behavior. Based on the theory, the combination of perceived behavioral control and behavioral intention can directly forecast the specific behaviors (Dwivedi et al., 2017).

TAM (Davis, 1989), is an adaptation of TRA theory in order to be used for predicting behavioral intention specifically of users of Information systems. According to the TAM, two critical beliefs, namely perceived usefulness, and perceived ease of use, play a pivotal role in shaping individuals' behaviors towards computer acceptance.

UTAUT (Venkatesh et al., 2003), was developed through a comprehensive examination and integration of eight prominent theories and models. It has four core determinants of intention: effort expectancy, performance expectancy, social influence, and facilitating conditions. This theory is widely used by many scientists and is proved to explain higher percentage of variance than other theories. (Venkatesh et al., 2003) proved that the UTAUT model was capable of accounting for nearly 70% of the variability in behavioral intention, whereas other models and theories, using the same data, could only account for 17% to 53% of the variability in behavioral intention.

TOE model was developed by (Tornatzky & Fleischer, 1990) and is based on Contingency Theory of Organizations. It is dominantly used to explore IS acceptance on organizational level. Within this framework, three fundamental factors were recognized as influential in organizational adoption: technology, organization, and environment (Ibrahim, Yasemin, Sevgi, & Turetken, 2012).

DOI is proposed by (Rogers, 1995). The DOI theory perceives innovations as being disseminated through specific channels within a particular social system over time (Rogers, 1995). Individuals are viewed as having varying levels of readiness to adopt innovations, resulting in an observable pattern where the adoption of an innovation by the population follows a roughly normal distribution over time (Rogers, 1995).

2.1 Factors on individual level

On such grounds, (Dabbous et al., 2022) extended the technology acceptance literature by proposing a behavioral model which takes into account the peculiarities of AI. This study combines TAM and the TRA, in the context of developing country, and argues that when explaining the intention to use a new technology, it is important to integrate organizational, social, and individual factors. This model, with the aim to explain employees' intention to use AI, is based on five factors: perceived usefulness, job insecurity, self-image, habit and organizational culture. (Dabbous et al., 2022) excluded variable named ease of use, which could be considered in further research. Job insecurity, as defined by (Tsakonas & Papatheodorou, 2008) is a "perceived threat of job loss and the worries related to that threat". Studies shows that Perceived usefulness has been one of the significant predictors of intention to use technology (Venkatesh et al., 2003) and it refers to the degree to which a service is perceived as advantageous in efficiently and consistently accomplishing a particular task (Tsakonas & Papatheodorou, 2008). Self-image is defined as the extent to which an individual believes that utilizing an innovation will improve their standing within their social system (Dabbous et al., 2022). Habit is also one of the important factors which has significant influence on humans' behaviour. It is defined as the degree to which individuals engage in behaviors automatically due to learned patterns (Limayem, Hirt, & Cheung, 2007). No less powerful factor is organizational culture which responsibility lies in creating a suitable environment that fosters the adoption and utilization of this technology. Organizational culture encompasses shared values, beliefs, and underlying assumptions that are commonly held by members of an organization (Miron, Erez, & Naveh, 2004). The study of (Dabbous et al., 2022) contributed by implementing organizational culture in combination with habit in the proposed model which are also proved to have strong impact on intention to use AI.
Another study (G. Cao et al., 2021) focused its research efforts on intention to use AI specifically in the area of decision making by exploring managers attitudes. They developed integrated AI acceptance-avoidance model (IAAAM), which integrated UTAUT and technology threat avoidance theory (TTAT), with an intention to cover not just factors influencing technology acceptance, but also the factors influencing individual's technology avoidance intention. Their model consists of ten factors: Attitude (an individual's favorable or unfavorable attitudes toward using AI) (Dwivedi et al., 2017), Performance expectancy (the extent to which an individual perceives that utilizing AI will lead to improvements in job performance) (Venkatesh et al., 2012), Effort expectancy (the level of ease linked to the utilization of AI) (Venkatesh et al., 2012), Facilitating conditions (the extent to which an individual perceives the presence of organizational and technical infrastructure to facilitate the use of AI) (Venkatesh et al., 2012), Peer influence (the extent to which an individual perceives that significant others believe they should utilize AI) (Venkatesh et al., 2012), Perceived susceptibility (An individual's perception of the probability that using AI will result in making poor decisions) (Chen & Zahedi, 2016), Perceived severity (an individual's perception of the extent of adverse outcomes associated with using AI to make bad decisions) (Chen & Zahedi, 2016), Perceived threat (the degree to which an individual perceives the use of AI for decision-making as risky or harmful) (Chen & Zahedi, 2016), Personal wellbeing concerns (the level of apprehension and stress experienced by an individual due to the use of AI) (Agogo & Hess, 2018), Personal development concerns (the level of concern an individual has about the extent to which AI inhibits personal learning from one's own experiences) (Duan, Edwards, & Robins, 1995). The results of this study only partially confirmed hypotheses from UTAUT model which can be explained by different context of the study indicating that the UTAUT model and its associated factors may not comprehensively capture the context of utilizing AI for organizational decision-making. An essential implication is that organizations should consider individual concerns when implementing decision-making systems based on AI and is likely to be a key factor influencing managers' perceptions of using AI.
Also, another research done by (Chatterjee, Rana, Khorana, Mikalef, & Sharma, 2021) focused on the specific use of artificial intelligence in CRM. This study used modified UTAUT model in order to explain adoption and user behavior in this specific AI usage. The modification implied that some moderators and constructs used in UTAUT, such as social influence, are dropped from the model, and some new constructs, which are characteristic for AI in CRM, such as attitude, as a mediating variable, and CRM quality, CRM satisfaction and compatibility, as exogeneous variables, are included. This study is an

