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Always Trust the Advice of AI in Difficulties? Perceptions around AI in Decision Making

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Abstract Artificial Intelligence (AI) has now evolved from a phase of being merely adopted as a new system to now fueling the decision-systems to generate specific data. Borrowing from the social sciences and emerging sub-body of mathematics research literature and theories around algorithmic knowledge and value realization leads to the formation of perceptions around the confidence of allowing AI to be at the heart of any domain's decision-making. This amalgamation of AI in decision-making systems (ADMS). The current study has undertaken attempts to link personal attributes to perceptions around ADMS with the boundary constraints of these perceptions, namely the stretch to which these perceptions vary across media and domain contexts. A scenario-based survey instrument has been used to collect the data from two sets of ADMS stakeholders, vis-à-vis owners and end-users of ADMS. Analysis of the collected data from this sample (N=558) reveals that these stakeholders are by and large anxious about the risks associated with ADMS. They have a mixed and general attitude towards the on-field usefulness and fairness of ADMS outcomes at the societal level. These generic frames of mind are driven mainly by the individual traits and involvement and accountability in the domain like a revenue-generating business, social(healthcare), and the oversight of ADMS. Theoretical, management practice, and societal impacts about these findings are also discussed along the current work's final sections.

Keywords: Artificial Intelligence, Automated decision-making, Algorithm, Farness, Perception.

1 Introduction

Ever-growing research and developments in the mathematical and algorithmic domain have fueled the rise and shine of Artificial Intelligence (AI) [1]. Furthermore, with the proper support of information systems scholars, AI's applicability across various business domains has been further strengthened and generalized for management practitioners. In the last decade, several business houses have evolved from merely adopting AI [2] as a state-of-the-art technique to more tightly integrating the same to decision-

making systems to generate the returns from the investment made while building the in-house AI practice. With AI in decision-making systems (ADMS) [3], [4], [5] business stakeholders' confidence in the decisions has seen both sides of the coin. With more involvement and understanding if AI vests higher confidence in the outcomes of ADMS, past success with the gut-based decision making endows more confidence in manual decision making.

ADMS has been driving the customer-facing services in the current business set-up, for instance: personalization, recommendations, contextual responses, better allocation of advertising budgets, and overall advertising [6]. ADMS has eventually secured its role in the backend systems like automatic detection of phishing emails, suspicious financial activities, and profiles. Additionally, ADMS paves its way to make a societal and public impact by fueling virtual health [7] response systems, automated speech recognition systems to cater application filling avoiding any erroneous data being captured, helping through e-governance, and the role in the healthcare domain is endless. The presence of ADMS in the judiciary domain is also catching up slowly but gradually, with law and enforcement. For instance, there is a handful of ADMS in the directional prediction of who should get an early release from parole vs. who should continue longer with parole, helping law and enforcement parole officers. This upheaves the argument around stakeholders' confidence, like business owners and customers in the base of business ADMS, doctors and patients in healthcare ADMS, government bodies and citizens in governance ADMS, law enforcement officers and law-abiding citizens in societal [8] ADMS.

Defining ADMS more in detail to analyze the above upheavals, the literature narrowly defines this as a "*technology-driven decision with no humans' involvement.*" [1] This statement further alleviates the convulsions. However, broadening the definition by stating: a robust mathematical framework trained on ever-growing volume, variety, veracity, and real-time data fueled by the latest state of the art (SOTA) algorithms, with the flexibility of over-ruling the decisions if required or felt the need of, might grant some confidence back to ADMS. A growing sub-body of research also tries to uncover the aftermath consequences of ADMS outcomes, along with the risks associated domain-wise and limitations. This research also reveals the percentage involvement of humans at every level of results of ADMS per domain, and then it evaluates the value it can bring in. This might further bestow some of the confidence and sense of ease towards ADMS. Having stated the above, much is yet to be explored in terms of the correlating stakeholder's perception (overall, technical, domain applicability) of ADMS on the factors of perceived usefulness, limitation, risk, and fairness.

