



The Evolving Role of Artificial Intelligence in Decision-Making: A Comprehensive Analysis of Barriers and Challenges

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ABSTRACT

Artificial Intelligence (AI) often suffers from a "science-to-service gap," where high-performing models fail to translate into effective real-world decision-making. This systematic literature review investigates this divide, identifying three critical barriers: inadequate technical reasoning, organizational resistance, and stringent regulatory compliance. To bridge this gap, we propose a holistic analytical framework anchored in three interconnected pillars: the human–AI relationship, predicated on mutual trust and complementarity; organizational preparedness, necessitating comprehensive cultural transformation and workforce reskilling; and ethical regulation, prioritizing process transparency and robust accountability. Our findings reveal that successful AI integration extends beyond technical optimization, requiring cross-disciplinary strategies such as participative design and collaborative human–AI audits. By synthesizing these dimensions, this study provides a strategic roadmap for enterprises to navigate systemic challenges, fostering a transition from theoretical AI potential to actionable, empowered, and human-centric decision-making systems in complex operational environments. Research indicates that proper application of MCDM techniques can relate AI outputs to real-life decision-making by structuring, enforcing transparency, and justifying AI-scoring results for use within an MCDA (Multi-Criteria Decision Analysis) framework, as demonstrated in complex use cases such as transportation planning.

1. Introduction

We draw on urban transportation planning, a multi-stakeholder, high-stakes real-time domain where benchmark scores from AI models for demand forecasting traffic optimization and service quality design routinely achieve state of the art but which suffers from persistent non-adoption. Transport, therefore, provides an empirical test case for the Operationalization Chasm. AI has transitioned from a laboratory oddity to an organizational imperative, and in 2024, 78% of organizations are working with AI (up from 55% year on year) [1]. This growth puts pressure on

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executives to deliver fast ROI from their investment, but integration costs and project risk are low-hanging fruit for many organizations. As decision-making becomes more automated, and less human oversight is accompanied by the use of algorithms that are rarely made transparent, regulators have grown increasingly wary of liability. With the required integration of AI into the healthcare domain, clinicians require continuing and ongoing changes in protocols and legal duties. The pace of FDA approvals of AI-enabled medical devices was 6 in 2015 and has subsequently risen to at least 223 by 2023 [2], a trend that supports improving confidence but also accountability for such a rapidly evolving domain.

Wang et al. [3] due to actions that show disproportionate differences over time between the expected adoption of AI technologies practices and their data use in practice (performance gaps), which Philips makes evident as monetary loss or even important breaches within compliance. This mismatch here in disparity singles out the core and multiple layers of complexities which naturally follows through larger scale AI system proliferation and integration throughout society. These kinds of complicated issues are increasingly arising in several industries, but model development and the evolution of AI best practices is a work in progress. Especially in high-stakes areas like managing and governing quality of data, compliance against legislative standards that change by the day or teaching staff to operate new complex AI driven tools and processes, effectively upskilling. Given this disconnect, there is a wide gap between AI adoption and performance (at times lethally undesirable) that may result in tragic financial toxicity e.g., Philips or non-adherence failure. While tools advance rapidly, there is no consensus in organizations on how to implement and adopt AI at scale. Important issues include providing quality data across systems, regulate AI decisions with high certainty, and enable human resources who work with rapidly changing technologies.

Some studies explored the ethical frontiers of AI [4], however, this study investigates technical and social-ethical bottlenecks that impede in-depth human-AI interaction, to explore new avenues for productive interactions. Responsible AI draws upon human intuition and machine intelligence. Drawing on previous literature specifically related to bot detection and Twitter analysis; we argue that AI is valuable for the way that data is prepared, interpreted by users and validated with context outside of a purely technical frame (i.e., R-squared).

