

The Role of Artificial Intelligence in Daily Life: Applications, Benefits, Societal Challenges, and an Ethical Framework

Krishna Kumar Yadav

Department of Computer Science & IT
JAIN (Deemed to be University), Bengaluru, Karnataka
kky.mdb@gmail.com

Mohammed Zabeeulla A. N.

Department of Computer Science & Information Technology
JAIN (Deemed to be University), Bengaluru, Karnataka
z.mohammed@jainuniversity.ac.in

Jawad Mohamad Abbas

Department of Computer Science & IT
JAIN (Deemed to be University), Bengaluru, Karnataka
jawadabbas313abbas@gmail.com

Shaik Dilchasmi

Department of Computer Science & Information Technology
JAIN (Deemed to be University), Bengaluru, Karnataka

Abstract—Artificial Intelligence (AI) has become one of the indispensable items of human existence in the contemporary world; altering how people work, communicate, learn and make decisions in virtually any of the aspects. This paper is a discussion of the different applications of AI in six of the most significant sectors of society health care, education, finance, communication, transportation and smart homes using empirically grounded mixed methodology. Quantitative data 130 people responded to the survey and qualitative obtained to the semi-structure interview 18. Findings prove that 84 percent of the respondents, daily, interact with AI-powered devices, yet, only 47 percent have a significant sense of the algorithm processes underlying AI-powered devices. Profited advantages are recognized to be efficiency ($M=4.4/5$), personalisation ($M=4.2/5$) and decision support ($M=3.9/5$). Conversely salient issues are data privacy (73%), algorithmic bias (61%) and potential job replacement (58%). The results of a heatmap, which cases six areas and six dimensions of effects, demonstrate that the same areas (finance and healthcare) are the most productive as well as perilous in the matters of privacy. Following the findings of our empirical study and existing studies, within the context of this paper, we suggest a five-pillar Responsible AI Framework (RAF) according to which the transparent, fair and accountable use of AI should be guided. The gap analysis results of the RAF suggest that there is an average implementation gap of [?]1.79 of all pillars that support the necessity of a structured policy intervention as a source of urgency.

Index Terms—Artificial Intelligence, Machine Learning, Daily Life, Healthcare AI, Education Technology, Ethical AI, IoT, Smart Systems, Algorithmic Bias, Digital Literacy, Responsible AI

Artificial Intelligence (AI) has become one of the indispensable items of human existence in the contemporary world; altering how people work, communicate, learn and make decisions in virtually any of the aspects. This paper is a discussion of the different applications of AI in six of the most significant sectors of society health care, education, finance, communication, transportation and smart homes using empirically grounded mixed methodology. Quantitative data

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I. INTRODUCTION

A. Background and Motivation

The volume of artificial Intelligence (AI) development dates all the way back to the mid-twentieth century and the question proposed by Turing - Can machines think? [1]. Previous paradigms of symbolic AI systems had been replaced by the data driven paradigms that buzz around the back of the exponential increase of our computational capability and the presence of massive datasets with annotations.

In the modern era, deep neural network-based artificial intelligence, natural language processing (NLP), and reinforcement learning systems can be found in both consumer goods of any kind and critical infrastructure. According to McKinsey Global Institute [2], by 2030, AI would contribute USD 13 trillion to the overall economic growth or 16% of growth over time.

The ubiquity of AI in our lives, such as in phone assistants and credit score algorithms, fundamentally questions the issue of human agency, informed consent and equal opportunity. Despite the pace of the AI adoption, there is still limited information on AI mechanisms that pose an asymmetry of information between the creators of the technology and its final users. This lack of knowledge is not only a gap in knowledge but it also has a direct impact on real-life harms when biased algorithms affect the hiring process, loan access or a doctor treating a patient [3].

B. Problem Statement

Although it is not in doubt that AI enhances the productivity and convenience of people, there is lack of empirical study on its overall effect on the society at large in both positive and negative ways. The majority of the available literature investigates a solitary point of focus (i.e. healthcare AI) without putting situational context to discoveries in a larger societal or ethical framework. Moreover, minimal research involves primary empirical evidence involving different groups of participants based on the Indian setting where the use of AI is quickly increasing among different urban and semi-urban cohorts. This research assists in closing this gap and integrates the quantitative measurement of the survey with the qualitative analysis of topics in 6 domains.

