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Assessing the Risk of Artificial Intelligence Impact on Decision-Making Automation in Digital Businesses

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A B S T R A C T

Artificial intelligence technology' quick development has drastically changed how digital firms make decisions. While AI-enabled automation has many benefits, such as improved scalability, accuracy, and efficiency, it also brings new hazards that businesses need to be aware of. The possible hazards of AI-driven decision-making automation are evaluated critically in this essay, with a focus on the consequences for operational dependability, business strategy, ethical issues, and regulatory compliance. The study finds important risk concerns such algorithmic bias, accountability problems, cybersecurity dangers, and decreased decision-process openness by examining current practices and literature. The results indicate strong governance structures, open algorithmic audits, and flexible regulatory laws as ways for companies to reduce these risks. In an increasingly automated corporate world, the insights offered in this article assist responsible and well-informed decision-making by promoting a balanced approach to incorporating AI into digital business models.

1. Introduction

The rapid progression of manufactured insights (AI) innovations has significantly changed the scenario of computerized commerce operations, especially within the domain of decision-making automation. As AI frameworks progressively accept parts customarily saved for human judgment—ranging from vital arranging to real-time operational choices—digital undertakings are encountering phenomenal levels of productivity, versatility, and data-driven understanding. However, alongside these advantages emerges a basic need to grasp and evaluate the potential dangers that AI poses when implanted in central decision-making forms.

Recent writing highlights both the opportunities and vulnerabilities related to AI-driven computerization in commercial settings. Studies have shown that while AI can improve the speed and precision of choices (Shrestha et al., 2024), it also presents challenges such as algorithmic bias, lack of transparency, moral concerns, and overreliance on automated yields (Saxena & Kumar, 2023). In addition, the integration of AI in financial decision-making has raised concerns over governance, accountability, and organizational flexibility. These dangers have ended up being particularly relevant as businesses embrace complex AI models without continuously having the internal capacity to translate or review their components effectively (Lee & Huang, 2025).

Despite a growing body of research on AI applications in trade, there remains a gap in methodically evaluating the opportunities related to decision-making computerization. This consideration aims to fill that gap by focusing on three central objectives:

- ✧ (O1) To identify and categorize the key risks associated with AI-driven decision-making in digital and advanced business contexts.
- ✧ (O2) To assess the impact of automation on the quality, transparency, and accountability of decision-making processes.
- ✧ (O3) To propose a practical risk assessment framework that supports organizations in proactively managing the challenges posed by AI-based decision-making.

The significance of this investigation lies in its potential to advise both scholarly discourse and administrative practice. As AI continues to advance and integrated into vital and operational capacities, understanding its implications is no longer discretionary but essential. By evaluating AI-related dangers within a structured system, this paper contributes to a more reliable and informed adoption of mechanization

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innovations in trade contexts—ensuring that development does not come at the cost of reliability, morals, or organizational flexibility.

Although there are various positive elements, the application of AI in decision-making poses significant risks to informatics and the economy. AIs and their black-box decision making is inherently intractable, which means there is no transparency, interpretability, or accountability. Often, this reasoning is deliberately concealed (Müller & Kranz, 2025) which makes it impossible for stakeholders to trust the automated processes and assess the outcomes. Additionally, bias reinforcement through algorithmic decisions making poses severe and social consequences, resulting in discrimination.

A positive take aside, automatic decision making revolving around AI brings with it negative aspects related to informatics and the economy that require grave consideration. The black-box decision making approach along with the intractability of AIs renders all forms of accountability and transparency a mystery. The lack of clarity often clouds the reasoning behind the decisions (Müller & Kranz, 2025) and creates barriers where stakeholders fail to trust the automated processes and evaluate results. In addition, depending too much on an algorithm for decision-making raises concerns about how biases can be strengthened, leading to equally discriminatory results with far more ethical and social consequences.

Another important informatics issue arises from accountability in AI-assisted decisions. When autonomous systems make economically important decisions with no human interface or supervision, it becomes rather impossible to define tasks and responsibilities accurately. The absence of accountability in harmful consequences resulting from AI decision-making algorithms makes it impossible to mitigate legal liability and damages, as well as erode trust in stakeholders (Kumar et al., 2023). For automated systems of decision-making to work optimally, there should, therefore, be proper governance structures and institutions to clearly define liability and corrective measures to dysfunctional automated systems.

