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Micro-foundations of Artificial Intelligence Adoption in Business: Making the shift

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Abstract Artificial Intelligence has gradually materialized as an independent research field within information systems and business domains. The new forms of work evolving in the business require substantial experimentation, lead generations, and real-time recommendations. This has driven the extraordinary increase in the adoption of Artificial Intelligence technologies. Even with front runner organizations across the domain envisioning the advantages of early adoption of Artificial Intelligence technologies, some organizations scuffle the adoption owing to various barriers. This paper analyzes the characteristics that lead to and factors inhibiting the adoption of Artificial Intelligence at the organization-level. Through this paper, we report the results of Twitter conversations involving small and medium scale organizations about their level of adoption of Artificial Intelligence and barriers that they are facing. Through this analysis, we provide insights and agenda to help the executives of small and medium scale organizations to prepare for the adoption of Artificial Intelligence.

Keywords: Information Systems, Artificial Intelligence, Adoption, Barriers, Chatbots, Roboadvisor.

1 Introduction

The overall rise of the digital transformations among business houses fueled by Artificial Intelligence (AI) [1] has become one of the crucial drivers of scalability, flexibility, and real-time business operations. These operations range from catering the customers with appropriate promotional strategies, live support, real-time recommendations, and a personalized bundle of products. This has led the investments in AI across the world to grow at an astonishing rate. A report by Gartner in 2016 reported the adoption of AI by 9% of the organizations. By the end of 2019, AI adoption and production-alization have increased by 25% in the business organizations and are set to double itself in the next five years [2]. This shows the pace at which the organizations are embracing AI as part of business objectives.

Today AI comes as one of the critical innovation objectives and key results (OKR) when it comes to organizational goal settings [3]. With the advancements in the data

storage and processing capability, AI has been driving the digital transformation OKRs. The view of organizations has evolved from looking AI as an innovation cost center to an essential business solution. Large scale organizations were the first ones to adopt while small (start-ups or boutique consulting firms), and medium (service-based) enterprise organizations (SMO) have now started [4] seeing AI has a business necessity. What comes as an interesting report published by PwC is that AI will contribute up to \$15.7 trillion to the global economy in 2030 [5]. A handful of industry reports suggests [6] that adoption of AI will give organizations to improve operations performance across lead generation, marketing, catering customers by creating a competitive advantage. Hence in totality, all these lead us to believe that the adoption of AI leads to an organizational increase in revenues, reduction in costs, and improved business efficiency.

However, many business organizations are still unclear on or are at the stage of deciding the business use case for the application of AI adoption. These organizations also struggle in identifying the right skill-sets needed for an entire pipeline of evaluating, building, and deploying AI solutions. Although several organizations across the globe are adopting AI, little research exists in the domain of adoption drivers and barriers[7]. Furthermore, a study of these drivers and barriers at the business organization level has remained marginally represented in the literature [8]. The proposed research is one of the first studies that analyze the adoption drivers and barriers and contributes towards the Information Systems (IS) literature a framework, which can be used by existing or start-up business houses to do a value assessment and roadblocks which can slow down the adoption of AI.

In this context, we propose a unique framework of an amalgamation of customer experience theories [9], with every potential business house being referred to as a customer of AI solutions and experience(good or bad) as drivers or barriers of adoption. Moreover, this research also provides empirical evidence that overcoming the not so good experiences (barriers) of AI adoption leads to a higher degree of AI practicing. The current research focusses on the state of the art AI technologies as products like chatbots, roboadvisors, virtual reality, augmented reality, recommendation engine has driven digital marketing, deep learning.

The prime objective of this study is to identify the factors responsible for impacting the advocacy of AI from the lens of adoption experiences. We use social media analytics (SMA) framework applied to the conversations and experiences shared on social media platforms (SMP) like Twitter by technical stakeholders in SMO by mining the original tweets posted by them. We further use the opinion mining approaches like topic modeling and sentiment mining. To guide our research analysis, we have undertaken two research questions:

RQ1: How stable is the identity and scope of the definition of AI technologies?

RQ2: What are the drivers, barriers, and initial experience towards AI adoption among the organizations and the users of these technologies?