C. Research Objectives

TABLE I
RESEARCH OBJECTIVES GUIDING THE STUDY DESIGN AND ANALYSIS

ID	Research Objective
O1	Examine AI integration in daily activities across healthcare, education, finance, communication, transport, and smart environments
O2	Quantify AI adoption rates and identify awareness–usage gaps among diverse participant cohorts
O3	Evaluate the magnitude of benefits and challenges associated with AI adoption (Likert-scale instruments)
O4	Assess public perception of ethical risks: privacy, bias, job displacement, and transparency deficits
O5	Propose a five-pillar Responsible AI Framework (RAF) with actionable policy recommendations

II. LITERATURE REVIEW

A. Foundations and Capabilities of Modern AI

According to Russell and Norvig [4], AI is counted as the computational systems that sense the surrounding and reason based on obtained information and behave rationally in reaching the assigned objectives. The modern AI integrates three major sub-disciplines: (i) machine learning (ML), which infers statistical models based on data; (ii) deep learning (DL),

which extracts benefits out of multi-layer neural networks to enable hierarchical feature extraction; and (iii) natural language processing (NLP), which enables machines to comprehend and produce human language. The convolutional and recurrent networks were transformational in their operations in the vision and language tasks and this was recorded by the authors LeCun, Bengio and Hinton [5] who were later to receive the Turing award in 2018 due to their contribution.

B. AI in Healthcare

One of the most landmark implementation contexts is the application of AI on clinical medicine. Topol [6] argues that AI will radically transform the relationship between physicians and patients by automating common diagnostic procedures and rendering precision medicine sustainable. Esteva et al. [7] demonstrated that the convolutional neural network could also perform a dermatologist level of accuracy in classifications of 129 450 lesions on the skin. More recently, AI-based diagnostic systems have, in fact, demonstrated excellent performance in the detection of diabetic retinopathy, tuberculosis on chest radiographs, and covid-19 on CT scans with the timelines dropping to hours down to seconds [8]. Nonetheless, Obermeyer et al. [9] have found that one of the healthcare algorithms that are widely used was systematically under-referencing high-risk care programmes to Black patients, proving the clinical risk of biased training data.

C. AI in Education and the Workplace

The intelligent tutoring systems (ITS) are founded on dynamic utilization of instructional material as a factor of the learner personal profiles with a standard deviation of effect up to 0.4-0.8 standard deviation compared to traditional teaching [10]. Writing assistance, automated grading and curriculum design are some of the larger language models (LLMs) that are becoming embedded. The World Economic Forum [11] estimates that there will be 85 million jobs lost through AI-driven automation and 97 million new jobs generated by 2025 in the world of work - a net positive, but concentrated around high skills and which requires high retraining costs.

D. Ethical Dimensions

Algorithmic fairness has become one of the key concerns in AI ethics scholarly study. Barocas and Hardt [12] find four different types of fairness criteria – individual, group, counterfactual, and causal – that are often in mutual tension such that they cannot simultaneously be satisfied. The GDPR (EU, 2018) and the Recommendation for the Ethics of AI by the United Nations Educational, Scientific, Cultural and Sport Organisation [13] set binding and advisory frameworks for the use of AI respectively, requiring transparency, data minima and the right to explanation. In the Indian context, the Digital Personal Data Protection Act 2023 brought in a consent-based approach to data governance with explicit provisions of algorithmic accountability. Despite these advances in regulation, the capacity to enforce them and technical capacity to audit remains unevenly spread across jurisdictions.

III. LITERATURE SURVEY

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IV. METHODOLOGY

A. Research Design

An explanatory sequential mixed method design was adopted. In Phase 1 a quantitative online survey was distributed to 130 participants during four weeks. Results of the surveys led to development of Phase 2 interview protocols that allowed for qualitative elaboration of statistically significant patterns. Triangulation of quantitative patterns with interview themes enhances both internal validity and transferability of findings.

