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(Generative) AI and Machine Learning Solutions: From Data to Decisions

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Abstract

Recent innovations in Artificial Intelligence (AI) have led to the development of new paradigms in machine processing, shifting from data-driven, discriminative AI tasks to advanced tasks, enabled by generative AI. These technologies allow companies to manage extensive volumes of both structured and unstructured data and produce actionable insights with remarkable speed and precision. Through the application of generative AI, businesses can create predictive models that reflect market scenarios, customer behaviours, and competitive dynamics. The current paper researches the relationship that exists between generative AI and machine learning, emphasizing their roles in market analysis and business development. The two terms are often used in both scientific and media contexts, at times interchangeably, and at other times with distinct meanings. The paper reviews relevant literature and aims to offer a foundation for (interdisciplinary) discussions and future studies on the topic. As businesses adopt these innovations, it is essential that they focus on ethical considerations in order to create systems that deliver both value and integrity, which is crucial for achieving long-term success and sustainability in a business environment, influenced by AI. The paper seeks to be a vital resource for researchers, students, and practitioners seeking insight into the complex journey to data-driven decision making through (Gen)AI.

Keywords: (generative) artificial intelligence, machine learning, ethical considerations, (business) decision-making

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1. INTRODUCTION

Machine learning (ML) and AI have rapidly established themselves as transformative factors within the technology sector, managing innovation in multiple industries. The strength of AI lies in its capability to learn from data – an ability that is facilitated by ML. Specifically, ML is the key driver of the majority of AI technologies customers interact with today. It has significantly altered various industries, stimulated innovation, and enabled machines to carry out activities that were previously regarded as uniquely human, including language understanding, image recognition, and predictive modelling.

Despite of the ongoing debates regarding the sentience of AI, the most recent developments in ML and deep learning (DL) have broadened the scope of conventional, data-centric AI functions such as predictions, classifications, and recommendations to include the creation of original and innovative content. Widespread partnerships between humans and intelligent systems in both business and personal contexts have been influenced by the integration of AI in numerous ways, particularly in the areas of process optimization and decision-making (Burström et al., 2021).

Undoubtedly AI technologies have revolutionized the manner in which businesses engage with data and make decisions, resulting in unprecedented developments in both society and the economy (Fügener et al., 2021). Moreover, although there has been a modest yet steady increase in publications addressing AI-related themes over recent years, ML only began to gain significance in academic literature post-2017. The delayed acknowledgment of ML, regardless of its earlier implementation and proliferation within the industry (Brynjolfsson & McAfee, 2017), may prompt inquiries regarding whether research has adequately addressed the topic in a timely manner.

The increasing popularity of AI (Fujii & Managi, 2018) has resulted in the term frequently being used as a synonym for ML. While it is true that both terms often appear in similar contexts, they are not synonymous. Thus, this paper aims to clarify the relationship between these two concepts by exploring the contribution of ML in the context of AI. Additionally, the current research contributes to a deeper understanding of the nature of both concepts and to more terminological clarity and guidance – as a starting point for discussions and future research. Moreover, as businesses step into the new age of generative AI (GenAI), comprehending the fundamental principles and differences inherent in GenAI as a swiftly advancing technology is becoming increasingly important.

GenAI – a field of AI, focused on generating new data or content that is similar to the original, including images, texts, music, or code – can be applied for various objectives, like data augmentation, content creation, data synthesis and data transformation (Epstein et al., 2023). The study of GenAI is a developing and interdisciplinary area that includes the application of

GenAI techniques in order to develop or improve visual representations of large and complex data sets.

Recently, GenAI has evolved into a revolutionary technology, altering how businesses approach market analysis and decision-making. This technology serves as a powerful tool, capable of generating vast amounts of data that facilitate a deeper understanding of market trends. By offering such insights, GenAI is ideally positioned in a context where data is abundant and emerging patterns are somewhat challenging to identify.

Modern businesses can gain significant insights from the data they collect through online interactions with their customers. Some are employing natural language processing technologies that can comprehend the various languages and terminologies specific to various sectors and industries (Wu et al., 2022). Others are using AI expert systems to retrieve information from intricate documents and datasets, robotize workflows and business processes, and facilitate effective and precise decision-making in a flexible manner both on-site and within a hybrid cloud environment (Weber et al., 2023).