The rest of the paper is organized into four sections. In the second section, we provide a methodological overview of the related literature. In the third section, we explain the research questions and formulate hypotheses. In the fourth section, we describe the methodology of the research undertaken. Furthermore, in the fifth and sixth section, we discuss the findings, interpretations, and conclude with the future research directions.

2 Prior Literature

The literature review consists of the following subsections: we start with defining state of the art AI technologies, AI adoption and barrier theories, and customer experience frameworks.

2.1 Artificial Intelligence

The notion of AI is not entirely new; it was first developed around 1950s in the computer science discipline with the primary focus towards automation [10]. It has ever remained persistent ever since Professor John McCarthy has described AI as “science and engineering making the machines do the repetitive task of humans” [11]. In the early 1980s, Lighthill [12] proposed the usage of AI addressing the problem of automation using robots with fundamental logical programming. In current times, the application of the AI is a lot wider than what it was proposed forty years back. It has started to become an essential component of any business by providing solutions like chatbots [13], robo advisors [14], virtual reality [15] shaping, and helping marketing, product, and customer service teams. AI encircles several frameworks to produce these techniques like deep learning [16], [17] expert systems, and recommendation engines.

The prior work done in the field of AI represented through the literature highlighted in the previous paragraph focusses on data, tools, and techniques of AI that can be used to strengthen the performance of the current system employed in the domain. Most of these works of literature are focused on the end implementation of AI techniques considered in silos in various domains. However, very little work exists in the domain of IS literature, suggesting the initial opinions, sentiments, and learnings while pursuing the path of AI adoption. We feel that there is a need to create work around these pivots, which can be used as a case study for the future SMO as they embark on their journey of AI adoption. We intent on filling this gap with the proposed work.

2.2 AI adoption and barrier theories

The adoption of any innovation technique in an organization goes through various stages. There are three broad stages: initiation, adoption, and implementation. Rogers [18] have proposed various sub-phases within the adoption stage and has been proven across various domains and techniques. Pierce and Delbecq [19] have proposed the sociological theory of innovation, which starts with the ‘pressure to change.’ This makes the organizations identify the problem and to learn technology and acquire resources to make the changes for the better good. Authors [20] in the domain of adoption of innovative techniques have further proven that late adopters of the techniques have

been at a loss. There exists a gap in the IS literature to understand the adoption of AI through the lens of innovation adoption theories.

To this date of writing the current manuscript, there exists a considerable number of research in IS, learning the barriers of adoption of various technologies like a cloud [21], blockchain [22], [23], mobile commerce [24], internet banking[25]. These studies pivot the barriers faced by the policy-makers in a business organization to political, economical, return on investments (ROI), skill gap, and overall experience. Reviewing the barrier literature in the IS domain reveals that these factors must be considered differently when adoption is to take place in a business house. For instance, the political barrier translates to support from top management towards adoptions [26], [27], economic barriers translate to initial cost of set-up and privacy risks [27], [28], skill gap translates to lack of skilled employees [28] and overall experience translates to resistance by the employees to up-skill themselves or to change[29], [27]. However, we feel that there is a need to explore further the barriers in the adoption of AI by business organizations, which will widen the IS literature.

2.3 Experience of AI adoption

The employees of the business organization using AI techniques and technologies are primarily the end-users. Hence it is an exciting aspect to view their experiences of using AI from sociological theories. With a thorough review of the literature, we interpret that two most qualifying candidates emerge as premises, experience as a response of using technology as an offering [30], [31] or as a response to an assessment of the quality of the technology [32]. Extending these premises further, some of the studies[33] see the experience driven by characteristics of the technology rather than customer's (user's) response to use the technology.

These studies have primarily focused on the extraordinary, different from regular or ordinary as the characteristics of the technology. Basis these characteristics of the technologies, the experience can range anything from weak to strong. The literature follows to explain that these experiences ranges are a continuum and cannot be tested as a dichotomy. At the time of developing this manuscript, to the best of our knowledge, there is no or minimal literature that tests the characteristics of AI on the experience of the employee (user of AI). We feel that there is a need to widen this literature, and the proposed research will help to fill this.