example of modifying existing model by adding new variables, which are specific for AI-CRM. By this study authors confirmed all formulated hypothesis, and argue that by introducing new variables, they strengthened the model (Chatterjee, Rana, Khorana, et al., 2021).

2.2 Factors on organizational level

In the study of (Chatterjee, Rana, Dwivedi, & Baabdullah, 2021) we can see an example of combining two theories TOE and TAM which are used for predicting AI adoption and behavioral intention on different levels – organizational and personal, here in the context of the manufacturing and production companies. The present study has investigated the influence of cultural factors on the adoption of a new technology (such as big data) within an organizational context.
Further, in the study of Venkatesh, who is the creator of UTAUT model, are given directions of further research in this area, suggesting four opportunities: 1) examining antecedents/determinants that are specific for certain technology, which could include: individual characteristics (such as personality), technology characteristics (such as quality), environmental characteristics (such as culture of innovations); 2) formerly mentioned variables can be used as a moderators in the new models; for instance, it is possible that individual characteristics can moderate the impact of one or more UTAUT predictors (such as performance expectancy) on intention or usage, and that can be case with other variables as well; 3) these mentioned variables can also have a direct influence on intention to use (a suitable example of that is an advancement od UTAUT to UTAUT2 model, adding habit as a predictor); 4) The outcomes and consequences commonly examined in the literature on technology adoption, such as intention, behavioral expectation, and usage, warrant further investigation (Venkatesh, 2021).

3. DISCUSSION AND CONCLUSIONS

Prior research on the adoption of AI has predominantly relied on theories and models of Information Systems/Information Technology adoption. However, it is questionable whether such models correspond to the specificities of artificial intelligence in full and whether there is a need to improve them through the introduction of AI specificities. To overcome the beforementioned problems and include all the significances of artificial intelligence, some of authors tried to combine and mix existing models and theories, while other tried to add new constructs in existing models. Research which resulted with new proposed model called IAAAM is done by Cao (G. Cao et al., 2021), and they argue that conventional models of technology adoption, such as TAM and UTAUT, are not adequate for studying the adoption of AI as they primarily concentrate on functional technologies and fail to comprehensively explain the decision-making process in the context of AI adoption. Similar problems exist when exploring other innovative non AI services (Raut, Célić, Dudić, Ćulibrk, & Stefanović, 2021), like e-government, which resulted in unified model of e-government adoption (UMEGA) by (Dwivedi et al., 2017). These two papers only partially confirmed hypothesis and showed inconsistent with prior models such as UTAUT, TAM, TRA, etc., which caused them to propose a new model. That is inconsistent with prior research, where UTAUT model was capable of accounting for nearly 70% of the variability in behavioral intention (considering previous research on classic IT technologies). Regarding future research, (Oliveira & Martins, 2011) believe that for the adoption of complex new technologies, it is crucial to integrate multiple theoretical models in order to attain a more comprehensive understanding of the phenomenon of technology adoption.
In support of the more profound research of the factors that influence individual behavior goes claim that a more pragmatic vision of the future, envisioning a collaborative context where AI works in conjunction with humans, rather than a scenario where AI replaces humans across industries (Sun & Medaglia, 2019). As Dwivedi adds, researchers have a significant contribution to make in examining the numerous obstacles to AI interaction and the psychological factors associated with change in the workforce and society at large. In (Dwivedi et al., 2021), which describes general perspectives on emerging challenges, opportunities and further agenda for research in AI, it is stressed that the social influence have also been identified as potential barrier to the wider acceptance and implementation of AI technologies. Social obstacles associated with unrealistic expectations towards AI technology and limited awareness of the values and benefits offered by AI technologies are identified as important (Sun & Medaglia, 2019).
From the extended literature review and personal experiences, authors propose to take in consideration the following specific factors that may also influence behavioral intention and AI acceptance: Ethics, Security, Privacy, and Trust. The presence of inherent bias within AI algorithms and the involvement of humans working closely with intelligent machines present substantial challenges in terms of trust, human

safety, and ethical considerations (Dwivedi et al., 2021). Also, unrealistic expectancies of AI, fear of change and many other variables are to be explored in the context of AI acceptance.

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