The thesis that, in the current digital landscape, the exponential increase in data generation has led to an unprecedented demand for advanced algorithms that can learn from this data and make informed decisions, is put forward. Furthermore, the paper emphasizes that the vast amounts of data enable the algorithms to enhance their accuracy and efficiency. Despite the significant potential, challenges continue to exist. Key issues include ethical concerns related to privacy, biases present in data, and the potential impact on employment. Moreover, the complexity of AI systems often complicates the understanding of decision-making processes, leading to concerns about accountability.

The study itself is qualitative or literature-based. For the purposes of this paper, the following methods have been employed: content analysis and synthesis; descriptive analysis; tabular method. In order to validate the concepts of the paper, the research data has been primarily sourced from secondary materials, which consist mainly of journals and peer-reviewed articles, drawing from various interconnected domains, including (Gen)AI and ML. This methodology has been selected due to the insufficient consolidated knowledge in this area. The publications that have been selected are analysed in relation to the research issue. The literature that has been reviewed for the purposes of the paper has mainly been published in recent years. By relying on updated literature, the paper captures current insights and innovations, thus ensuring its relevance and applicability within the dynamic fields of (Gen)AI and ML. However, due to their high relevance and contribution to the current research, there are some exceptions in the literature with earlier publishing years.

Specifically, the paper is structured as follows: The first section decodes the (introduction of) AI.

The review briefly outlines the transition from symbolic AI and expert knowledge to ML and generative models (GM), with the objective of comprehending these changes. After establishing a contextual foundation for the concept of AI, the study describes the foundation of AI and delves into ML. Understanding this trajectory is essential for directing the research, steering future pathways, and tackling the intricate consequences of advanced AI. Next the GenAI is explored. Specifically, the next section seeks to emphasize some main concepts in GenAI. Furthermore, the study addresses making decisions based on data by utilizing (Gen)AI. Finally, this study highlights that it is important for businesses to stay alert to the ethical concerns associated with the use of (Gen)AI. The concluding section summarizes the findings and highlights specific future research directions.

2. BACKGROUND AND RELATED WORK

The area of AI has established a significant presence in both research and practical applications across multiple fields over the last several decades. Initial AI research has been profoundly shaped by philosophical texts, logical theories, and fictional narratives (Buchanan, 2005). The advent of computer science as a discipline started in 1931, which also played a crucial role in shaping the field (Schmidhuber, 2007). In the wake of the computing technology revolution during the early 20th century, AI research began to take form, leading to the development of foundational AI theories (Sloman, 1998).

Undoubtedly, the domain of AI has expanded considerably in recent decades, fuelled by improvements in computational capabilities, extensive data resources, and ML algorithms. In order to distinguish GenAI from other AI concepts and offer a foundational understanding, this section will provide a concise summary of AI and its subfields, namely ML and DL.

2.1. Artificial Intelligence

AI is a broad term that describes a machine (or process) capable of responding to environmental stimuli (or new data) and subsequently altering its operations to optimize a performance index (Russell & Norvig, 2010). The AI model undergoes a repetitive process of parameter adjustment and trial and error during its training on data through reinforcement rules (Bellini et al., 2022). The main goal is to minimize the difference between the model's predictions and the experimental data, which acts as the performance metric. After the AI model has been trained, it is capable of analysing new data and making informed decisions.

For a considerable period, the leading paradigm in AI has been centered around symbolic representations, conceptualizing intelligence or intelligent behaviour primarily as the manipulation of symbols that reflect elements of the real world. This approach operated on explicit rules, utilizing formal logic and expert systems in order to execute reasoning tasks. Nevertheless, symbolic techniques have been heavily dependent on manually encoded knowledge. This rendered them inadequate for dynamic or open-ended environments characterized by uncertainty and unstructured data. Since the onset of the 2010s, the deep

learning revolution has led to remarkable achievements in tasks driven by perception (LeCun et al., 2015).

AI has undergone a significant transformation since its beginnings, progressing from initial logic and rule-based systems to contemporary data-driven and GM. The widespread partnerships between humans and intelligent systems in both corporate and personal contexts have been influenced by the integration of AI in numerous ways, particularly in the areas of process optimization and decision-making (McAfee & Brynjolfsson, 2016).