2. Theoretical Foundations and Key Concepts

Figure 1 below provides the conceptual model on which this study analysis is based. This framework shows the chasm between what AI can do technically, and its adoption in decision making in practice. It defines three interrelated barriers: challenges to the collaboration of humans and artificial intelligences (e.g., trust, mental maps, data quality), organizational adaptations (e.g., culture, skills, incentives) and ethical governance requirements (e.g., transparency, accountability, regulation). By overcoming these obstacles by incorporating responsible AI, organizations imbued with the power of AI are then able to use it to translate outputs into decisions. This is ultimately how better decision quality, higher trust, broader adoption and enhanced human agency can take place. Pillar 1 (Human–AI) leverages Cognitive Complementarity Theory, which prescribes the conditions under which human-AI dyads will outperform either alone. Pillar 2 (Organisational) development is informed by Dynamic Capabilities theory with a focus on how firms can identify the AI opportunities, capture them through reskilling and derive transformations in legacy processes. Pillar 3 (Ethical) involves Algorithmic Accountability Frameworks and mandates all AI/system decisions must be able to be attributed, contested and audited.

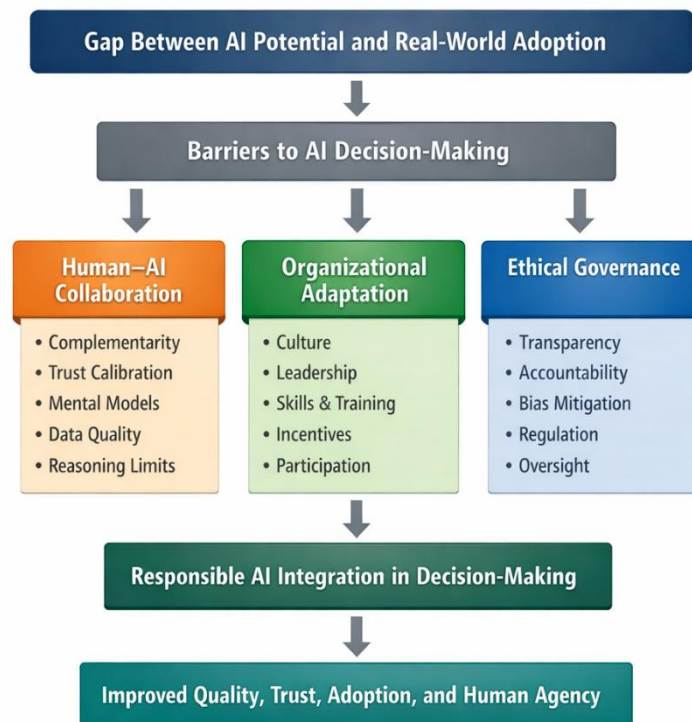


Fig. 1. Research framework

2.1 Human-AI Complementarity

The optimum state both 'best' and ('optimal') AND most "advantageous" state (both of which is being called SOI-SOM as well as a seemingly paradoxical notion (deliberately so) of an 'undesirably desirable,' - for - the - ken, has aptly been named 'interdependence' as Bansal et al. [5]. That particular term means a state that is synergistic so we have human decision-makers interacting with super advanced AI systems so well collaboration, that their combined performance (you can measure it in some width) actually greatly significantly exceeds the results attained by both actors together separately getting significant high metric points not just one but many at least unique index points. Notably, considerable empirical evidence demonstrates that true complementarity can only be achieved when the conditions are right, namely when those of humans and AI differ widely in their prediction error pattern, that is there is a relatively low degree of correlation in the prediction errors made by each method; and where the discrepancy in accuracy between the two remains within well-defined, controllable limits. Read the full text Sep 14, after defining the SCOPE trial with MASS and other similar studies published through October 2023. In visual classification tasks, complementarity was found to be maximum when both the Pearson correlation coefficient, the linear correlation between human and AI predictions, was kept below 0.25, and at the same time, the difference in accuracy between the human and AI predictions was less than 15 percentage points. In these best-case scenarios, think of a world where human accuracy is about 75% and AI accuracy is about 85%, together making decisions in areas that neither has very much error overlap with the other, the integration of requirements decision sources and their union can improve accuracies above 90%,

representing a major improved state. Importantly, hybrid human–AI pairs that display this kind of near-independent or quasi-independent behavior of prediction have been demonstrated to perform better than both: (1) humans working together in a group, and (2) AI systems working in concert on all completely separate sets of data. Practitioners wanting to assess and quantify these performance measures can either compute them in a systematic way by performing an in-depth analysis of overlapping errors through confusion matrices, or calculate correlation scores from the outputs of AI models to predictions made by humans when applied to the same dataset.