Borrowing from the social sciences literature and theories, in the current research undertaken, we extend the notion of orientation, source, and influence of heuristic algorithms on algorithmic appreciation and perceptions. This is achieved by investigating the data on the factors of fairness, usefulness, and risk. Using the representative sample (N=477) of professionals, who have also informed citizens outside their work, we try to draw insights into how the general or in-detail understanding and other traits can influence the frame of mind towards ADMS as part of primary analysis. As part of the follow-up, the secondary research, we try to analyze how exposure to knowledge, fo-

rums surrounding AI, and self-efficacy, demographical attributes further affects the development of the school of thoughts towards ADMS. Broadening the research scope, we have considered the automated responses, suggestions, and recommendations and the end automated decisions through AI leading to a specific outcome.

When it comes to ADMS leading to more customer-oriented outcomes, like personalized [9] search, recommendations, and results, we assume that a lower level of exposure initial technical knowledge among business and customers as stakeholders would lead the way. However, as we move to the societal impact of ADMS, a much higher understanding and understanding of technical aspects of the entire automated framework and intermediate human intervention is required. This takes the highest level when it comes to healthcare applications of ADMS are concerned with a lot at stake. To uncover more on these assumptions, with the support of initial literature review, we tend to tackle the below research questions through the current study:

RQ1: To what degree the business and technology domain knowledge is needed to gain confidence about fairness, risk, and usefulness of ADMS.

RQ2: To what extent the demographics orientation and presence play a role in gaining confidence about fairness, risk, and usefulness of ADMS.

The rest of the article is structured as follows: in the second section, we start with uncovering the literature artifacts supporting the assumption above, which could help us formulate the hypotheses statements to test the above. We then explain the methodology deployed to find the insights in section three, followed by section four results. We conclude with theoretical and practice implications and future scope of work, and limitations of the current study.

2 Prior Literature

2.1 AI in decision-making systems

ADMS has been conceptualized as automated frameworks that can collect the data, denoise for usage, structure for a model, select the suitable model, generate the outputs, penalize if the outcome was incorrect, reward if it was correct, and then learn from the mistakes to move to the next iteration of results. The last couple of feedback loop steps are where the learning and self-improvement of the entire ADMS take place. Hence the ADMS is perceived by the inventors is that while an initial couple of steps are mechanical in terms of the data, the latter half of self-learning from the feedback loop is where the socio-technical application of the outcomes plays a crucial role. While the model algorithm is encoded as a set of mathematical rules, resulting in the formulation of a mathematical equation, it updates the weights in these equations that have to be driven by socio-technical implications to make and ADMS successful. ADMS can overall be thought of as a combination of the following elements: data (that fuels), the algorithm used in the model (at the heart of ADMS), and the implication of the outputs generated(self-learning). Now ADMS can further be divided into the following types: high manual intervention at the beginning of data collection and taking a call at the end of

output generation, medium manual intervention required to make sure ADMS does not generate extreme outputs which could entirely disrupt the socio-economic or law and order in any form, and finally the third type being no or zero manual intervention required in any of the stages.

The level of human intervention or human involvement and the domain decide the "gear and hype cycle" stage" the current ADMS is for any discipline. For instance: healthcare application of ADMS, with zero human involvement performing critical surgeries, might leave the stakeholders in the fear cycle. However, extremely personalized advertisement, recommendations, search results might put the same ADMS in a hype cycle. Like that, governmental applications and law and order applications of ADMS with moderate human intervention might put the stakeholders somewhere in the middle of the fear and hype cycles. Literature suggests that for every technology to be successful, understanding the current position and drivers of the fear and hype cycles is essential. As part of the literature in the next section, we try to uncover the theory's support in building the same perspective.