Contemporary definitions of AI encompass the complete concept of human intelligence to machines, defining it as the ability of a machine to perform cognitive functions that are associated with human minds, such as perceiving, reasoning, learning, interacting with the environment, problem solving, decision-making, and even demonstrating creativity (Rai et al., 2019). However, it is surprising that, even with the regular use of the terms – AI and ML, there is hardly any significant academic clarification – except for the idea that ML is a somewhat vague subset of AI (Campeato, 2020), similar to other potential sub-disciplines of AI, such as expert systems, robotics, natural language processing, machine vision, and speech recognition (Collins, 2021).

Despite the discussions surrounding AI's potential sentience, the latest advancements in ML have broadened the traditional, data-driven AI tasks such as predictions, classifications, and recommendations to also include the creation of unique, realistic, and creative content.

AI is currently composed of several distinct subfields. While each of these subfields may focus on different challenges within AI, yet they all share overarching objectives related to the advancement of intelligent machines and programs. The subfields of AI encompass as follows; neural networks; ML and DL; computer vision; natural language processing; and robotics. The first two subfields will be discussed in the following sections. It should be noted that although, neural networks may be perceived as a type of ML model, neural networks have remained a distinct subfield, as they have not been originally presented as a model to be learned, but as a methodology for achieving machine intelligence (McCulloch & Pitts, 1943).

2.2. Machine Learning: The Foundation of Current AI

ML, which is also called classical AI, is a type of AI that allows systems to learn from data instead of through direct programming (Hurwitz & Kirsch, 2018). ML encompasses a range of techniques that are often applied to resolve a wide array of real-world issues, using computer systems capable of learning to address a problem instead of being directly programmed (Koza et al., 1996).

Similarly, Nayarisseri et al. (2021) define ML as a subset of AI that focuses on the training of new data through an adaptive methodology, like neural networks, without the need for the explicit programming of new rules, which is a requirement for other algorithmic types like

expert systems. This indicates that ML enables computers to adjust and generate new results without requiring the input of additional instructions. These instructions, known as algorithms, consist of programmed sets of rules that guide the computer program in its operations to achieve a desired result. According to Pandey et al. (2019), ML algorithms can be categorized into three primary groups (see Table 1).

Table 1. Categorizing ML

ML Type	Characteristics
Supervised Learning	The machine is given labeled data (data that contains accurate answers). It subsequently uses this data to identify patterns and generate predictions.
Unsupervised Learning	The machine is provided with unlabeled data, and it must independently detect patterns or relationships. A common application of this approach is customer segmentation in marketing, where the machine recognizes groups of customers based on their buying habits, without any previous knowledge of customer classifications.
Reinforcement Learning	The paradigm is based on behavioral psychology. A machine acquires knowledge by interacting with its environment and receiving feedback in the form of rewards or penalties. This approach is commonly employed in AI designed for gaming (like DeepMind's AlphaGo).

Source: Adapted by Pandey et al. (2019) for the purposes of the paper.

ML algorithms are characterized by their discriminative characteristics, which involve processing data for the purposes of classification, regression, or clustering, as well as establishing decision boundaries. Notable examples of these algorithms are decision trees, k-nearest neighbours, and support vector machines (Ray, 2019). Both ML and DL represent subfields of AI that have greatly impacted the area.

DL, a more contemporary advancement in ML, can be referred to as neural networks that model intricate data representations and automatically identify correlations and patterns within extensive datasets (Samtani et al., 2023). Consequently, DL possesses the capability to handle high-dimensional data across various fields, encompassing one-dimensional data such as signals and texts, as well as multidimensional data like images, videos, or audio (LeCun et al., 2015). These innovations have led to a multitude of applications across different fields. In the context of digital markets, for instance, DL can enhance pricing strategies, function as recommendation systems, predict demand, and identify fraudulent consumer reviews (Zhang et al., 2023).

Driven by progress in DL methodologies, deep GM have surfaced as a category of DL models capable of generating novel content derived from existing datasets, thereby opening up a range of new opportunities for AI applications (Deja et al., 2022). These models are designed to comprehend intricate data distributions, enabling them to generate outputs that closely mimic real-world data. By employing statistical methods, the aim of deep GM training is to acquire high-dimensional probability distributions from a limited training dataset and to produce new, analogous samples that serve as an approximation of the foundational class of training data (Ruthotto & Haber, 2021).