3 Hypothesis development

3.1 Opportunities and benefits of AI for the business sector

Rogers [18], in his theory, has proposed the importance of communication channels as an essential element in adoption where the adopters share their experiences and information. In the social media space, we use Twitter as the channel for sharing our experiences and information for others to learn and adopt. Literature [34] on AI suggests that business decisions are based on intuitions, and intuitions are based on patterns

and trends learned through simulations on a large scale of data using AI techniques like deep learning. If so, then the business executives attend the real-time questions aided by intuitions, which are driven by AI. This leads us to believe that AI becomes an identity of business decisions.

There can be different identities of AI when it comes to business applications like perceived usefulness, cost, affordability, more real-time. When organizations perceive the use of AI, they tend to adopt this technology quickly. Post-adoption, the organizations which know start innovating through AI. As the degree of adoption or diffusion of AI increases, it eventually takes the shape of an identity of the business house with perceived use and advantage. This leads us to form our first hypothesis to answer RQ1.

H(1): The operational improvement and enablement is leading the AI to become the identity of SMO

3.2 Adoption barriers of AI for the business sector

The findings of the literature show that there could be multiple barriers of adoption of an innovation pivoted around cost [28], privacy [27], the resistance of the employees to embrace [28]. Furthermore, few of the business houses feel that they are not getting the complete ROI from the technology. These barriers can further be translated as transformational and incremental barriers. There is also evidence that these techniques, if not supported by the right pieces of training of the employees, might turn out to be a barrier for adoption. This leads us to form our second hypothesis to answer the first part of RQ2.

H(2): The unsurity and unclearness of the advantages of AI might be a barrier towards adoption.

3.3 Experience as a barrier of AI for the business sector

Employees of an organization perceive every technology differently. This partly drives the experience [32], [33] of using these techniques and technologies. The overall organization's adoption is built on the experience of the end-users (employees) of the technology. It is a perceptual issue that could arise out of firsthand experience and emotions of these issues. User (employee) friendliness is a noteworthy element to be tested when it comes to the adoption of AI at the organization level. This leads us to form our third hypothesis to answer the second part of RQ2.

H(3): A negative employee experience towards using AI might be a barrier towards adoption in a business organization.

4 Research methodology

4.1 Research instrument

This study investigates the drivers, barriers, and experiences of organizations towards the adoption of AI. For this, we have used Twitter as the channel of communication and the tweets posted as the instrument and words as a unit of analysis.

4.2 Data collection

We have collected tweets around trending hashtags like #ArtificialIntelligence, #AI, #Chatbots, #Virtualreality, #Augmentedreality, #industry4.0, #roboadvisor. The associated hashtags of #ArtificialIntelligence were determined based on collection of first 1000 tweets and mining it for hastag association rules. The resulting dataset consisted of 3,54,782 tweets posted by 60,142 users. We have further deployed some control mechanisms to make sure that the tweets are posted by actual users and not bots by pulling few historical tweets of these users and looking at the trend of posting these tweets in terms of hour of the day, day of the week. We have further dropped any tweet which had either only media embedded or an HTTP URL or was less than ten characters. This gave us a dataset of tweets with optimal length. We have further removed any stopwords from the tweets. This step is important as tweets are the unit of analysis.

We have further created a subset of the dataset by restricting our analysis to the SMO. For this, the tweets posted could be from the representatives of these firms like “principal engineer,” “technical architects,” “principal data scientists,” product managers,” “customer support heads.” This subset was created in a two-phase manner. The first phase consisted of selecting users who have more than 10,000 followers and following. In the second phase, we have downloaded the user account level information from Twitter, and only accounts chosen to be part of the subset were those which had an association with any organizations and have a designation as part of their profile information. The resultant dataset for the analysis was reduced to 1,56,345 tweets posted by 46,302 users.

4.3 The social media analytics framework

With the words of the tweets posted by the users as the unit of analysis, we primarily use the content analysis tools of the social media analytics framework (SMAF). Content analysis tools and techniques have been accepted in the IS literature for mapping words to the sentiment and the more comprehensive theory testing and development [35], [36]. The primary and the most significant outcome of the content analysis is the sentiment polarity score [37]. These polarity scores can further be divided into negative, positive, and neutral. For the current research to analyze the

drivers, barriers, and experiences, we are restricting to positive and negative sentiments. To interpret the meaningful insights from the large volume of texts, we are using word clouds [38] for each group of users (positive and negative sentiments). Latent Dirichlet Allocation (LDA) [39] has been used for topic modeling as it provides a way to control the number of words and identify the emerging theme within groups. There were 100 topics of 10 words, each of which were computed with LDA.

