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Determinants and Barriers of Artificial Intelligence Adoption – A Literature Review

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Abstract. Different theories, models and frameworks have been used to study technology adoption, some explaining the determinants of adoption at the individual level, some at the organizational level and some at both. As Artificial Intelligence (AI) is gaining traction in many sectors, it will be beneficial to understand the determinants and barriers to AI adoption. In this paper, an attempt has been made to review journal articles and other reports pertaining to AI adoption and understand the adoption theories used and the factors that facilitate and those that hinder AI adoption. Articles on adoption studies of autonomous vehicles, big data analytics, robots and cognitive engagement applications dominated the list of journal articles. Diffusion of Innovation, Technology, Organization and Environment Framework and the unified theory of acceptance and use of technology (UTAUT) were some of the dominant theories/frameworks used. Factors influencing adoption at the individual level were related to trust, security, purchase price, intrinsic motivation, social influence, utilitarian benefit whereas at the organizational level, it was related to the technical competencies, strategic road mapping for AI, top management support and the digital maturity of the organization.

Keywords: Artificial Intelligence Adoption; AI adoption; Technology Adoption; Adoption Theories.

1 Introduction

Artificial Intelligence (AI) which is machine intelligence that enables them to perform cognitive human like functions is one of the hot topics of discussion these days. Adoption is the process of implementing a technology new to the organization and the acceptance and use by the users in the society. But there are many challenges faced by organizations in their adoption journeys. It will be beneficial to know the extent to which AI has been adopted by organizations in their various functions and to also know the determinants and barriers of AI adoption. According to the McKinsey Report (Nov 2019)¹, adoption of AI continues to increase and there has been significant increase in revenue and reduction in costs especially among the AI users who have adopted AI in

¹<https://www.mckinsey.com/featured-insights/artificial-intelligence/global-ai-survey-ai-proves-its-worth-but-few-scale-impact>

multiple business activities. 58% of the survey respondents had used at least one AI capability in at least one business unit. But there are other companies who have been lagging behind in AI adoption.

Against this backdrop of the results of the survey with respect to real life AI adoption, it will be useful to get an understanding of the factors that facilitate AI adoption, the factors that hinder adoption and the factors that determine the rate of diffusion of AI in the organization. It will also be beneficial to understand the interactions of the users with the AI systems in order to understand the factors influencing the AI adoption at the individual consumer levels. The adoption process may be a complex phenomenon being influenced by various factors.

In order to have a comprehensive understanding of the adoption behavior of the users and organizations, it is necessary to understand the different theories and frameworks used in studying AI adoption. These theories may be further extended to suit new adoption cases.

There have been many articles published on technology adoption and more recently on AI adoption in specific areas such as smart manufacturing [16], medicine [53], robotics [23], smart homes [39], virtual assistants [32], autonomous vehicles [1] and Big Data Analytics [4]. It will be beneficial to both the researchers and the practitioners to know the factors that facilitate AI adoption in the different areas. The managers can use this as a guide in implementing AI in their organizations. It will also help them in understanding how to increase the adoption rate amongst the individual users. The researchers will also be able to use this information in their future research initiatives on AI.

A comprehensive and systematic review of the articles on AI adoption has been done in this paper. Articles were taken from Science Direct and Google scholar using the descriptors “Artificial Intelligence adoption”/ “AI adoption”/ “AI adoption theories”/ “AI determinants and challenges”. Only recent articles published in reputed journals were included. A total list of 45 articles on AI adoption in different areas were selected.

The research questions addressed in this study are: What are the dominant theories/frameworks that are used to understand AI adoption at the organization and individual level? What are the determinants and barriers to adoption at the organization and individual level?

1.1 Theories/frameworks used to study AI adoption

Technology-organization-environment framework. The Technology-organization-environment (TOE) framework describes factors in the context of technological, organizational and environmental elements that influence adoption and implementation of technological innovations. The TOE framework has been used to study CRM adoption stages [11], SaaS adoption [35], adoption of mobile reservation systems in hotels [51].