Specifically, GM aim to understand the underlying data structure and the processes of generation (Jebara, 2004). GM have existed for many years, with examples such as hidden Markov models and Bayesian networks designed to address statistical challenges related to time series or sequences (Regenwetter et al., 2022). However, deep GMs that utilize neural networks have led to a remarkable enhancement in the quality of generated content in the recent developments within the domain of GenAI. Consequently, the objectives of deep GMs are distinct from those of traditional discriminative AI models (such as ML) as they prioritize the probabilistic creation of new data rather than identifying the decision boundaries of existing data – such as classification, regression, or clustering (Weisz et al., 2023). In the next section, this paper will concentrate on deep GMs as the foundation of GenAI and provide a summary of the principal deep GMs that have influenced the development of GenAI (see Table 2).

2.3. GENERATIVE ARTIFICIAL INTELLIGENCE

GenAI is a form of AI that can create a wide range of content, including text, images, audio, and video (Chui et al., 2022). Typically, GenAI is characterized as a form of AI focused on generating data or content from pre-existing datasets. This technology possesses the ability to produce high-quality, contextually appropriate content that is hard to distinguish from that created by humans, leading to discussions about whether it exhibits initial indicators of AI (Bubeck et al., 2023). The key distinction between GenAI and traditional AI lies in the foundational model initially introduced by Stanford University’s Centre for Research. This is a ML model that has been trained on a large dataset, which can be modified to address a range of issues (see Deloitte AI Institute, n.d.).

The primary models in GenAI can be classified into several categories. Each of these models applies different strategies to generate new data, providing particular benefits in dealing with various data types and complexities (see Table 2).

Table 2. Main concepts in GenAI

GenAI Type	Characteristics
Generative Adversarial Networks (GANs)	They are made up of two neural networks: a generator and a discriminator. The generator's role is to create synthetic data, and the discriminator's function is to evaluate the authenticity of that data. Both networks are trained simultaneously in a manner where the generator aims to trick the discriminator, and the discriminator strives to distinguish between real and generated data. This adversarial training process continues until the generator creates data that the discriminator cannot easily identify as being different from real data.
Variational Autoencoders (VAEs)	These models include an encoder that converts input data into a latent space and a decoder that reconstructs data from that latent space. Throughout the training process, VAEs focus on optimizing reconstruction accuracy and ensuring that the latent space conforms to a predetermined distribution, usually a Gaussian distribution.

Autoregressive Models	These models create data by estimating the next element in a sequence, drawing from prior elements. Models such as GPT-3, developed by OpenAI, are based on this concept. They employ large-scale neural networks to model the distribution of sequences and create coherent text by sampling from this distribution.
Diffusion Models	Diffusion models are a type of generative models that create data by mimicking a stochastic process, which progressively introduces noise to the data, followed by a reversal of this process to restore the original data. Recent developments in diffusion models have led to exceptional performance in image generation tasks, surpassing GANs and other generative models.

Source: Adapted by Kingma and Welling (2022), Goodfellow et al. (2014), Brown et al. (2020), Chen et al. (2025) for the purposes of the paper.

To utilize deep GMs in GenAI applications, these models can be trained to produce new data and facilitate a range of use cases (the paper refers to deep GMs used in GenAI applications as GenAI models). It should be noted that the process of training a GenAI mode may differ from training a discriminative AI model, primarily due to the incorporation of semi-supervised learning, which combines learning methodologies that utilize a limited set of labelled data (so-called supervised data) followed by a substantial amount of unlabelled/unsupervised data (Kingma et al., 2014).

The application system serves as a medium through which users can engage with a GenAI model. Prompting, a distinctive feature of GenAI, allows end users to utilize natural language to communicate with and direct the GenAI application (for example large language models) in order to generate specific outputs such as text, images, or various other forms (Liu & Chilton, 2022).

The latest paradigm shift has introduced GMs, which are not only able to analyse data, but also – to generate original content across various fields such as text, images, and code. GenAI models create their outputs based on inputs by drawing from their training data, subsequently utilizing the existing data to generate new outputs that are similar, yet not entirely identical to the original data. The models showcase an extraordinary degree of flexibility and creativity. However, they require substantial computational resources and introduce new challenges related to control, bias, and the accuracy of the outputs they generate (all of these will be discussed in a later chapter). The shift between these paradigms has significantly enhanced the capabilities of AI, evolving from limited, rule-based applications to extensive, data-driven, and creative endeavours, which has essentially transformed its possibilities and societal implications (see Table 3).