2.2 Perspective towards ADMS

There has always been work stating any automated system driven by algorithms being more efficient and rational than human-based decisions. The perspective has been built a long time, with the results being proven statistically with drug effectiveness in patients to launch satellites by predicting weather conditions and wind speed. Hence the confidence is being driven by the statistical certainty that the results bring along with them. In other words, the heuristic nature of the results and algorithm is one of the critical factors for the stakeholders to form a perspective of the result from ADMS. Literature also suggests that the lesser a stakeholder anthropomorphizes any algorithmic black box, the more they might consider the outcomes as generalizable or objective. Computer Are Social Actors (CASA) framework suggesting that algorithms running and controlling software must be regarded as autonomous, with assumptions decided by humans and the correctness of outcomes by the domain applicability and the impact. For instance: 98.00% accurate results can be considered ok in some domains but cannot be considered in the health domain, requiring the third decimals' highest accuracy.

Several prior studies have conceptualized the same, suggesting that there could be other factors, too, leading to the perspective towards ADMS. For instance, any user might not let go of any single incorrect personalized recommendation generated by a machine/algorithm as a human. Hence, the results from ADMS are inscrutable. Although the results generated from ADMS on average are always efficient and correct as compared to human gut feeling based decision, still being the fact that driven from automated systems, the general perspective remains the same that it cannot go incorrect at any single point of time and that it has to self -learn in the real-time to improves the blend of the results.

2.3 Personal traits leading to the formation of perspective towards ADMS

Delving further into the reasons behind the shaping of the mindset discussed in section 2.2, we use some of the specific pivots of literature factors. The first factor that the

literature suggests is "understanding" of algorithm and domain. As a government representative, if a person has specific knowledge of the domain and some amount of knowledge around the ADMS self-train itself, he/she should be able to make more informed decisions on the outcomes of ADMS in any crisis. On similar lines, a doctor is already expected to know about the medical domain, if also caught up on how an ADMS predicting Diabetic Meletus, could use the judgment of margin of error he/she can live with before suggesting a remedy for the patient.

On similar lines, the stakeholders' [10] personal beliefs in the algorithms' heuristic nature drive perspective formation. This is also partially caused by the individual factor of safety towards the quality of the outcome. Another essential factor that emerges from the literature review beyond the understanding and quality is the demographics, more precisely the age. Age as a factor from time and again has played a crucial role in deciding the formation of perspective towards any new technology, acceptability and hence even the AMDS can not stay untouched from the effect of the same[11].

3 Hypothesis development

Prior research indicates that understanding is an essential factor in how an individual (any stakeholder) might perceive new technology's value. Hence, borrowing from the previous investigations, it becomes critical to include understanding as an important actor of the stakeholders driving the opinion formation towards ADMS. The details of this understanding, however, have miscellaneous results. Some of the prior works highlight the understanding of mathematics when it comes to forming a perspective of the algorithms behind AI, while others indicate the level of domain understanding to decide the importance and confidence in AI fueling ADMS. A small section of the literature suggests the elementary level of education of the end-used ADMS, and stakeholders [12] who have invested in ADMS capability have an association with understanding AI.

Building on similar thoughts from prior literature, when it comes to forming a point of view on algorithmic fairness while making decisions, a higher level of understanding of the mathematics and coding on the platform on which ADMS is developed seems to have a higher correlation. Hence given the mixed indication from the prior literature to form better insights around ADMS, we propose the below hypothesis to be tested:

H1: *Technical and domain knowledge will have a driving relationship on an individual's perspective of ADMS.*

Designed on the entire framework of large-scale automated data collection, building model and self-learning loop from the penalty and reward of the outcome has been the central theme of ADMS. Users of ADMS as one of the stakeholders unknowingly act as data creators and, at times, might share more on the personal data without realizing it. If a human handle the data collection and usage, he/she might choose to drop these to maintain an individual's privacy by intervening in the processing pipeline. However, with no manual intervention, the input framework of ADMS might be intelligent enough to separate personal information from the actual data for training the AI model.