Diffusion of Innovations. The Diffusion of innovations (DOI) explains the rate at which new technology and ideas diffuse in organizations and how and why they spread. DOI can be used to study adoption of technological innovations at both the organization

and individual levels. DOI has been used in mobile cloud computing adoption [8], in financial markets [9], autonomous vehicles [43], and Big Data Analytics [20].

Unified Theory of Acceptance and Use of Technology (UTAUT). UTAUT is a technology acceptance model that uses the three constructs, performance expectancy, effort expectancy and social influence to explain user intentions to use an information system. Another construct, facilitating conditions is used to explain user behavior. UTAUT has been used to study the clinician adoption of health information systems in developing countries [5], adoption of mHealth by the elderly [18], in predicting multigenerational tablet adoption practices [29] and in autonomous vehicle adoption.

Technology Acceptance Model. TAM, introduced by Davis (1986) was used for modelling user acceptance of information systems, with two primary factors viz perceived ease of use and perceived usefulness. Tam has been used in the extended form in investigating acceptance of telemedicine services adoption [19], in implementing citizen centric technology in developing smart cities [37], in studying the antecedents to virtual reality hardware acceptance [31] etc.

2 Research Methodology

The literature review was done by doing a search in science direct and Google scholar for research and review articles. The keywords used were Artificial Intelligence adoption, AI adoption, AI adoption theories and AI determinants & challenges.

All the papers mentioned above were reviewed and analyzed in detail. The journal name, the year of publication, AI adoption topic and application, the domain, the theory used to study the adoption process, the determinants of adoption and the barriers to adoption mentioned in the papers were noted down. The articles covered AI applications in many areas such as cognitive engagement (CE), cognitive process automation (CPA), big data analytics (BDA), computer vision (CV), in autonomous vehicles (AV), robots and in medicine.

2.1 Theories, Frameworks, Models and Methods used in the papers

Apart from the dominant theories/frameworks mentioned above, the following were also used in the papers to understand the AI adoption process.

Table 1. Details of theories/frameworks/techniques used

Name	#	Level	Application
Technology, Organization and Environment	6	Organization	CPA, BDA
Diffusion of Innovation	6	Both	AV, BDA
Unified Theory of Acceptance and Use of Technology	4	Individual	AV, Robots, Medicine

Technology Acceptance Model	3	Individual	AV, CE, BDA
Dynamic Stackelberg Games	1	Individual	AV
Best Worst Modeling and Binary Choice Model	1	Individual	AV
Uncertainty Reduction Theory	1	Individual	AV
Agent Based Modeling	1	Individual	AV
Theories of Risk Perception and Trust	1	Individual	AV
Cognitive Appraisal theory, Cognitive Dissonance Theory	1	Individual	Robots
Technology, Organization and Environment	6	Organization	CPA, BDA
Watching Eyes Effect	1	Organization	Robots
Bandura's theory of Self-efficacy	1	Individual	Robots
The 'Media Richness Theory'	1	Individual	CE
Multivariate Probit Model	1	Individual	CE
Uses and Gratification theory	1	Individual	CE

Dynamic Stackelberg Games (DSG). Stackelberg game has been used to show how asymmetric information influences strategic decisions of new technology adoption and how better information is not always a good thing [58]. This game theory was used to find an optimal subsidy policy considering the asymmetry of information between the government agency and the subsidized entities and market forecast uncertainties [28].

Best Worst Modeling and Binary Choice Model. Best-worst scaling is a survey method that can be used for examining individuals' attitude towards technological innovation. It uses the extremes, best and worst items, most and least appealing factors that influence attitude towards adoption. The Binary Choice model is further used to understand how these attitudes influence the purchase decision [38]. This can be used to study AI adoption at an individual level.

Uncertainty Reduction Theory (URT). According to URT, individuals try to reduce uncertainty by seeking information. Uncertainty arises when one is unable to determine the actions of another. Uncertainty is inversely proportional to trust. According to URT, uncertainty is decreased by acquiring information about the other person [13]. This has been used to study whether explanations promote acceptance of innovations.