Table 3. Comparative analysis of various paradigms – Symbolic AI, DL, and GMs

Characteristics	Symbolic AI	DL	GMs
Knowledge representation	Explicitly uses symbols, rules, and logic	Implicit representation through neural network weight	Combine the two approaches by representing knowledge through data probability distributions
Learning methods	Based on manual programming	Applies backpropagation	Refine likelihood functions and utilize adversarial training
Reasoning capabilities	Inference through logic	Pattern recognition	Data probability-based reasoning
Capability to Address Uncertainty	Limited	Probable	Solid
Data Specifications	Fewer data	Significant datasets	Significant datasets
Clarification	Easy to understand	Difficult	Difficult
Scalability	Restricted	High	High
Utilizations	Expert systems, natural language processing, and automated planning	Image and speech recognition, natural language processing	Data augmentation, generative artwork

Source: Author's for the purposes of the paper. Based on Russell and Norvig (2010), Hooshyar et al. (2024), van Breugel and van der Schaar (2024), Odeh (2024), Zhao et al. (2022), Felin and Holweg (2024), Confalonieri et al. (2021), Ramalakshmi and Asha (2024).

In conclusion, AI field has progressed through various paradigms –symbolic AI, DL, and GMs– each with its own specific traits. To summarize, the table above outlines the primary distinctions among the above-mentioned patterns. Analysing the shift from symbolic AI, known for its proficiency in logical deduction and planning, yet facing challenges with real-world ambiguity (Sharma, 2025), to data-centric methodologies reveals the advantages and drawbacks of the paradigms. Statistical techniques have opened up new possibilities in pattern recognition, computer vision, and natural language processing (Manakitsa et al., 2024), while generative models mark a substantial progression towards the creation of new data.

3. DATA-DRIVEN DECISION MAKING THROUGH (GENERATIVE) AI

In the past, decision-making has been influenced by intuition and experience, often resulting in a bias towards certain decisions, despite the availability of extensive data. In contrast, in today's AI-driven environment, organizations are capable of extracting more detailed information and applying the data that has been generated to make their strategies more objective (see Table 4).

Table 4. Enhancing data-driven decision making through GenAI

GenAI application for	Characteristics
Synthetic Data Generation	A significant advantage of GenAI is its capability to create synthetic data for simulation purposes. In the context of predictive market analysis, businesses can utilize AI to simulate various market scenarios or potential outcomes, such as the launch of a new competitor, changes in regulatory policies, or changes in consumer behaviour. This enables companies to experiment with different strategies and evaluate their potential influence on the market without needing actual data from real-world events. By employing synthetic data, businesses can analyse a wide range of scenarios and make informed decisions regarding how to address potential risks or take advantage of emerging opportunities. This strategy also assists in addressing the limitations of relying solely on historical data, which may not always accurately reflect future conditions.
Real-Time Data Integration	GenAI demonstrates significant effectiveness in merging real-time data from multiple sources, such as social media, online forums, market reports, and consumer feedback. Through the continuous processing and analysis of this data, GenAI can identify emerging patterns and signals that may be missed through traditional techniques. For example, AI can evaluate social media sentiment in real-time to assess consumer attitudes towards a product, service, or brand, assisting businesses in recognizing potential market opportunities and/or risks. The real-time integration guarantees that the forecasts, generated by AI, are not solely based on historical data, but also take into account current market dynamics, allowing businesses to make decisions that are both appropriate and timely.
Market Predictions	Established market prediction strategies rely on historical data and linear models that may not adequately reflect the complexities and dynamic characteristics of contemporary markets. On the other hand, GenAI introduces an advanced, data-driven framework for market predictions by employing ML and statistical models to predict future trends with greater precision and adaptability.
Data-Driven Insights	GenAI is highly effective at converting large datasets into actionable insights. By employing advanced algorithms and data processing techniques, AI can assess a wide variety of factors, including historical sales figures, consumer behaviour, economic indicators, and social media sentiment. This enables businesses to discover hidden patterns and correlations that may be overlooked with standard analysis methods.
Consumer Behaviour Analysis	GenAI improves the understanding of consumer behaviour through the analysis of extensive datasets related to customer interactions, purchase history, online activities, and demographic details. AI models are capable of recognizing patterns in consumer purchasing decisions, the factors that affect their choices, and their responses to marketing strategies. By modelling these behaviours, businesses can achieve a high degree of accuracy in predicting future consumer actions.
Scenario Modelling	GenAI is effective in scenario modelling, enabling businesses to examine multiple "what if" scenarios and predict their likely outcomes. By simulating various market conditions, including alterations in supply chain disruptions, economic recessions, or changes in consumer sentiment, businesses can predict how these changes will affect their operations and profitability. This leads to more informed decision-making and the opportunity to adapt strategies before a potential crisis emerges. AI-enhanced scenario modelling assists businesses in visualizing the possible risks and benefits of diverse strategies, providing a clearer understanding of the future and allowing companies to make data-driven decisions.
Trend Forecasting	Employing historical data and ML, (Gen)AI can forecast the emergence of new trends in various industries, consumer behaviour, or market preferences. Such predictions surpass basic extrapolation, as they reveal changes in market dynamics that are likely to affect future growth or demand. Through precise trend forecasting, businesses can strategically position themselves to seize new opportunities at an early stage, thus gaining a competitive advantage and promoting innovation. GenAI enables companies to stay ahead of market trends, ensuring they are not merely reacting to current conditions, but are also proactively influencing their future growth trajectories.
Enhancing Predictive Market Analysis	Traditional methods of market analysis often depend on static models and historical data, which may be inadequate in the rapidly evolving, data-rich business landscape of today. GenAI, known for its capacity to learn from extensive datasets and create new insights, presents a more dynamic and effective means of predicting market trends, consumer behaviour, and potential disruptions.