5 Findings

In the current research undertaken, collected data (tweets) were analyzed to identify experience and sentiments towards adoption and usage of AI using a mix of methods adopted from SMAF, which are rooted in computer science theories and inferential statistical analysis in the social science domain. We start by first illustrating a comparative view of the sentiments (polarity scores) of the tweets in the overall group (3,50,000 tweets from 60,000 users) and the focused SMO considered for this analysis (1,56,345 tweets posted by 46,302 users).

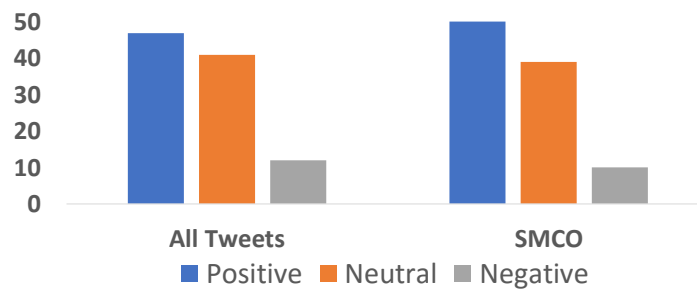


Fig. 1. Percentage polarity in groups

In general, it can be interpreted that more tweets are with positive sentiments towards AI. However, there is a considerable size of the group, which is neutral and a negative group. A manual investigation of the neutral tweets indicated that the SMOs are still not sure about the advantages of AI or are not confident in adopting owing to the current skill-set gap of the employees. The negative group might see some barriers to using AI technologies. With industry 4.0 around the corner, SMO falling in the neutral and negative group must learn from the experience of the SMO in the positive group and embark on the journey of adoption before it becomes a necessary commodity. The outcome of the current research will act as a contribution towards the literature of the success stories of AI adoption in IS, which can be used by SMO thinking to take the route of AI.

Subsequently, we attempted to visualize the 100 topics that were identified using LDA within respective groups. The most occurring topics identified from LDA on tweets basis the frequency of their occurrence in each group are plotted using the word cloud. A manual framework was also deployed to remove any verb part of the speech

to make sure that we do not lose on identifying any important emotion, experience related words. This framework was tested for intercoder reliability and validity. Further, the incomplete words in the frequency map, which had spelling mistakes, were also corrected before this analysis. In this approach, the topics that occur more frequently among the respective groups will have a larger font size as compared to the words that occur less number of times among the group.

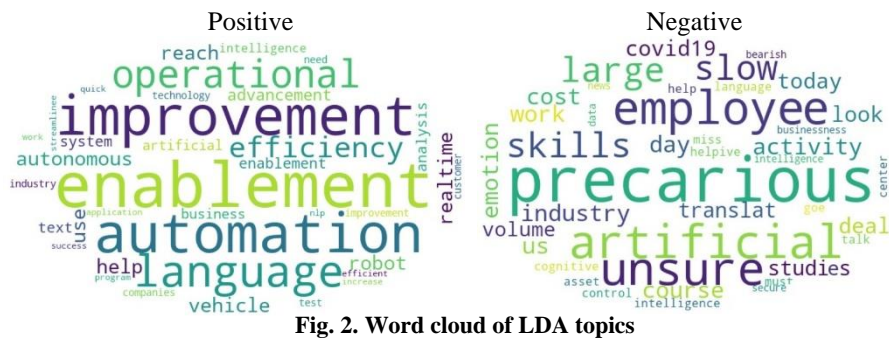


Fig. 2. Word cloud of LDA topics

From the word cloud created within respective groups, it is evident that much focus is on words like enablement, automation, improvement, efficiency and efficient, advancement, real-time customers, autonomous system streamline, reach and need. However, when we steer the analysis to the SMO, which falls in the negative sentiment group, the focus of the words shift to precarious, unsure, skills, employee and emotion, large, bearish, cost, must be secure.

After that, we have created the community diagram of the topics based upon the association among the topics that emerged from the topic modeling. The community diagram is expected to validate the themes emerging from the LDA rooted in the literature discussed in the earlier section based on the words co-occurring in the same community. In the community diagram, the classes are represented by respective colors, and each class in a silo represents a theme.