B. Instruments and Measures

Primary data was gathered through the use of a survey with 30 Likert questions (Google Forms, n=130) about the frequency of use of AI tools, perceptions about benefits, and ethical concerns as well as 18 semi-structured interviews (Zoom, 35 min average) about lived experience with AI tools. Secondary information was obtained through academic journals, UNESCO, WEF and McKinsey reports. Cronbach alpha for the survey was $\alpha=0.83$ which is an indication of good internal consistency.

C. Sampling and Participant Profile

A purposive sampling of active AI users from four occupational groups such as students, IT professionals, healthcare workers, and educators and Survey respondents were ranging from 18 to 62 years old ($M=31.4$, $SD=10.2$). Interview participants were determined using maximum variation sampling in order to include a variety of views, and saturation was achieved at the 14th interview.

D. Data Analysis Procedures

Quantitative data were analysed in the R Studio 4.3 software using descriptive statistics, frequency tables, independent samples t-tests and Pearson correlation analysis. Qualitative data underwent Braun and Clarke's [14] six-phase thematic analysis that were managed in NVivo 14. Participant quotations are anonymised (e.g. P1-P18).

V. RESULTS AND DISCUSSION

A. AI Sector Adoption Trends (2018–2024)

Secondary data from industry reports was synthesised to identify AI adoption trajectories across six key sectors over a seven year period (Fig. 1). Finance has been leading the charge with an adoption rate going from 28% in 2018 to 79% in 2024 with the use of algorithmic trading, automated credit scoring and fraud detection mandates that have a measurable return

on AI investment. Healthcare represents the steepest growth gradient (+56 percentage points) - catalysed by the pandemic of Covid-19 - which saw the dramatic acceleration of AI integration in diagnostics, tele-medicine and drug discovery pipelines. Education AI increased slowly from 12% to 70%, thanks to the spread of intelligent tutoring systems, as well as the global shift to online learning during the pandemic years. Retail and e-commerce achieved the second highest adoption of 77% commercial imperative of personalised recommendation engines. Smart home adoption, although growing from 8% to 58%, is behind other fields because of the cost of installation, problem with interoperability, and continuing consumer hesitancy regarding privacy. Transport AI (63%) is held back by regulatory certification process in deploying autonomous vehicles.

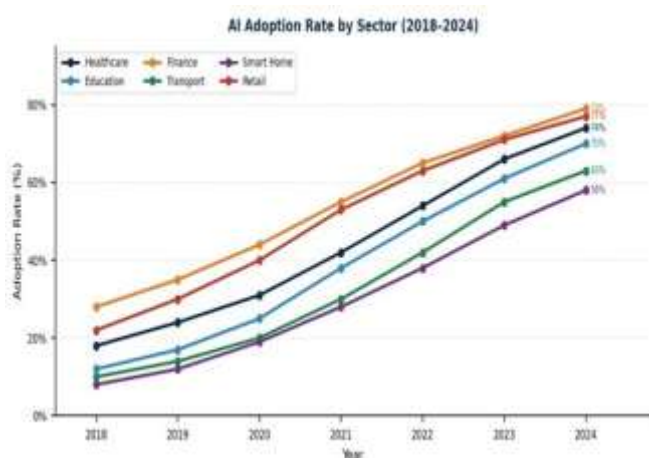


Fig. 1. AI adoption rates by sector, 2018–2024 (synthesised from McKinsey, WEF, and IBM industry reports).

Figure 2 shows a glaring divergence between how aware people are of AI tools and how they actually use them in their everyday lives on eight categories. Recommendation systems record the most significant positive gap – use (85%) often surpasses awareness (83%) – confirming the significant number of millions of users interacting with AI-powered content curation on streaming and e-commerce platforms without even consciously being aware of it as AI. This “invisible AI” phenomenon is particularly consequential, as it gets around the question of choice-it is possible to choose not to participate. Autonomous vehicles show the most negative gap, standing at a 64% awareness and only 18% usage which could be accounted to prohibitive cost and limited regulations and approval in India. Healthcare AI has the lowest awareness (57%) in spite of the rapid clinical deployment, indicating a public communication deficit that may have the potential to undermine patient’s ability to make informed consent decisions about the use of AI assisted diagnosis. Finance AI awareness (52%) is also worryingly low considering that credit scoring algorithms have a direct impact on the access to loans and financial services for millions of citizens.