Source: Adapted by Selvarajan (2019), Pattanayak (2021), Nama et al. (2023a; 2023b) for the purposes of the paper.

It should be noted that AI algorithms highlight the significance of prediction derived from historical data. Taking into account this, the importance of prediction is reinforced by the early researchers of AI, who claim that prediction is the essence of intelligence (Bronstein et al., 2017). Undoubtedly, the predictive power of AI is substantial, and some (Davenport, 2018) assert that prediction plays a crucial role in decision-making. This statement is also supported by Agrawal, Gans, and Goldfarb (2022), who highlight that, AI is a prediction technology and that prediction is fundamental to the decision-making process.

In terms of prediction, Agrawal, Gans, and Goldfarb's (2022) statement can be summed up by highlighting a relatively prevalent causal sequence, which transitions from data to information, then to prediction, and finally to a decision. The authors state that data delivers the information necessary for making a prediction, and that prediction itself serves as a crucial component in the decision-making process. This related sequence, namely from data to information to prediction and decision, undoubtedly possesses intuitive appeal and reflects the capabilities of AI: they process extensive amounts of inputs and data, analyse the information, and subsequently generate predictions that inform decision-making.

The challenge associated with data, however, lies in the fact that the data that is currently accessible is unlikely to serve as the most effective source for information and predictions when making decisions oriented towards the future. Data represents a moment in time from the past. Even large volumes of data are not likely to facilitate the ability to foresee future events (Felin et al., 2025). A mechanism is necessary for forecasting into the future and recognizing the pertinent data, or for producing new data.

Indeed, in the context of standard decisions, prediction is undeniably a valuable instrument. Data-driven prediction can be exceptionally effective in scenarios that are predictable, particularly those that align with or extend from historical data. This aligns with the strengths of AI and prediction-oriented cognition, which excel in minimizing surprises and reducing errors. However, many forms of decision-making do not focus on error reduction through the use of available data.

Exactly the opposite is true in the realm of strategy where the influential prospects and resources do not rely on data that is readily accessible. On the contrary, crucial decisions within a strategy framework necessitate the formulation of a theory based on a diverse set of beliefs, which outlines a causal pathway or rationale for testing the theory, conducting experiments, and collecting new evidence to substantiate the belief. As noted by Camuffo et al. (2024), certain decisions have major effect yet they are infrequent, making them unsuitable for processing through algorithms. Consequently, decision making grounded in theory is not solely concerned with accurately portraying the environmental framework, bounded rationality, or heeding customer feedback; instead, it focuses on formulating a prospective theory and causal reasoning regarding experimentation and value creation (Felin et al., 2024).

It can be argued that if organizations have utilized identical prediction and perform a series of mechanical AI operations, the results are expected to be similar. In order for the strategy to create value, it must be distinctive and tailored to the company. This distinctiveness is linked to unique convictions and the formulation of a theory-driven rationale for value creation that competitors cannot foresee.