Consider a radiology practice called "Apex Medical Diagnostics," that implemented a carefully designed shared radiology workflow, specifically to create a baseline diagnostic accuracy for each individual of all the employed radiologist on its payroll (i.e., effectively creating an objective and quantifiable gold standard performance target for its army of human specialists), while running an identical quantitative assessment against a state-of-the-art deep learning model. By retrospectively analyzing cases, the practice might discover that when an AI's image interpretation conflicts with a radiologist's, combining their outputs yields sensitivity rates of 92–93%, surpassing both independent human review (82%) and AI-only use (86%). Using confusion matrices and tracking decision outcomes, organizations can demonstrate measurable gains from human-AI complementarity by quantifying the overlap in errors. Further research is needed to understand the specific conditions required for complementarity as organizations transition toward hybrid models.

2.2 Mental Models and Appropriate Reliance

Success in collaboration relies on decision makers having accurate mental models of what AI can and cannot do. Using these internal representations, reliance strategies are learned to identify when the individual should overrule AI recommendations for what a human would instead do. Studies show that decision makers tend to under-rely on AI (automation bias or over-reliance) or under-utilize AI [6]. For example, even developers cannot explain how advanced neural networks reach their decision processes due to what is called a "black-box" syndrome. We explicitly describe this gap by identifying and analyzing the most common user assumptions in detail, we then present a comparison of these expectations against the actual limits determined experimentally (as shown in Table 1) and finally indicating clearly where mismatches exist between user expectations and system capabilities.

Table 1
Common User Misconceptions vs. Actual AI System Limitations

Common User Misconception	Actual AI System Limitation
Objectivity: AI always makes objective, entirely correct decisions.	Data Bias: Outputs are heavily influenced by training data biases and limited by the quality of the input data.
Contextual Awareness: The AI understands context and social nuance like a human.	Causal Reasoning: Most AI lacks deep contextual or causal reasoning and may miss subtle cues obvious to humans.
Confidence as Accuracy: A high-confidence output from an AI system guarantees a correct answer.	Calibration Issues: High-confidence predictions do not guarantee correctness; AI can be "confidently wrong."
Inscrutability Equals Unreliability: If an outcome cannot be explained, the AI is inherently unreliable.	Black-Box Nature: Advanced systems have complex inner workings; ongoing research (XAI) is required to improve interpretability.

2.3 Adaptive Structuration Theory (AST) Framework

Acceptance and Structure Theory (AST) is a more advanced system for tailoring AI decision-making systems to act within wider social contexts, as presented by Rossiter [7]. AST advocates for a deeper knowledge of AI and organization structures based on thorough, long-term discussions (both over weeks and months) as opposed to short meetings focused exclusively on technical designs or task-based processes. Hotz highlights the significance of existing processes, institutional control and the environment surrounding AI creation and employment. This takes a multi-pronged approach to enabling organizational response in areas where human activity intersects (and sometimes collides) with economic and political power, so that ethical and human-centred AI deployment can occur. Table 2 describes individual policies, incentives, and workflow changes linked to the dimensions of AST.

Table 2
Mapping AST Dimensions to AI Adoption

AST Dimension	Definition in AI Context	Organizational Exemplar
Appropriation	How users adapt AI to fit frontline needs.	Clinical staff providing input on AI customization to ensure it fits daily workflows.
Spirit	The intended purpose or "soul" of the technology.	Tying bonuses to accurate AI compliance reporting to reinforce risk-reduction goals.
Modalities	The rules and resources that mediate action.	Mandatory AI usage checkpoints embedded within existing decision software.
Structure	The institutional routines and hierarchies.	Multi-level governance committees that align AI with established decision hierarchies.
Interpretive Flexibility	The degree to which users can interpret AI outputs differently.	Training programs that encourage staff to share and debate different interpretations of AI guidance.

3. Pillar 1: Barriers to Human-AI Collaboration

As such, the first dimension in our model is friction between human cognition and AI functionality.