Agent Based Simulation Modeling. It is used to model heterogeneous individuals who behave differently and are linked together. It is used for simulating the actions and interactions of autonomous agents to assess effects on the system as a whole. Combination of DOI and Agent Based Modelling can be used to model adoptions [43].

Theories of Risk Perception and Trust. These theories may include factors such as perceived benefit and risk, anticipated perceived and trust while studying adoption [25].

Cognitive Appraisal Theory, Cognitive Dissonance Theory. Cognitive appraisal consists of the primary appraisal process where a person examines a situation and finds out how that event will affect him and the secondary appraisal process where a response is arrived at. The outcome stage will determine how willing or reluctant they are, to accept the use of AI devices [17]. According to cognitive dissonance theory, individuals like to have consistency in their beliefs, opinions and behaviour. When there is lack of agreement, the attitude will change to resolve the dissonance.

Multivariate Probit Model. The multivariate probit model, a generalization of the probit model can be used to describe technological innovation diffusion. It is used to examine decisions with choices that are interdependent by estimating several correlated binary outcomes together. It was used in a study to describe the diffusion of smart homes [39].

Watching Eyes Effect. People behave altruistically in front of watching eyes to maintain a positive social reputation. This has been used to study robotic adoption [27].

Bandura's theory of Self-efficacy. Self-efficacy is the confidence in oneself to be able to influence events. A study was done to show how self-efficacy with regard to robot use is associated with its acceptance [23].

The 'Media Richness Theory' (MRT). This shows the relationship between the qualities and features of the communication task and the communication channel used for it. The theory has been used a lot in research related to e-government to examine why citizens continue to use the traditional methods [3].

Uses and Gratification theory. Uses and gratification theory is used to explain why people prefer to adopt certain media or innovation. The assumption is that the consumers are not passive. A study was done to understand the adoption of Alexa and other technological innovations [32].

3 Determinants and Barriers to AI Adoption

3.1 Autonomous Vehicles:

Adoption of Autonomous Vehicles topped the list of topic wise articles with 13 articles under this category.

Table 2. Autonomous Vehicles adoption

Facilitating Factors
Purchase subsidies, AV related infrastructure [10].
Individual's need, cost, overall impression, word of mouth [43]
Rate at which autonomous technology improves over time, status and environment consciousness, disability, age, gender, income, education [12]
Perceived safety, perceived usefulness [56]
Household composition [6], Parking cost [38]
Self-fulfilment including quality of life, security, responsibility [33]
Being technologically savvy, perceived benefits [24]
Coefficient of imitation such as observability, coefficient of innovation such as compatibility, relative advantage [40]
Barriers
Changes to established routines, perceived risk, perceived concerns, lack of accountability, lack of trust, system failure, privacy concerns, deprivation from the joy of driving, overreliance on AV, loss of driving skill, perceived dread [1].

3.2 Big Data Analytics

Table 3. Big Data Analytics adoption

Facilitating Factors
Top management support, organizational data environment [49]
Cloud provision and platforms, stronger and clearer privacy and governance, innovativeness approach, competitiveness and resources [52]
Barriers
Adapting the organizational processes to the new technology, managers feeling threatened due to fear of losing their jobs to the new technology.

3.3 Cognitive Engagement

Table 4. Cognitive Engagement

Facilitating Factors
Social influence, hedonic motivation, performance expectancy [17]
Utilitarian hedonic and symbolic benefits, social attractiveness [32]
Novelty of AI activity, attitude towards the organization [48].
Barriers
Adaptation challenges and use for elderly people, interaction with other technologies [34].
Lower communication richness and expressiveness [3], more complexity and ambiguity.