Even though it is possible to identify patterns in data and formulate hypotheses regarding them, it is often crucial to rely on an expert's knowledge to interpret these patterns in the context of the company's capabilities and values. This combination allows businesses to capitalize on AI for its speed, precision in decision-making, and capacity to manage large data volumes. It is combined with the human skill to make intelligent decisions based on intuition, experience, creativity, and ethical principles.

In general, the current paper argues that decision-making of the company does not have to solely be entrusted to AI. However, AI and models inspired by AI rely on historical data and predictions rather than any forward-thinking theoretical causal reasoning. And depending on data and predictions imposes a significant limitation on decision-making and cognitive processes. Thus, this paper highlights the significance of diverse beliefs in human cognition and the necessity for developing theory-based causal logic that facilitates problem-solving, experimentation, and the creation of new data.

To put it in another way, (Gen)AI tools can be employed by individuals, like economic agents, to generate new value or assist in decision-making processes. In case AI is to serve as a cognitive instrument that provides a competitive edge, it must be applied in distinctive or company-specific manners, as AI relying on universally accessible training data will inevitably produce generic and nonspecific results. To ensure that AI serves as a valuable tool for strategy and decision-making, it requires customization and purpose-training. It has to be tailored to the theories, datasets, and proprietary documents relevant to decision-makers like companies (Singh et al., 2024).

Furthermore, any implementation of AI must be intentional regarding the selection of training data that is employed when aiming for distinctive AI-generated results. Ultimately, the results produced by an AI, designed to utilize particular data, are also influenced by human agents who determine which data is significant for the current decision-making process. This presents a chance to explore how humans may uniquely engage with AI to create these tools. Initial research (Babina et al., 2024; Gregory et al., 2021) has started to examine how companies leverage AI to enhance innovation or how different human-AI collaborative solutions facilitate improved decision-making.

GenAI has already amazed and thrilled global businesses with its capacity to redefine the execution of knowledge work within various industries and business operations throughout the

economy. In areas like sales and marketing, customer operations, and software development, it is set to revolutionize job functions and improve efficiency.

The applications of GenAI are spanning from marketing and sales to the IT department (Chui et al., 2022) and businesses that are seeking to integrate GenAI into their operational framework have to first identify the aspects of their processes that can be automated by (Gen)AI, which will have the most rapid impact. Since (Gen)AI is a swiftly evolving field with new advancements emerging weekly, the following section seeks to compile key implications and new risks associated with the use of (Gen)AI that have occurred up to the present.

4. ETHICAL CONSIDERATIONS AND EMERGING RISKS OF USING (GENERATIVE)AI

With the widespread adoption of GenAI, serious ethical and regulatory challenges are surfacing in multiple sectors. According to Sharma et al. (2020), without appropriate governance frameworks, inequalities will continue to exist. Furthermore, the increasing importance of (Gen)AI for both the economy and society has created an urgent demand for regulatory measures. Various nations have adopted unique strategies and consequently, the regulatory environment for AI has evolved into a complex system, characterized by a diverse array of regulatory frameworks and guidelines that have been developing up to this point. However, an essential initial step involves AI designers, developers, and policymakers starting to conceptualize how AI systems can be structured to promote human welfare, improve human well-being, and enhance – rather than undermine – the significance of being human.

Simultaneously, the global nature of AI has made international collaboration crucial. Many organizations have begun to establish non-binding frameworks intended to serve as guiding principles for nations' collaborative efforts. These frameworks emphasize the significance of responsible AI (often referred to as human-centric AI). While there is no universally accepted definition for the concept of responsible AI, it typically refers to the development and implementation of AI technologies in an ethical, transparent manner, and in accordance with human values, ultimately resulting in fair and accountable AI systems that prioritize the well-being of individuals (Ryan & Stahl, 2021; OECD, n.d.-a; n.d.-c).

Moreover, responsible AI emphasizes the active involvement of users, stakeholders, and industry experts in every stage of the AI development cycle, which includes both the design and development phases as well as practical implementation. The goal is to comprehend and incorporate human viewpoints into the processes of decision-making and system development in AI. By fostering human-machine interaction, the aim is to establish AI systems that are intuitive, comprehensible, and user-friendly for individuals, thereby narrowing the divide and enhancing the interaction between humans and technology. In a manner akin to the Human-Centred Systems framework, outlined by Cooley (2000), human-centric AI turns away from the mechanistic view of technological and societal progress.