3.1 Technical and Data Challenges

The data trilemma: Given that datasets used as input into large AI systems are not often, if at all, homogeneous in quality and entirely free of bias we naturally face what is an inherently complex listed problem during both the creation of such a system and its dissemination. This makes regards, reliability, fairness and accuracy profoundly complex and demanding for developing and implementing these AI models due to lack of consistent high-quality unbiased data. A detailed analysis of A. Introduction First, according to the results of a survey conducted on 1290 companies by the OTCT Group in 2025, about 72% choose data quality as the most important barrier preventing widespread adoption of these systems [8]. Risk-assessment tools used in judiciaries that predict when a criminal will commit another crime misidentify minority defendants as high risk at almost double the rate of non-minorities [3]. Data bias: organizations should (1) perform audits on a regular basis to ensure the data being modelled is not skewed in one population too much, and that it represents samples of the real population adequately as well as (2) applying synthetic data generation that will better incorporate marginalized or unseen demographics. Multiply these strategies with an openly

available and transparently documented methodology of them at what exact steps, and processes that you went through to get there, now you will go a long way in adding a lot more strength and credibility of your AI models especially when it comes to strict high-pressure testing environments where there is a lot at stake and accuracy as well as fairness is paramount importance regarding critical decision making.

Legacy System Integration: Integration challenges usually arise naturally when these new artificial intelligence systems find their use in increasingly obsolete, old or legacy IT environments and systems; where the rapid onset of performance bottlenecks severely limits or outright kills the technology environment's operational efficiency as a whole. While middleware solutions can offer stop-gap or short-term resolutions to these problems, they do not adequately resolve the root and chronic architectural imbalances that are prone to emerge over long timeframes [9]. Meaning for organizations it implies a need of complete modernization not just on technical front but regarding the transformation of their organizational culture to leverage and unlock the full potential & transformative power offered by AI in order to further align their leadership, teams and services at all levels.

Reasoning Limitations: While AI systems have achieved enormously credible improvements in performing a wider range of specific tasks with higher performance than humans, they are still facing enormous challenges with complex causal reasoning and an understanding of contextual information. The ability to reason across multiple steps, meaning use intermediate reasoning steps as a basis for drawing conclusions through connected logical chaining; is vital and key to many complex real-world applications that require an understanding of underlying structures and dependencies. However, even with these urgent needs, the existing AI systems have significant and heavily-documented deficiencies and constraints in this crucial field.

3.2 The Slowdown Paradox in Software Development

That begs a lot of attention, given that this tends to miss out the gap between benchmarked performance by algorithms and the actual workflow of developers. With growing attention from academia, such as the finding of the "Slowdown Paradox," productivity research, particularly in professional services. These industries now experience productivity decline not indicated in studies with narrower views of production input. For example, a randomized controlled trial in 2025 announced with great fanfare and involving expert software developers, showed that using AI tools even caused an increase of 19% in task completion time. It is especially surprising, given the expectation that the help of AI would speed up the completion tasks by around 24% [10]. This surprising result can ultimately be due to four main contributing factors: (1) developers typically over-engineering and, somewhat redundantly over-polishing the code produced by AI systems, (2) additional cognitive load of continuous context switching between multiple tasks/tools they have to juggle in parallel plus the surrounding ecosystem that takes extra time collecting collaborative feedback from different stakeholders, (3) cumbersome debugging of AI-sourced suggestions that while seemingly plausible include plethora pernicious, if subtle and critical bugs across the pipeline, and (4) the need for comprehensive documentation outlining how these AI products actually work as well as their inner mechanisms leading to sample outputs at a granular level. While AI agents solved 87.3 per cent of tasks from the SWE-bench benchmark, software engineering in realistic environments requires not only technical skills but also the resolution to complex system integration issues along with sustainable maintenance of software [11]. Thus, the primary takeaway from these results is that software developers ought to be cautiously optimistic about AI tools, learn new tools

and techniques as needed to adapt their workflows and most of all focus on continuous learning and professional development if they want to be able to benefit from leveraging AI without hurting productivity overall.