This paper starts with an exhaustive review of literature containing models of economic growth to assess the risk of artificial intelligence on the automation of decision-making in digital businesses.

2. Literature review

The integration artificial intelligence (AI) into digital organizations has advanced significantly because of the need for competitive advantage, greater efficiency, and accelerated innovation. The landscape of economic informatics has AI because of its unprecedented ability to automate decision making, analyze large amounts of data, and improve predictive capabilities.

The gaps created for the broad approaches of risk mitigation are supported with an emphasis on clear algorithmic verifications, explaining procedures, and audit systems that are interdisciplinary encompassing technology, ethics, law, and economics (Gonzalez & Lee, 2024).

One business policy for fostering transparency is to carry out unconditional verification of biases in algorithmic procedures with the possibility for correction towards equity and compliance regulation. In addition, as social norms can be reinforced, the automation of decision making on IT systems becomes sustainable with the assistance of well-defined ethical boundaries governing AI systems.

Furthermore, a significant advancement is the implementation of flexible regulations that change in tandem with technological advancements. In order to properly handle the quickly changing landscape of AI technologies and guarantee that regulations stay applicable and efficient, policymakers are encouraged to establish dynamic, flexible regulatory frameworks (Park et al., 2025).

By enabling proactive risk identification and control, such adaptive techniques help preserve economic stability and strengthen stakeholder confidence in AI-driven digital business processes.

The article concludes by offering a thorough analysis of the hazards associated with AI that affect the automation of decision-making in digital enterprises from an economic-informatics standpoint. In order to provide a thorough grasp of the relationship between AI-driven automation and the ensuing informatics risks, this paper examines important issues such algorithmic bias, cybersecurity, transparency, and accountability. Furthermore, it emphasizes the need for well-informed regulatory laws and governance frameworks that strike a balance between ethical corporate practices and technical innovation, allowing for the long-term incorporation of AI into the digital economy.

Table 1. Literature Review

Reference	Purpose	Subjects	Sample Design	Conclusion
(Brynjolfsson et al., 2019)	Investigate the discrepancy between rapid AI advancements and stagnation in productivity statistics.	Firms integrating AI across various industries.	Analysis of productivity data and AI adoption rates across multiple sectors.	Identifies a lag between AI adoption and measurable productivity gains, attributing it to implementation challenges and the need for complementary innovations.

Reference	Purpose	Subjects	Sample Design	Conclusion
(Erik Brynjolfsson et al., 2019)	Identifies a lag between AI adoption and measurable productivity gains, attributing it to factors like implementation challenges and the need for complementary innovations.	Analyze how AI impacts productivity and the potential reasons for observed productivity paradoxes.	Firms integrating AI into their operations across various industries. Various industries adopting AI technologies.	Analysis of productivity data and AI adoption rates across multiple sectors. The study identifies a lag between AI adoption and measurable productivity gains, attributing it to factors like implementation challenges and the need for complementary innovations.
(Wamba et al., 2021)	Explain how organizations can leverage AI technologies in their operations.	Various organizations adopting AI.	Systematic literature review of existing studies on AI implementation.	Highlights the importance of understanding value-generating mechanisms when integrating AI into business processes.
(Shrestha et al., 2020)	Explore the integration of deep learning algorithms in organizational decision-making.	Organizations implementing deep learning solutions.	Conceptual analysis based on existing literature.	Discusses how deep learning can enhance decision-making but also presents challenges such as complexity and interpretability.
(Möhlmann et al., 2021)	Examine how algorithmic management affects workers on online labor platforms.	Workers engaged in online labor platforms.	Empirical study involving worker interviews and platform data analysis.	Finds that algorithmic management can lead to increased efficiency but also raises concerns about worker autonomy and fairness.
(Schemmer et al., 2021)	Differentiate between intelligent decision assistance and automated decision-making.	Knowledge workers utilizing AI systems.	Literature review and conceptual framework development.	Advocates for explainable AI to support knowledge workers, emphasizing the balance between automation and human oversight.
(Wamba-Taguimdje et al., 2020)	Investigate the impact of AI-based transformation projects on firm performance.	Firms undergoing AI transformations.	Case studies of organizations implementing AI projects.	Concludes that AI can significantly enhance firm performance when aligned with strategic objectives and properly managed.
(Bawack et al., 2021)	Develop a comprehensive framework for AI research in business contexts.	AI researchers and practitioners.	Analysis of existing AI research and practical applications.	Provides a structured approach to understanding and conducting AI research, emphasizing practical insights.
(Wamba et al., 2022)	Explore the benefits and challenges of AI in operations and supply chain management.	Companies implementing AI in supply chains.	Survey and interviews with industry professionals.	Identifies significant benefits such as efficiency gains, alongside challenges including data quality and integration issues.
(Johnson et al., 2022)	Propose a method for incorporating human expertise into AI systems.	AI systems dealing with complex problems.	Conceptual development and case study analysis.	Suggests that integrating human knowledge can enhance AI performance in complex and poorly structured domains.
(Wamba & Queiroz, 2023)	Analyze the role of responsible AI in	Digital health initiatives employing AI.	Bibliometric analysis of	Emphasizes the need for responsible AI practices to ensure