There has been supporting in the earlier research showing how an individual's assumption of unique ability to protect personal data (self-efficacy in online mode) might lead to impact [13] his/her perspective of ADMS and, more specifically, AI in that framework. Hence to us, this becomes an essential construct to tested in the model, and we formulate our hypothesis as below:

H2: *An individual's self-efficacy will have a driving relationship on an individual's perspective of ADMS.*

Borrowing from the IT and technology adoption kinds of literature, demographics of the stakeholders investing, owning, using, and consuming the results play a vital role in driving new technologies [14]. We hypothesize that adoption eventually builds confidence in the technology being adopted and used with time. Literature also suggests that adoption is driven by the perceived usefulness, fairness, and ease of usage. Also, the prior literature indicates that the social acceptability with factors like age and gender also plays a critical role. However, in previous experimentations, gender as a factor has turned out to a non-significant one, but age always has been a significant one to drive adoption. Hence, we hypothesize that as adoption goes confidence in the technology being adopted (in the current research referring to ADMS), the demographic factors driving adoption will also cause the perception built for ADMS. With this, we arrive at our third hypothesis as:

H3: *Demographic factors will have a driving relationship on an individual's perspective of ADMS.*

4 Research methodology

Participants in this study were carefully selected by profile selection and shortlisting through professional networking. Some professionals were also chosen through professional social media platforms (SMP) like LinkedIn and were requested to participate in the survey. Another primary source selected for the study was the listeners of the AI podcast platform like "AI Galore," which provides technical mentorship and guidance to the stakeholders planning to pursue or set-up AI as a technology domain. It also provides mentorship to users of AI systems [15] by sending just one email a day. Survey forms were sent out as part of the regular newsletter by randomly selecting the participants' sample from the listeners. Each participant was requested for their consent to participate in the survey and that their inputs captured in the study will be used for the academic research in the field of AI.

Once participants provided the informed constraint, initial questions are placed to gauge the participants' level of knowledge on the factors like mathematics, AI, domain, societal impacts known, and any programming language knowledge. The participants were then provided a reading material on ADMS and how the outputs' applicability can be explored in several domains. These professional participants were then asked for their point of view on ADMS. Post answering the initial questions, and the participants were then assigned to random scenarios: business usage of ADMS, governmental or

societal usage of ADMS, law and enforcement usage of ADMS, and finally, complicated health care use of ADMS. These scenarios roll-up to business [16], society [17], law, and enforcement, and health domains. The participants' strategies were borrowed from the vignette-experiment ideology with three levels: ADMS vs. human decision X self vs. others accepting the output X high vs. low impact with the domains designed. The participants also communicated that the ADMS decisions were based purely on data and algorithms with no human interventions.

Technical knowledge ($SD = 1.21$, $M = 3.3$), domain knowledge ($SD = 1.25$, $M = 5.07$), privacy with online self-efficacy ($SD = 1.05$, $M = 2.29$) were considered as in the independent variables with each recorded through three different questions on the understanding of the mathematics behind algorithms, overall AI framework and domain implication of the decisions. The notion of equality was considered a control variable to ensure that the participants and the data captured are from a level playing domain. Furthermore, borrowing from the adoption literature, the perceived value, fairness, risk in decision making using ADMS outcomes were considered dependent variables. All these factors have been borrowed from the IT and other technology adoption literature.

The domain scenarios that the assigned participants had to evaluate the ADMS outputs on were perceived value ($SD = 1.59$, $M = 3.27$), fairness in decisions ($SD = 1.62$, $M = 3.78$), and the risk associated ($SD = 1.83$, $M = 3.94$), with the AMDS outputs when implemented in any of the scenarios. All the participants were then given checkpoint questions to cross-verify the inputs entered through them to cross-verify the results and the robustness of the same. Multivariate linear regression models were finally built on the three dependent variables, and only the factors that came out significant in all three were yet considered significant. We deployed a mechanism to strictly remove any responses that sounded unsure or did not correlate to the decision-making as the core of the current research undertaken is decision-making through ADMS.