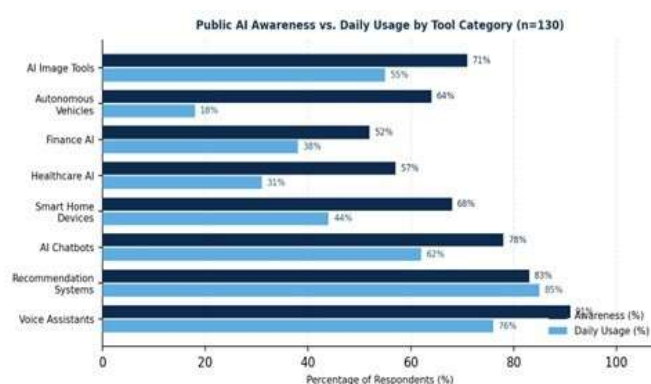


Fig. 2. Awareness vs. daily usage across eight AI tool categories (survey respondents, n=130).

Figure 3 compares mean scores of perceived benefit and ethical concern on six domains on a five point Likert scale. The healthcare AI has the most positive score of the benefit (4.4) - the early detection of the disease, and the decrease in the errors in diagnosing the illness were mentioned by the respondents as transformational benefits. The next important item that follows (4.1) is finance because fraud prevention and real-time risk assessment are useful. But finance is also second highest on the worry question (4.3) with the long-known examples of discriminatory algorithms in lending and the untransparency of automated decisions on credit which offer very little redress to the victims. The devices of smart home are associated with the highest ethical concern with a score of 4.4, although it has a relatively average score of benefits (3.7). Interviewee P9 described this dilemma: “I find the fact that my smart speaker is always listening (trade-off) very uncomfortable but I know that it is always listening, which is not something that I am comfortable with.” Education AI has the highest ratio of risk benefit where the benefits of the sector are 4.2 compared to only 3.2 concerns, and this indicates the sector has been relatively controlling the implementation of AI with or less perceived risk. The lowest concern (3.1) is transport since it implies that the popular attitude to GPS and logistics optimisation is that the applications are used in a predominantly benign way.

Five common themes had been identified after thematic analysis of the 18 interview transcripts. Convenience and Efficiency was the most prevalent theme and was uniformly shared by all the groups of participants. P7 said: AI has been able to save me at least two hours a day, I do not even know how I would go back to manual processes. This feeling was very intense among IT professionals and students who are already using AI writing assisting hope, codes completion tools and smart scheduling systems. The most emotional theme was Privacy Anxiety. The participants brought out more the sense of being observed than being helpful particularly using voice assistant machines at home. P3 replied: I taped my laptop camera a long time ago - now I am expected to believe in an AI speaker in my living room? The respondents of

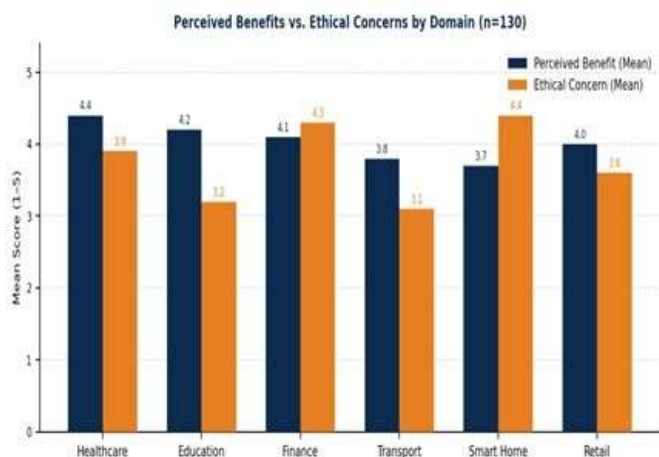


Fig. 3. Mean perceived benefit vs. ethical concern scores by domain (Likert scale, 1=Low, 5=High, n=130).