Reference	Purpose	Subjects	Sample Design	Conclusion
	digital health applications.		academic publications.	ethical and effective digital health solutions.
(Al-Qudah, 2022)	Investigate the application of AI in promoting sustainable finance and technology.	Financial institutions and tech companies using AI for sustainability.	Review of AI applications in sustainable practices.	Concludes that AI can play a pivotal role in achieving sustainability goals when applied thoughtfully in finance and technology sectors.

Source: authors

Firms that adopt artificial intelligence technologies report notable improvements in operational efficiency and more effective resource allocation, which in turn enhance both sustainability and profitability (Smith & Anderson, 2023). Despite these advantages, several scholars have raised concerns regarding the broader implications of AI on decision-making processes, particularly in terms of informatics and economic risk. A significant challenge to stakeholder trust and regulatory compliance lies in the opacity of deep learning algorithms. As Müller and Kranz (2025) argue, organizations often struggle to provide sufficient justification for decisions made by such systems, which complicates both internal accountability and external oversight. These references provide a comprehensive overview of the current research landscape concerning the impact of artificial intelligence on decision-making automation in digital businesses.

3. Methodology

This research utilizes a theoretical and literature review approach within a qualitative, interpretive, and exploratory research paradigm. The goal of this study is to analyze the potential risks, and economic effects AI technology can impose on the digital business's decision-making processes. Instead of using primary empirical evidence, this research applies a systematic literature review methodology to gather, analyze, and integrate diverse academic and industry publications, thereby forming a solid conceptual framework of the phenomenon.

The escalating development and diffusion of AI technologies in digitally enabled enterprises has piqued considerable scholarly interest. Even though there is a rich multidisciplinary AI research corpus dealing with diverse business functions and global activities, there is still a gap in assessing the risks and opportunities associated with decision-making computerization.

This study aims to fill the gap by synthesizing and critically evaluating existing literature to construct a comprehensive model for risk assessment of AI in digital decision-making systems. The literature contains a well-defined framework for assessing various risks of decision automation through artificial intelligence, albeit under different titles and conceptual approaches. Below the table are some relevant and related examples:

Table 2. Major AI Risk Management Frameworks

Framework/ Institution	Main Objective	Key Elements	Scope of Application	Advantages	Disadvantages
AI Risk Management Framework / National Institute of Standards and Technology (USA), 2023	To provide a structured, flexible framework for identifying, assessing, and mitigating AI-related risks	- Transparency - Fairness - Accountability - Effectiveness - Continuous monitoring	Cross-industry, public and private sectors (global applicability)	-Comprehensive and modular -Recognized by industry - Promotes risk-aware innovation	-Complex for smaller organizations -Implementation may require technical expertise
Ethics Guidelines for Trustworthy AI/ High-Level Expert Group on AI (European Commission), 2019	To foster ethically aligned AI systems centered on human values in Europe	7 Key Requirements: - Human agency and oversight - Technical robustness and safety - Privacy and data governance - Transparency - Diversity and fairness - Societal and environmental well-being - Accountability	Policy design, research, public and private sectors in the EU and beyond	-Ethics-centered -Widely cited and adapted - Promotes social trust in AI	-Non-binding - Lacks operational implementation details