5 Results and Findings

The linear regression model results on the three dependent variables are represented in table 1. Before finalizing the model version, multiple iterations were tried with the step-wise introduction of the variables and step-wise dropping the variables to make sure the models' directional sense tells the same story across all the iterations. We also compared the r-square of the models to check for robustness; however, each variable in step-wise addition increased the overall r-square; we then had to rely on adjusted r-square to take a call on the models. Adjusted r-square is also reported in the table1. However, building the model is more to check the statistical significance of the independent variables on the dependent variable, and hence the actual value of the model fitness in terms of adjusted r-square or improving it further was not in the scope of the current research undertaken.

	Value	Fairness	Risk
Intercept	4.75 ***	4.68 ***	4.24 (0.26) ***
Gender (female)	- 0.27 *	0.02	0.22
Age	- 0.02 ***	-0.015	-0.016**
Education	0.18 **	0.15 **	0.14 **
Understanding	0.32 ***	0.28 ***	0.14
Equality	0.15	0.16 *	-0.13
Online Self-efficacy	0.17 *	-0.11 **	0.223 **
Online Privacy	-0.19 *	-0.24 ***	0.36 ***
Adjusted R2	0.25	0.19	0.23

Table 1. Regression outputs

Ad-hoc analysis of the responses reveals that almost 45% of the respondents scored perceived above the overall average, which established the value in pursuing the outcomes driven by ADMS or fueled by AI [1], while 30% scored below the mid-point. This creates an optimistic picture in the minds of stakeholders from the owners' and consumers' perspective. Fairness [3] in the decision saw a more even distribution of the respondents with roughly equally (~28% above, 29% below, and rest around mid-point) distribution of the overall respondent's sample. This created a small question mark on the self-learning loop of ADMS from the penalties of wrong decision and the rewards on the correct decision. However, with merely equal distribution, it is not easy to interpret and pass an opinion. This picture becomes further clearer when moving to the risk associated with the decisions of ADMS. With a precise skewed distribution of 70%, not optimistic vs. only 22% optimistic raises the implication or impact radius of any incorrect choices.

The effect of personal traits or characteristics on the point of view on value, fairness, and the risk was further evaluated using ordinary least square (OLS) regression models. The personal features that the participants were comfortable sharing were gender, age, level of technical knowledge, level of domain knowledge, privacy belief, self-efficacy. Pretty much except for privacy concerns related to ADMS, the rest of all the factors have come out to be significant with a positive relationship across all the models. However, equality was only significant with a positive relationship in the model of fairness, but insignificant in the rest of the models, and hence can not be generalized and will be treated as a non-driver overall in the process of perception formation on ADMS. The model results also support hypotheses statements H2 and H3 on an individual's self-efficacy and demographics having a significant relationship with the perception of ADMS. The higher the privacy threat, the more negative the relationship is strong with the AMDS perception.

Similarly, the stronger the self-efficacy of opinion on personal data, the stronger the formation of the perception of ADMS. To investigate this relationship of the personal traits on value, fairness, and risks, we built a multilevel model using a generalized linear model (GLM) with factors as the scenarios. The results of the model are presented in table 2.

	Value	Fairness	Risk
<i>Fixed effects</i>			
ADMS vs Human	0.18 (0.12)	0.14 (0.11)	- 0.06 (0.11)
<i>Context</i>			
Business (vs. Law and order)	- 0.24 (0.11) *	- 0.15 (0.11)	0.16 (0.1)
Health (vs. Law and order)	0.36 (0.11) **	0.44 (0.11) ***	0.07 (0.11)
<i>Decision X Domain</i>			
ADMS X Health	0.15 (0.16)	0.15 (0.16)	- 0.17 (0.16)
ADMS X Business	0.13 (0.16)	0.01 (0.16)	- 0.25 (0.16)
<i>Impact of the decision</i>			
High (vs. low)	0.09 (0.07)	0.09 (0.07)	- 0.37 (0.06) ***
<i>Subject</i>			
Self vs. Others	- 0.13 (0.07)	- 0.05 (0.07)	0.06 (0.06)
Intercept	4.75 ***	4.68 ***	4.24 (0.26) ***
Gender (female)	- 0.27 *	0.02	0.22
Age	- 0.02 ***	-0.015	-0.016**
Education	0.18 **	0.15 **	0.14 **
Understanding	0.32 ***	0.28 ***	0.14
Equality	0.15	0.16 *	-0.13
Online Self-efficacy	0.17 *	-0.11 **	0.223 **
Online Privacy	-0.19 *	-0.24 ***	0.36 ***