the survey identified the Algorithmic Bias as present in 61 percent, but based on qualitative data, it was obvious that most of the survey respondents were unaware of how bias is introduced into the AI systems, despite being aware of it, but not that without digital literacy education. The highest level of Employment Uncertainty was experienced on the part of the healthcare workers and educators who believed that AI was an immediate threat to their professional employment. P15 noted: “The radiologists in my hospital are already being told their reporting volumes would reduce by 40 per cent in three years.” Conversely, IT practitioners were more likely to positively perceive AI automation (augmentation not replacement), as observed in the high skill and low-skill occupational reactions to automation.

B. Sector-Specific Applications and Risk Profiles

The main applications of AI and the main profiles of risks of six sectors are recapped in Table 1. There is a general pattern across the board, where the more multi-dimensional and complex the risk profile, the greater the adoption rate. It is in line with the overall rule that the greater the incorporation of AI, the more those who are in the possession of the potential good and surface area of bad.

VI. RESPONSIBLE AI FRAMEWORK (RAF)

On the basis of the empirical evidence and the extant governance discussion, the paper will introduce a five pillar model named Responsible AI Framework (RAF), which aims at closing the divide between the current practice of artificial intelligence (AI) application and ethical norms that the society finds desirable. The RAF is based on the four well-known governance documents, including the principles of the Organisation of Economic Cooperation and Development of Artificial Intelligence [15], the Ethical recommendation of the United Nations Educational, Scientific, Cultural and Sports Organization (UNESCO) [13], the Artificial Intelligence Act of 2024 of the EU and the Digital Personal Data Protection

Act of 2023 of India [16]. All the pillars are distinct areas of governance where there is substantive lack of implementation relative to empirical evidence.

A. Pillar 1 — Transparency

Transparency involves the capacity of the AI systems to be disclosed to technical auditors and final users. Only a half of the survey participants claimed that they are aware of how AI tools take decisions that can impact them. The RAF provides a set of recommendations aimed at compulsory publication of model cards of all consumer facing AI systems, standardised explainability reporting based on the guidelines described in the AI RMF by NIST, and the third-party audit that is to be conducted on an annual basis. With a decision making process based on artificial intelligence, whose results in healthcare and financial realms have a direct impact on human lives, the explainability is not only desirable, but also a moral necessity.

B. Pillar 2 — Fairness

The fact that algorithmic bias existed was familiar to 61% of the respondents, yet, in most cases, the respondents were extremely superficial in their comprehension of the nature of its operation. An appeal to the R.F.A. to make demographic audits of training data sets, both when models are built, as well as quarterly independent audits of bias in high-impact a.I. systems applied to credit, hiring and the criminal justice system. It is worth noting that the article by Obermeyer et al. [9] had already revealed that the US healthcare algorithm (had it been implemented commercially) was actively discriminating against Black patients - we understand this as a warning indication, which squarely comes to play in the context of various AI implementations in the altered demographic situation in India.

C. Pillars 3–5 — Accountability, Privacy, and Digital Literacy

The biggest gap in the RAF is accountability ([?]2.2) which demands the establishment of autonomous national bodies to oversee artificial intelligence functions and criminal investigators on the basis of independence, which can audit, impose fines and enforce corrective actions. Privacy ([?]1.6) would be better addressed on the basis of privacy-by-design, which needs to be constructed at the level of systems architecture, and the minimisation of data and the restriction of purpose should be structural, as opposed to procedural. The most amenable gap is Digital Literacy ([?]1.3), in which AI fundamentals are mandated as a part of secondary school learning - how algorithms operate, what data they consume and what rights over it students should have, how to be an informed citizen participant and not merely an agent subject when interacting with AI systems.