Framework/ Institution	Main Objective	Key Elements	Scope of Application	Advantages	Disadvantages
ISO/IEC 23894:2023 – AI Risk Management/ International Organization for Standardization, 2023	To ensure safe, secure, and controlled deployment of AI systems through structured risk management processes	- Risk identification - Assessment and treatment - Lifecycle management - Documentation and monitoring	Global industries and regulators implementing AI systems	-Internationally harmonized -Applies to full AI lifecycle -Supports compliance and audits	-May be too general -Implementation costs may be high for SMEs
Algorithmic Impact Assessment (AIA)/ Government of Canada, 2020+	To evaluate the ethical, legal, and societal impact of algorithms in administrative decision-making	- Algorithmic transparency - Risk classification - Stakeholder consultation - Public disclosure of assessments	Public sector (Canada), adaptable to other public administrations	-Promotes transparency and accountability -Stakeholder engagement -Early regulatory model	-Limited to public sector -May not scale well to complex commercial AI systems

Source: authors, by using (23) (8) (13) (10)

Starting from these aspects, we can see the evidence of a theoretical economic model based on the specialized literature, which would validate the three proposed objectives of our study from an economic perspective. We can consider an integrative conceptual model for assessing the risks of decision-making automation through artificial intelligence in digital businesses. This model can integrate concepts from information economics, agency theory, behavioral economics and cost-benefit analysis, to highlight the implications of decision-making automation through artificial intelligence (AI) in digital businesses. Each of the four interrelated components that comprise the proposed model advances the primary goals of the research and represents an essential component of decision-making automation. It looks to identify and categorize the primary risks associated with AI-driven decision-making in complex and digital business environments, as well as evaluate how automation impacts the quality, accountability, and transparency of such decisions. The model also seeks to give organizations a practical framework for risk assessment so they can proactively address the challenges posed by AI-based decision-making.

Thus, the information dimension (I), referring to information asymmetry and decision-making opacity, has as its basic theory the Information Economy (Akerlof, 1970; Stiglitz, 2000), and the problem would be that AI models often act as "black-box models", generating decisions that are difficult to understand or interpret for human decision-makers (Müller & Kranz, 2025). The economic risk would be caused by the fact that there are information asymmetries between stakeholders (managers, customers, investors), which leads to decision-making inefficiencies and loss of institutional trust. Thus, a connection between O1 and O2 is observed, in the sense that this dimension highlights the risks regarding the lack of transparency and the negative impact on the quality of decisions.

On the other hand, the responsibility dimension (R), with reference to governance and agency theory, has Agency Theory as its basic theory (Jensen & Meckling, 1976), and the problem would be that the automation of decisions dilutes responsibility and creates difficulties in decision-making traceability, especially in the absence of a robust governance framework (Kumar et al., 2023). The economic risk would be caused by the fact that there are increased agency costs and difficulties in establishing legal or ethical liability in the case of erroneous decisions. Thus, the connection between O2 and O3 is observed in the sense that the model validates the need for a formal framework for responsibility and assessment of AI risks.

The economic dimension (E) with reference to cost-benefit and decisional value, has as its basic theory Cost-Benefit Analysis (Boardman et al., 2017), and the problem would be that the integration of AI generates economies of scale and decisional efficiency, but also involves hidden costs: implementation costs, reputational risks, losses from wrong or biased decisions (Harrison & Zhou, 2023). The economic risk would be caused by the fact that there is low resource efficiency if automation is not accompanied by decisional quality control mechanisms. Thus, the connection between O1 and O3 is observed in the sense that the model supports the idea of a framework for assessing the economic and decisional risks associated with AI.

The behavioral dimension (B), with reference to trust and cognitive bias, has as its basic theory Behavioral Economics (Kahneman & Tversky, 1979), and the problem would be that AI algorithms can reinforce existing biases in the data and generate discriminatory or unfair decisions. This affects stakeholder trust and can lead to suboptimal economic decisions. As an economic risk, there are systematic erroneous decisions, affecting financial planning, market strategy and customer relations. Thus, the connection between O2 and O3 is observed, in the sense that it supports the importance of a critical assessment of the impact of AI on decision-making quality and correctness.