3.3 Collaborative Solutions and Enhancements

The Manager's Rule: Efficient Breakthroughs From 2022-2024 the inference cost to obtain GTP-3 only two orders of magnitude lower. Within this period, all levels of performance showed an astounding decrease 5-levels of performance fell by a factor of 280 and energy efficiency improvements progressed annually at an incredible rate of around 40% [12]. Known as the Small Model Revolution, this strongly indicates that small models (with less than 10B parameters) now achieve performance indistinguishable from their large counterparts - only 1.7% worse in effectiveness [3]. The rule-of-thumb for managers is deceptively simple, yet its impact profound: If you're operating within a relatively clearly defined scope of work for which the data is stable and trusted, test if it makes sense to try out with a smaller model first (and be able to subject what you're finding), looking to scale-up only when optima's resources and operational effectiveness can be achieved.

Technically, structural causal models are an innovative perspective design that facilitates semi-verbal causation and reasoning beyond correlation-based methods. They allow AI to perform joint inference at a higher level with learnt relational patterns for more meaningful decision making. Narrative-based interactive training clarifies the limits of AI in order to better calibrate trust towards humans, whereas traditional active learning increases functional trust in AI pedagogy by 32 percentage points [13].

The principle of complementarity is pronounced and reinforced in hybrid intelligence frameworks, where a lot of the analytical steps in some types (e.g., prediction in time series forecasting) are assigned to highly advanced AI systems along with compute processing steps as well. Critical value judgments and decisions are intentionally remaining with humans. Foundationally, this partition attempts to use human thinking and machine work efficiency for collaboration purposes. Methodology a comparative study of the use of artificial intelligence (AI) in diagnostic imaging Decision-making and study design: Background/goal: Hybrid approaches decrease diagnostic errors by >27% compared with AI-only decision making [14].

4. Pillar 2: Organizational Adaptation Challenges

4.1 Power Dynamics, Culture, and Resistance

Power Dynamics and Leadership Inertia:

AI frequently questions power structures, creating discomfort around accountability, accountability and jurisdiction that leads to pushback. And resistance to change usually comes from people feeling that their traditional sources of power, influence or control are slipping away. More and more senior managers feel an escalating shiver of discomfort, fear, anxiety as AI systems increasingly rattle control of large parts and vital fields of jobs that previously, and in most cases to be balanced complete exclusion from common societal activities fully carried out by human workers in the real world. They understand that their traditional managerial power and functions of supervision like what decisions they are able to make which would have significant impact, quite possibly diminished or even made irrelevant in the new workplace. As described in detail by

Theodorakopoulos et al.², the phenomenon of executive skepticism represents a decisively greater and more detrimental obstacle to successful AI-based project implementation and halts progress in almost 44% of organizations surveyed³. Such skepticism is most accurately pronounced in 2025, and most consequentially felt due to instances wherein pivotal, high-stakes decisions are happening where trusted human judgment the primary decision-making process courts danger of being supplanted by advanced machines. Knowing from conceptualisation through to evaluation off employees gaining a more extended support, lesser resistance and anxiety whilst indicating that they are key factors within the workplace.

Cultural Resistance:

Companies with a high culture of experimentation have 3.5 times lower adoption failure rates than companies without such cultures [15]. However, knowledge workers in these forward-thinking organisations usually experience passive resistance because of fear of becoming redundant and this affects their motivation, engagement and performance. The key theme is about exploration and growth, constantly pushing the boundary. Thus, it is crucial for organizations to deliberately create space and chances, and support a culture of lifelong learning. Just as crucial is nurturing an enabling climate free of low-hanging fruit which embraces breakthrough technologies and advocates for experimentation to achieve innovation, growth and sustainability.

4.2 Talent Shortages and Misaligned Incentives

Skill Gaps:

The shortage of AI-skilled professionals has been growing progressively, mostly in data science and especially in AI ethics. The difference between demand and supply results in short-term problems lasting for a very long time in many industries. According to General Assembly 2025 nearly two-thirds (63 percent) of organizations experience material project delays attributable to talent shortages. In order to solve this issue, firms are encouraged to rescale their workforce and expand recruitment of top competitors while working closely with universities and training centers to retain the experts.