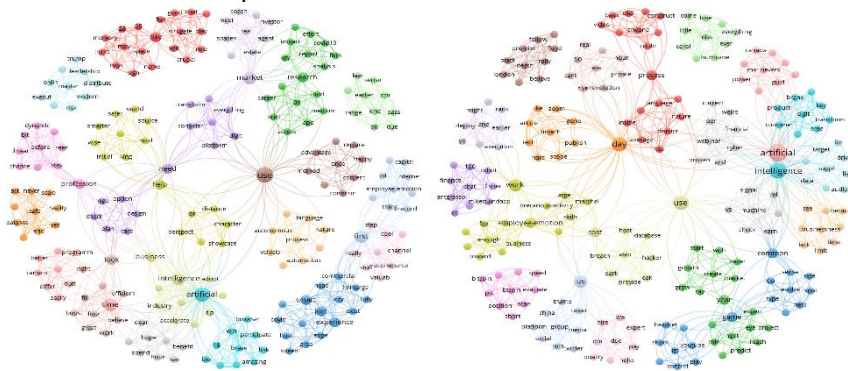


Fig. 3. Word community diagram in positive and negative respectively

From the community diagram, there are 16 themes developed with the positive SMO groups, which are: time, research, market, need, industry, accelerate, efficient, safe, and more. These 16 themes of the words association can act as premises for further hypothesis development and can be tied back to different theories highlighted in the literature. Few of these themes are further connected, highlighting that multiple premises support each other for the adoption of AI.

While analyzing the community diagram of the SMOs falling in the negative group that is emerging is the employee-emotion. This theme can act as a separate premise for hypothesis development and be linked back to the employee user experience. Other themes that emerge are skills, unsurity, and safety. These themes can be further used to explain the theoretical model explained in the introduction section to develop deep-dive research into barriers of adoption.

6 Discussion

6.1 H(1): The operational improvement and enablement is leading the AI to become the identity of SMO

Our first finding indicates the evidence of improvements in operational efficiency in the SMOs who have adopted AI technologies. These have specific proofs of topics like quick to market, automation, and real-time customer recommendation and support, which helps businesses to make informed decisions [34]. With the inferential interpretation of these insights, we can accept the hypothesis 1 in favor of AI improving and enabling efficiency and automation.

6.2 H(2): The unsurity and unclearness of the advantages of AI might be a barrier towards adoption

Our second finding indicates the evidence of cost, unsurity, and skills being the barriers of AI adoption in AI. Findings of IS [28] literature for the adoption of other innovations have historical evidence of cost being the most significant barrier. Being unsure is partially related to cost in terms of ROI and security. With these pieces of evidence in the current analysis, we accept the hypothesis 2 in favor of cost, unsurity, insecurity, and skills being barriers for SMOs to adopt AI.

6.3 H(3): A negative employee experience towards using AI might be a barrier towards adoption in a business organization

Our third finding through the topic modeling and community diagram is the employee-emotion and experience. Employees [32], [33], irrespective of SMO or significant business organizations, look at the perceived benefit and experience they like to have while

using a particular technology. Through topic modeling, employee-emotions is a separate pivot emerging from the discussions of SMOs within the negative group. In the community diagram, this theme is connected to the ‘not-sure’ cluster. Using this evidences, we can accept hypothesis 3 in favor of employee emotions as another barrier in the adoption of AI.

7 Conclusion and future scope of research

This research aims to explore the drivers, barriers, and experiences of the adoption of AI in the SMO. An inferential SMA framework has been utilized to validate the hypothesis answering the research questions around what is driving the adoption of AI and the barriers hindering. If these factors are addressed with factors like knowledge, training, trust, security, making sure that employees do not feel outdated with the adoption of state of the art AI techniques will make the adoption a smooth process. As AI is increasingly being used in industries, studies are required to understand determinants which facilitate or impede adoption [40].

As the future scope of work, we would like further develop the hypotheses rooted more firmly in the theories which revolve more around socio-cultural elements of human encounters with an innovation like AI. Further IS researchers can also refer to the current paper as a starting point to build the initial theoretical blocks for the adoption of AI.

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