We can synthesize the model into an economic decision-making risk assessment function:

$$\text{RAMA risk} = f\,(I,R,E,B)$$

Where:
• I = Information asymmetry (e.g. algorithmic opacity score)
• R = Lack of accountability (e.g. algorithmic governance level)
• E = Cost-benefit ratio (e.g. decisional ROI + indirect costs)
• B = Behavioral and institutional bias (e.g. trust and fairness score)

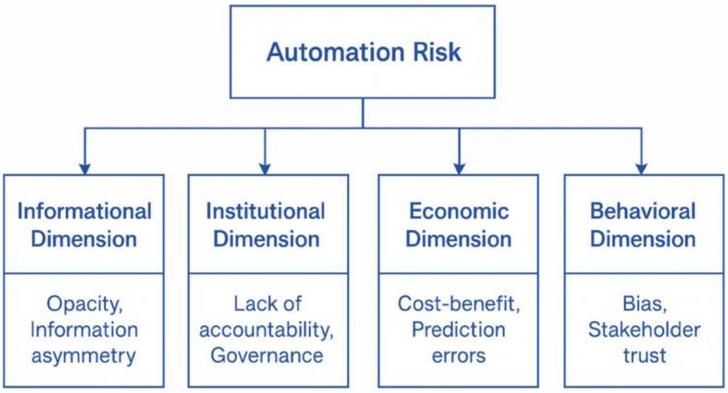

Figure 1. Automation risk of model
Source: autors

Considering the figure above, we can see that each dimension corresponds to a series of indicators. Thus, the information dimension, the information asymmetry date and algorithmic opacity aim to measure how transparent, interpretable and explainable an AI system is in making economic decisions. Indicators such as the algorithmic interpretability score (SIA), which measures the degree to which users can understand the AI decision (scale: 1–5). Then, the degree of access to explanations (Explainability Access Index) indicates whether the model provides explanations for the decisions made (binary or percentage). Algorithmic auditability time, i.e. the time required for an expert to be able to analyze an AI decision (in hours/days). Level of technical documentation, i.e. the existence and quality of the documentation provided about the model. This dimension would be relevant to trust and transparency.

Regarding the institutional dimension, the accountability, governance and regulation dates, this would aim to measure the existence and quality of the accountability mechanisms for automated decisions. Dimension indicators, such as the existence of an internal AI governance framework, show the presence of an AI policy/oversight team (yes/no). Clarity of decision-making responsibility can be identified by who is responsible for an AI decision (scale: 1–5). Degree of compliance with standards (e.g. ISO 23894, NIST), measured in (%) compliance with the requirements of the standards and the presence of a human intervention mechanism (Human-in-the-Loop), i.e. an availability score (binary or ordinal). This dimension would be relevant to accountability and regulation.

In the third, the economic dimension, based on costs, efficiency and resource allocation, would aim to measure the financial and economic impact of automated decisions, including prediction efficiency and risks. The main indicators would be given by the AI decisional ROI (Return on AI-based Decision-Making), i.e. a ratio between economic benefits and implementation costs, but also by direct and indirect costs of AI errors, i.e. losses caused by erroneous automated decisions (in foreign currency). The reliability score of economic predictions, i.e. the assessment of the accuracy of AI predictions compared to reality (e.g. RMSE, MAPE) would be important to assess the rate of human decisional substitution with AI, in the sense of analyzing the proportion of fully automated decisions (%). This dimension would be relevant for efficiency, optimization and economic impact.

The last dimension, the behavioral dimension, the date of abias, equity and stakeholder trust, would aim to assess the ethical and social risks generated by AI, such as discrimination, lack of trust or effects on organizational culture. The main indicators would be given by the algorithmic bias index (Algorithmic Bias Index), which detects the presence of biased decisions (e.g. towards gender, ethnicity, etc.).

The decisional fairness score (Fairness Score), another indicator, would show how fairly each segment of users/customers is treated. The level of trust of users in AI (Trust-in-AI score) resulting from internal or external surveys with scales: 1–10. A number of ethical or legal complaints regarding AI involve the analysis of officially registered incidents. This dimension would be relevant to reputation, ethics and also social acceptability. For practical use, each dimension can be scored, and the total score can be used for classifying the level of risk (low, moderate, high), comparison between companies or industries and decisions regarding investments, regulation, AI implementation.

Objective	RAMA Dimension	Validation
O1: Identifying risks	I, R, E, B	Modelul definește cele 4 categorii principale de risc
O2: Assessing the decisional impact	I, B, R	Decision quality, transparency and accountability are assessed through the 3 dimensions
O3: Proposing an evaluation framework	I+R+E+B	The RAMA model functions as a theoretical risk assessment framework

Figure 2. Correlation of the RAMA model with research objectives
Source: authors

According to the RAMA model matrix, each dimension can be assigned a risk score (from 1 to 5), assessed internally or externally, based on a questionnaire, audit or simulation.