The average implementation gap of [?]1.8 that has been measured by all five pillars points to the absence of structural building up of the present AI governance in terms of the pace and intensity of AI implementation. The smallest difference is shown in Privacy ([?]1.6) which can be explained by the regulation changes imposed by GDPR and DPDPA

TABLE II
AI INTEGRATION SUMMARY ACROSS SIX SOCIETAL SECTORS

Sector	Key AI Applications	Adoption	Primary Risks
Healthcare	Disease detection, medical imaging, robotic surgery	High	Data breach, diagnostic bias, liability
Education	Adaptive learning, automated grading, ITS	High	Digital divide, over-reliance
Finance	Fraud detection, credit scoring, algorithmic trading	Very High	Discriminatory lending, systemic risk
Transport	Navigation, autonomous vehicles, logistics	Medium	Safety, liability, regulation lag
Smart Home	Energy management, security surveillance	Medium	Privacy invasion, device vulnerability
Retail/E-com	Recommendations, inventory, customer chatbots	High	Consumer manipulation, data misuse

TABLE III
FIVE-PILLAR RESPONSIBLE AI FRAMEWORK WITH GAP ANALYSIS SCORES (SCALE 1-5)

Pillar	Principle	Expected	Current	Gap	Recommendation
P1	Transparency	4.5	2.4	2.1	Publish model cards; mandate annual explainability audits
P2	Fairness	4.6	2.7	1.9	Diverse training data; quarterly third-party bias audits
P3	Accountability	4.4	2.2	2.2	Clear liability chains; independent AI oversight board
P4	Privacy	4.7	3.1	1.6	Privacy-by-design; full DPDPA 2023 compliance
P5	Digital Literacy	4.2	2.9	1.3	Mandatory AI literacy in secondary and higher education
Overall Average	4.5	2.7	Mean implementation deficit	1.8	Across all five pillars

and Accountability ([?][2.2) and Transparency ([?][2.1) are the priorities that need to be fulfilled by policymakers. It is important to mention, however, that Digital Literacy ([?][1.3) the least difficult pillar points to the fact of the so-called quick governance wins, which can be obtained in less time than the (compared to the cost of AI implementation and promotion) cost of doing so. Based on the available policy tools to scale AI literacy of the nation, India has a current policy vehicle, the National Education Policy 2020.

VII. CONCLUSIONS

This paper confirms that Artificial Intelligence is widely and irreversibly embedded in the modern lifestyle and is altering how people in India and around the world obtain medical care, education, money, move throughout urban centers and arrange their households. The empirical analysis of 130 survey participants and 18 semi-structured interviews presents the result that there are high rates of adoption of AI (daily usage rate of 84 percent) but high in diversity of the occupational cohorts, and high in the levels of knowledge deficit - only 47 percent of the participants demonstrated the knowledge of the algorithmic processes of the tools they use on an everyday basis. There are three findings of particular significance. The first is the awareness-usage gap i.e. people in millions are using AI without even being aware that they are using it which is a structural obstacle to informed consent and democratic responsibility. Second, the situation of a high-benefit and high-risk stance in terms of finance and healthcare AI necessitate formation of sector specific governance structures, where it

comes to developing structures around innovation, as well as the protection. Third, the information that we have founded on the RAF gap analysis reveals that the average implementation gap is [?][1.8 along the five pillars of governance and this fact demonstrates that the creation of regulations and institutions have failed to keep pace with the actual implementation of the technologies. A more evidence-based approach to the future is proposed by the Responsible AI Framework outlined in this paper. The legislative orders and other independent oversight bodies should overcome transparency and accountability loopholes. Privacy should not be attached to the AI system as an afterthought. And the most practical pillar of all is digital literacy, which must be elevated to a national educational priority and ensure that in the next generations, young people will be engaged with AI as critical and informed citizens and not just consumers. The weakness of this study is that, the sample was narrowed down to urban Karnataka, hence it could not be generalised to the rural and linguistically diverse population, and the study had a cross-sectional nature, hence, no causal inference could be made. Future research must incorporate longitudinal research designs of cohort samples to track the outcomes of the AI literacy interventions, cross-national comparative studies involving semi-urban and rural groups, and randomised trials of certain strategies of RAF implementation in various institutional contexts.

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