Misaligned Incentives:

While this sentiment may resonate, fading public interest in tech companies pressured to deliver immediately has disastrous economic implications for of these organizations, many of which are under extreme financial pressure related to the highlighted belief that AI projects will generate a return on initial investment within 18 months [16]. To help with this, Playbook provides guidance in the form of transitional milestones related to personal goals / KPI from pilot initiatives. This includes milestones related to the measurable improvements in work process, efficiency and validation test to transform Proof of Concept into proven value. This Phased approach helps you see where you are in the Financial Year and increases your chances of funding approval and confidence from stakeholders.

4.3 Participatory Design and Cultural Transformation

Resolving this multifaceted and spine-wide organizational issue demands ongoing and extreme effort at all steps of the AI life cycle, collaborating intimately with front-line decision makers in the

field. Mokokota [17] as one of the more recent authors who reference a simulation which used participative design methodology and found that it reduces the total implementation process time by overall 41% compared with more traditionally means of design output, demonstrated these tangible benefits during their largescale simulation in South Africa. Not only will the artificial intelligence significantly strengthen government roles but adapting to technology needs serious institutional powers, as well as a radical cultural shift towards creating psychological safety, that encourages staff members to raise questions and concerns about algorithmic outputs (which has a far greater probability of being more widely accessible and less intimidating than experience with colleague feedback). Additionally, individual field-practitioners conduct such red teaming exercises autonomously to open this veil of its inherent failures which provides innovative perspectives on more instrumental vulnerabilities in AI [19], falling a few examples from progressive leaders like the Google guys promoting this positive space around it.

5. Pillar 3: Ethical Governance and Regulatory Complexity

5.1 Transparency Deficits and Algorithmic Bias

As AI systems become a larger part of making significant decisions with far-reaching consequences, they are still run in opaque black boxes that close information gaps between developers and users creating both statistically unbridgeable accountability gaps but also theoretically - due to ethical concerns that we shall explore below - practically unbridgeable trust gaps between the system user and the developer. These are very reasons why organizations find it difficult to justify black Box decisions, making it more difficult for AI to venture beyond narrow use cases without transparency and explainable AI (XAI). Transparency is a collective responsibility of everyone. So the teams involved in such a project may opt for Collaborative Human-AI audits, which are periodic evaluations that assess how explanations have been constructed and evolved, enabling better understanding of the rationale behind AI decisions so they can be properly relayed to citizens.

Protected groups experience increased harm from AI systems trained on flawed historical data. One example is COMPAS, which was shown to over-predict recidivism for Black defendants and, as a result, entrenching judicial biases. Recognizing that bias can occur at any point in the AI development process and taking steps towards making an AI fairer, more representative and inclusive requires input from frontline workers, users and communities, policymakers and regulators. Also, the recommendation algorithms of AI pose ethical questions since they prioritize engagement and lead to amplification of toxic content, violence, divisiveness among people and unethical behavior.

5.2 Regulatory Fragmentation and Political Vulnerabilities

At the same time, U.S. federal agencies were busy creating myriad and sometimes contradictory AI regulations, so that by 2024 there were at least fifty-nine different pieces of legislation from dozens of distinct U.S. federal government entities that made for a confusing, even redundant, patchwork quilt of regional and national AI rules for multinational organizations [12].

- **Illusions of Certainty:**

During the COVID-19 pandemic, a large-scale global crisis, epidemiological models were prioritized over ethical social values of individual liberty and human agency resulting in diminished public trust and confidence regarding perceived government legitimacy and effectiveness.

Conversely, AI-backed probabilistic predictions greatly enhance participatory democracy like with participatory budgeting where communities account for management of public funds. These AI outputs, along with countless others, are yet another beneficial input to the decision-making process that offers powerful and transparent evidence allowing for equitable and inclusive democratic action.

- **Technocratic Drift:**

Instead, what artificial intelligence produces is the false and misleading appearance of providing a simple, universal, one-size-fits-all answer to complex and multifaceted political dilemmas that directly threatens to render any meaningful and substantive democratic dialogue obsolete by encouraging the view that broader social, historical, cultural context is stripped off of numerous political issues so they can be treated merely as technical problems. However, the troubling technocratic drift can be effectively counteracted only if a rich diversity of perspectives and voices is at least welcomed, let alone actively encouraged and meaningfully integrated into the pathways toward decision-making so that solutions developed remain firmly embedded in the richer tapestry of social values, cultural norms and ethical considerations crucial to democratic governance.