Dimension	Risk level (1 = low, 5 = high)	Key indicators
R – Responsibility	X	Existence of a clear AI governance policy
A – Algorithmic Transparency	X	Degree of interpretability of the model
M – Mitigation of Bias	X	Data fairness control mechanisms
A – Adaptability & Impact	X	Cost-benefit ratio, added economic value

Figure 3. Total decisional risk assessment
Source: authors

In the case of the high values of the RAMA risk model, it would indicate a high probability of economic inefficiency, reputational losses and erroneous decisions in the context of decision automation through AI. RAMA is a model proposed by the authors, inspired by established standards and theories, but formulated in a unique integrative framework, adapted to the automated decision-making economy. The applicability of the model would be welcome for AI-based decision-making audit, public policy design for AI regulation, comparative research between industries with different levels of automation, as well as impact assessments in digital transformation.

The model could be used by digital firms for internal audits of automated decision-making systems and by policymakers for regulations in AI governance. Economists could also use it to estimate the macroeconomic impact of AI integration and investors to assess portfolio risks in companies' dependent on decision-making AI.

The RAMA model also provides a coherent and theoretically validated framework to analyze, understand, and evaluate the economic decision-making risks associated with artificial intelligence in digital businesses. By addressing the four dimensions (informational, accountability, economic, and behavioral), the model supports the achievement of the paper's objectives and provides a solid foundation for future research or digital governance policies.

4. Conclusions

This paper examined the intricate connections between AI and the automation of decision-making and economic risks related to digital businesses, and it resulted in the development of the RAMA model— a pioneering conceptual framework for measuring risks of AI-powered decisions. Based on an exhaustive analysis of literature drawn from information economics, agency theory, behavioral economics, and cost-benefit analysis, the model articulates a theoretically grounded and viably useful method for pinpointing and classifying the acute AI dilemmas exposing organizations to risks.

Given the themes of the study: (O1) identifying the risks of AI-based decision-making, (O2) analyzing how automation impacts the AI-governed decisions and assessing the needed transparency and accountability, and (O3) creating a risk framework that guides businesses in managing the identified risks, the RAMA model aimed at achieving those goals by providing the four information (I), Institution (R) Economy (E), and Behavior (B) core dimensions. Each dimension indicates an area of emerging risk, including algorithmic opacity, accountability voids, negative socio-economic consequences, and erosion of stakeholder confidence, all of which have been raised collectively in the contemporary discourse on AI governance and digital strategy.

This research's interdisciplinary integration and the proposed model, which can be scaled, tailored, and used across various industries while accounting for their unique risk profiles and technological maturity, constitute a significant contribution. Corporate strategists, legislators, and consultants for digital transformation can all use the RAMA framework to bridge a methodological gap by providing a common lens for evaluating the effects of automating decision-making in a rapidly changing AI ecosystem.

The study has limitations despite its conceptual strengths. The RAMA model has not yet been verified by empirical fieldwork because it is a theoretical and literature-based study. The direct observation of actual organizational dynamics and possible unforeseen consequences of automated decision systems in situ is limited by the lack of primary data. Furthermore, the model does not yet include dynamic feedback loops, which are a feature of many contemporary AI applications. Examples of these loops include adaptive learning systems and real-time monitoring.

Future studies should concentrate on a few important areas in order to build on these foundations. First, the RAMA model's applicability and generalizability will be improved by empirical validation through case studies, interviews, or quantitative risk assessments across various industries. Second, the operational usefulness of the model would be enhanced by additional improvement of indicators and metrics within each dimension, especially with regard to measuring algorithmic bias, stakeholder trust, and governance maturity. Third, combining explainability frameworks with real-time AI auditing tools may make it possible to create a dynamic RAMA that can be continuously evaluated.

Finally, future research should explore the implications of AI decision-making on macroeconomic variables, such as labor displacement, market efficiency, and regulatory innovation. Models like RAMA will be essential in striking a balance between innovation and accountability, efficiency and equity, and automation and human oversight as AI technologies become more and more integrated into economic systems.

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