When we start deep diving into the results at the scenario based, we learn that there is no significant difference in perceived values between ADMS and human while comparing health vs. societal and business vs. societal fairness perception formation. Rather ADMS outputs were considered more fairer than human interventions when it comes to business. There was no significant difference observed in impact as well. When it comes the perceived value in the mixed effects, clearly healthcare stands out that tend to gain the most out of ADMS [18]. Testing the boundary conditions, ADMS decisions are considered to more valuable as compared to human, and hence the trust is vested in the outcomes generated through AI [12]. When compared in the impact, ADMS outputs gains the value in low impactful areas of healthcare. Now there can be two reasons to that: either the confidence of the stakeholders is not built yet on ADMS when it comes to high impactful areas like automated surgeries, or the cost of building that high impactful healthcare ADMS could be very high. Investigating the reasons behind the same is currently beyond the scope of current research. Finally, when it comes to risk associated, with the ADMS outputs, the level wise model analysis uncovers that that there is not much difference in human vs. AI [19] based decisions at an overall level. However, when it comes to business, this difference becomes significant when comparing the ADMS output vs. human intelligence driven outputs.

6 Discussion

The current study is at a unique place where it draws assumptions from the literature technology like IT adoption [11], [20] while at the same time we are drawing our assumptions from the social sciences literature to be tested on a technology which is beyond adoption, however it is yet to gain the confidence of all the stakeholders in the value chain. The data collected through survey based instrument, reveals that the participants are split when it comes to perceived value, risk, and fairness. There is no strong consensus towards one, and this split further increase when we deep-dive into the analysis at the domain level application and bucketing the same to various impact levels. For instance: in high impactful [21] domain applications of ADMS, stakeholders still do not have a lot of perceived confidence in the outputs, however this does not get impacted when it comes to low level impactful applications of ADMS.

When it comes to business across the impact zones, ADMS outputs are considered above par when compared to human intervened decisions on value, risk, and fairness. This finding is an important contribution of perceived emotions towards AI, that stakeholders in business have moved way past mere adoption to vesting interest and confidence in ADMS [22]. This is applicable across all the impact levels. When it comes to societal impacts, the stakeholders are still unsure on the maturity of AI in decision making process. There is no clear indication of less confidence in high impactful like health care or high confidence like business. Hence the findings, did not reveal a very clear picture on the same [8].

Furthermore, personal traits of individuals play a very healthy role in driving the formation of perception towards ADMS outputs. Demographic attributes like age, gender and knowledge play a crucial role. The model uncovers that higher the knowledge of mathematical groundings of algorithms and programming knowledge topped with the domain knowledge too, might build more confidence in the outputs of ADMS. This leads us to believe that stakeholders with more knowledge might turn out more optimistic with ADMS. Secondly online self-efficacy in tandem with privacy concerns play an important role in confidence in the ADMS decisions.

7 Conclusion and future scope of research

We conclude the article with the thought that ADMS has slowly started becoming part of what we consume and see, how we consume and direct or indirectly, being part of society we do the consequences of these automated outcomes effecting out life in one way or the other. With the means of survey based data experimentation, the current research successfully revealed mixed emotions around societal impacts, but clearer views around business and healthcare domain applications of ADMS.

With the type of collection of the data, and increase in the penetration of social media data, the current study has a limitation of not considering the social media platform data as an important group to be analyzed. However, at the same this limitation also opens the future scope to validate these hypothesis and factors through the participants from social media platforms and see if the findings of the current study hold good there too.

Another limitation of the current study is to not be able to find the reasons behind un-
sureness with societal impacts of ADMS. As part of future scope or extended analysis
of the current study, we plan to uncover these factors as well.

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