- **Control Dilemmas:**

Hyper-strictness and micromanagement restrict AI performance and innovation; while lax oversight creates challenges around transparency, accountability, and ethics. The EU AI Act, which is expected to be introduced in the coming paragraph, is an example of well-balanced regulation.

5.3 Establishing Responsible Ecosystems

Before implementation of AI with real-world consequences in education, healthcare and finance algorithmic impact assessments are also mandated. Standardized tools like the HELM Safety or frameworks like FACTS [18] support this process with variable degrees of detail on ensuring ethical AI during its lifecycle from inception to deployment regarding interpretability, transparency and auditability.

As technology advances, regulatory environments that address these changes must be adapted, as shown by the EU AI Liability Directive which highlights liability and responsibility between deployers and creators of AI systems [20].

Table 3
Overcoming Adoption Barriers

Leadership Resistance	Exposure programs to successful AI implementations; dedicated AI steering committees
Data Challenges	Anonymization techniques; differential privacy; synthetic data generation
Ethical Concerns	Algorithmic impact assessments; third-party audits; bias bounties
Talent Shortages	Upskilling programs (internal); academic partnerships; rotational residencies
Scalability Issues	MLOps standardization; containerized deployment; hybrid cloud architectures

6. Role of Multi-Criteria Decision-Making (MCDM) in AI-Based Decision Systems

Multi-Criteria Decision-Making (MCDM) methods have been extensively applied in supporting complex decision processes that involve a number of conflicting criteria. Various levels of uncertainty are involved in all areas, from the individual decision-making processes within AI to the ethical challenges it raises as well as obstacles that result purely from technical or organizational constraints. Multiple-criteria decision-making (MCDM) methods including the analytic hierarchy process (AHP) and the technique for order preference by similarity to ideal solution (TOPSIS), among other hybrid aggregation frameworks, are frequently employed in AI-driven decision-making environments to structure complex problems that encompass multiple, sometimes conflicting criteria. Such methods are especially appreciated for generating interpretable AI systems by converting abstract model outputs into simple decision rules. Yet, in comparison to AHP the limit for bias is a subjective judgment: although some advanced MCDM frameworks exist that use AHP to support extensive aggregation techniques increasingly require more data-intensive sources of information resulting the winning solutions still heavily relying on personal judgments when it comes to weighting and stakeholder evaluation - thus bias just has been formalised but not negated [21-25]. This points to an important limitation: the sort of objectivity seen in MCDM is partly achieved by pragmatic decisions around methods as opposed to approach based on purely data-driven inference.

More generally, coupling MCDM with AI systems brings forth a methodological friction between static preference modeling and dynamic data-rich learning ecosystems [26-30]. Moreover, although AI performs well in evaluating large-scale and dynamic datasets MCDM usually assumes the agenda of criteria is stable and their weights are fixed so far which contradicts reality volatility of real-world decisions. Artificial intelligence (AI) merges with multi-criteria decision-making principles into one but formal methods behaviors like weighting and aggregation mask deontological issues. Such use, design and development of hybrid AI decision-support systems challenges norms around transparency, accountability and governance.

The challenges with AI, the research explain, are less technical and more about organizational, ethical and governance issues. It promotes better human- AI collaboration and institutional reform. Jevinger et al. [32] discover that AI mainly helps predictable, decision-making work across all public transportation sectors [31]. AI capability isn't limited; it's the realization, quality, privacy and costs of data that limits its ambition. Models trained in these ways have practical limits, for interactive applications, they are often lean closer to the externally-imposed than purely algorithmic.

Governing these processes Governance and trust emerge from our analysis as central enablers positioning AI to be deeply integrated into complex organisational processes. In contrast to much of the more prescriptive literature, our application is thin on authority and directive. We argue that at least in some cases, data integrity, system preparedness and infrastructure readiness challenges may feature significant obstacles misaligned with the sufficient resource availability. Such barriers present substantial impediments to the quest for in-depth automation, or significant AI applications even where benefits and advantages of AI are clear-cut and established. From a more technical perspective, this means the mechanisms that drive AI scaling are much less about gradual improvements in the sophistication of algorithms and much more about local institutional preparedness, data availability and quality, and an organisation's capacity to grapple with, and overcome, complex socio-technical transformation.