3.4 Robots

Table 5. Robots

Facilitating Factors
Performance efficacy, intrinsic motivation, facilitating conditions [27]
Competitive market environment and customer needs [21]
Robot use self-efficacy [23], social influence, trust, culture, prior experience
Barriers
Anthropomorphism [27], low levels of acceptance toward an intervention, privacy and ethical concerns, job insecurity.

3.5 Medicine

Table 6. Medicine

Facilitating Factors
Efforts required to install and use the tool [57]
Reproducibility [53]
Accuracy, trust [15]
Ability to explain and easily interpret predictions, robust regulatory framework for managing changes to algorithms, time to delivery, cost [26]
Initial trust has four determinants - propensity to trust, social influence, performance expectancy and effort expectancy [15]
Barriers
Algorithmic transparency and reproducibility [53]
Variations between experimental and clinical data, the need for regulators approve the computational methods [46], Error rates, potential risks on lives [15]

4 Results

4.1 AI Adoption Theories

Referring to Table 1. above, we see that the most dominant theories used to study AI adoption are Technology, Organization and Environment (TOE) and Diffusion of Innovation (DOI). TOE and DOI have been used in six articles each. TOE has been used to study adoption at the organization level where as DOI has been used both at the organization and at the individual levels.

TOE and DOI have been followed closely by UTAUT and its extension followed by TAM and its extension. Both UTAUT and TAM have been used at the individual adoption levels. We also observe that the topic of AV adoptions dominates the list of

articles. AV was followed by Big Data Analytics, Robots and AI uses in Cognitive Engagement in the count of number of articles.

Table 7. Dominant Theories

Level	Theories
Organization	TOE, DOI
Individual	UTAUT, DOI, TAM

Table 8. Application wise details

Application	Theories
AV	DOI, UTAUT, TAM, DSG, Best Worst Modeling and Binary Choice Model, Uncertainty Reduction theory, Agent Based Modeling and Theories of Risk Perception and Trust
BDA	TOE, DOI and TAM
Robots	UTAUT, Cognitive Appraisal Theory & Cognitive Dissonance Theory, Watching Eyes Effect and Bandura's theory of self-efficacy
CE	TAM, the Media Rich Theory, Multivariate Probit Model and Uses and Gratification theory

4.2 Determinants and Barriers

Aggregating the determinants and barriers from the different papers, there was a huge number of factors that facilitated and hindered AI adoption for the different applications.

At the organization level, the key determinants were found to be Organizational strategy and roadmap for AI, top management support, existing infrastructure, digital maturity, trust, skill base, competitive market environment, compatibility, relative Advantage, observability, cost of adoption, external pressure, Government support, privacy laws, organizational innovativeness etc. In the area of medicine, the key determinants were establishment of an eco-system of key players, regulatory approvals, anonymization of data and accuracy.

At the individual level, it was trust, cost, social influence, hedonic motivation, performance expectancy, utilitarian benefits, safety, intrinsic motivation, prior experience with AI tools.

5 Discussion and Implications for Managers and Researchers

This paper has done a systematic review of journal articles in the area of AI adoption and has summarized the dominant adoption theories used along with the determinants

and barriers to adoption for the different AI applications at the organization and individual levels. It has helped in creating a knowledge base which can be used by the future researchers while studying adoption of AI and other technological innovations.

The paper will also help the managers by providing an insight into the factors that facilitate and those that hinder AI adoption and the factors that determine the rate of diffusion of AI in the organization in the different application areas. It will be useful to study AI adoption at the individual consumer levels by understanding the interactions of the users with the AI systems. This information can be used while implementing AI in their organizations by knowing the customer needs and by addressing the apprehensions the users might have towards AI.

All the papers were selected from reputed Journals adding to the usefulness of the study. The paper can serve as a quick guide for both the researchers and the managers to know about the latest research details in AI adoption and know which theories to use and hence, what parameters to look for while studying adoption. The study was based on the study of 45 research papers comprising of the 7 application areas of AV, Big Data Analytics, Robots, Cognitive Engagement, Medicine, Computer Vision and Cognitive automation. Future research can be done in more detail in each of the above areas.

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