In addition, a very large body of research inside and outside of transport studies may be cited to conclusively illustrate how artificial intelligence (AI) can go far in optimizing traffic flow distribution while also solving the most complex interlinked global problems of urban mobility. This is done by

complementing conventional data streams with live data inputs and advanced analytic approaches to help manage transportation system more efficiently [33-35]. However, as Mirindi [34] on the other hand, is warning that the biggest barriers to widespread and effective deployment of AI technologies are now becoming less about creating/finding even more powerful/complex/cutting-edge algorithms. Instead of attributing it to algorithmic shortcomings, we argue that much of the opportunity with AI continues to go unrealized. We highlight some of the prevalent challenges organizations face across data governance, trust and regulatory hurdles that curb adoption in AI. The challenge is not so much designing better algorithms but grappling with the intertwining of complex socio-technical contexts and responsibly integrating AI into the organizational process to hold those responsible for high-impact, real-time decisions to account.

The majority of the studies we examined dismiss the notion that novelty, as such, will always assure speedy, successful AI. They instead cite the need for caution and moderation in drafting new laws or rules. It must happen despite a considerable knowledge deficit and it should disturb the existing data governance systems from technical infrastructure to organizational cultures, ethical oversight and decision-support frameworks.

7. Conclusion

Integrating decision-making in AI is a more profound revolution of knowledge work, than cloud storage or computation. Effortless collaboration of ethical AI with human workers quells cognitive biases that misconstrue the essence of AI and harm it. Another factor is Resistance & Organizational inertia that constrains tech Adoption. It essentially offers a road map connecting data and intelligence to action that will help organizations balance the provision of public benefits from AI with the ethical risks & harms it poses to society in the face of these constantly changing threats.

- Human-AI Collaboration: Focus on hybrid workflows, real-time calibration training and participatory design with end-users throughout the system development process.
- Organizational Adjustment: Constantly upskill workforce and create AI-savvy culture, build clear measurement milestones to align incentives and show result
- Ethical governance: Periodic review audits to maintain high data quality standards, reduce bias, and clear governance frameworks including third-party scrutiny.

What we need is an integrative multidisciplinary team that combines technical researchers together with social scientists, policymakers and domain experts, crossing the seemingly irreconcilable boundary between disciplines and fusing these for robust complex solutions to get us out of this mess. Key priorities include:

- Building uniform assessment metrics that capture true complementarity rather than phantom standards.
- Build regulatory sandboxes for high-stakes sectors such as healthcare and criminal justice.
- AI literacy programs across the organization.

There is an immediate and overwhelming need for comprehensive, substantial, and effective international governance regimes to be created at the scale of new applications of domestically focused artificial intelligence. The monumentally astounding and impossibly exponential speed at which AI progress is occurring is, in itself, almost beyond belief; the unprecedentedly rapid and staggering average time span of just under five months for training compute capacity to double creates a very short-lived, ephemeral, narrow and significantly hermetical temporal window within

timely, adequate and effective governing measures can be conceived, pursued and imposed [36]. The extent to which these extraordinary and revolutionary technologies, whether they manifest as immensely beneficial and enabling forces leading to high gains, augmentation, or enhancement of human intelligence or as a potentially harmful and malevolent force could have the opposite effect of eroding, diminishing, or degrading it, is fundamentally contingent on the crucially) decisions that are being made today (and in the near future) about how human-beings interact with/ interface with AI systems. Such as how much we enable, facilitate and optimize meaningful, productive and responsible interaction between humans and A.I., to what extent do we mandate collaboration and cooperation, to what degree do we cultivate peaceful human-A.I. coexistence? Only if we confront this immense challenge as one people, recognizing the multifaceted challenges brought about by relentless advancements in technology and organization, not to mention the necessity for tireless ethical scrutiny, particularly now when AI is enabled to bestow great gifts while simultaneously threatening all that makes humankind human.

Author Contributions

All authors contributed equally in preparing the manuscript and they have read and agreed to the published version of the manuscript.

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No data used for this study.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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