Regrettably, progress in the ethical sphere has been minimal compared to the rapid pace of technological innovation. Most of the recent statutory and regulatory frameworks, such as the EU Artificial Intelligence Act (2022), EU Digital Services Act (2022), Digital Markets Act (2022), and EU Cyber Resilience Act (2022), aim to create a secure, standardized, and resilient environment, yet their effects remain to be evaluated. The challenge posed by emerging technologies lies in the lengthy period required to comprehend the nature and implications of the threat landscape, along with the associated risks. While these regulations provide a framework, their effectiveness and alignment with ethical models and theories can be assessed after they are put into practice.

4.1. Governance and Regulatory Overview

The swift progress of AI introduces unparalleled challenges that current legal frameworks are inadequately prepared to handle. Conventional laws, designed for human-centric operations, find it difficult to adapt to the distinct complexities and dangers presented by AI. As AI technologies advance, the necessity for specialized legal structures tailored to AI becomes increasingly pressing. Numerous governments and international bodies are taking action to safeguard their citizens and the interests of businesses. Consequently, various regulatory agencies are formulating governance principles and guidelines aimed at assisting those that are actively involved in the development of AI, ML, and DL technologies, with the objective of mitigating and alleviating the associated risks. In particular, AI governance seeks to reduce risks such as privacy infringements, the misuse of personal data, bias, discrimination, and similar issues.

Policymakers in developing nations frequently highlight the prospective advantages of AI, which encompass poverty alleviation, healthcare enhancement, climate change action, productivity growth, and improvements in education and governance. Their policy dialogues typically focus on the myriad opportunities that AI presents for development, often overlooking the necessity for AI regulation (Klein & Patrick, 2024). Conversely, policymakers in more affluent regions tend to emphasize the dangers linked to AI, including political manipulation, misinformation, algorithmic bias, extensive surveillance, privacy violations, job loss, inequality, the proliferation of autonomous and nuclear weaponry, cybersecurity risks, geopolitical strife, and the potential emergence of a so-called superintelligence that may act against human interests, thereby prompting initiatives to regulate AI (see Table 5). As AI technologies have become more accessible through commercialization, the urgency for regulation to mitigate these risks has intensified.

Table 5. Artificial Intelligence governance

Country/ Organization/Forum	Acts/ Regulations
National AI Governance Efforts	
European Union (EU)	Coordinated Plan on AI
	EU Artificial Intelligence Act – the world’s first comprehensive regulatory framework for AI
	EU Digital Services Act and Digital Markets Act
United States (US)	National Institute of Standards and Technology (NIST) AI Risk Management Framework
	The Blueprint for an AI Bill of Rights
	States’ AI Regulation
United Kingdom	“Establishing a pro-innovation approach to regulating AI” White Paper “AI Regulation: A Pro-Innovation Approach”
China	National New Generation AI Plan
	Internet Information Service Algorithmic Recommendation Management Provisions
	Provinces’ AI Regulation
Canada	The Canadian Government introduced the Artificial Intelligence and Data Act (AIDA)
	Directive on Automated Decision-Making
Brazil	Brazilian AI Strategy Brazilian Artificial Intelligence Bill
Japan	Social Principles of Human Centric AI
India	The National Strategy for Artificial Intelligence (#AIForAll)
	Principles for Responsible AI
	Operationalizing Principles for Responsible AI
International AI Governance Efforts	
The Organisation for Economic Co-operation and Development (OECD)	OECD's AI Principles
	OECD's Recommendation of the Council on AI
G7	Hiroshima AI Process
Council of Europe (CoE)	AI Convention
United Nations (UN)	Resolution “Seizing the opportunities of safe, secure and trustworthy artificial intelligence systems for sustainable development”
The EU-U.S. Trade and Technology Council (TTC)	TTC Joint Roadmap on Evaluation and Measurement Tools for Trustworthy AI and Risk Management

Source: Summarized for the purposes of the paper based on COM (2018), Madiaga (2024), European Commission (n.d.), Kerry (2023), House (2022), Friedler et al. (2023), HM Government (2021), Schildkraut and Zhang (2023), Cvetkova & Moore (2023), Secretariat (2020), OECD (n.d.-a; n.d.-b; n.d.-c), The Conference toward AI Network Society (2017), NITI Aayog (2018), G7 Hiroshima Process (n.d.), Rotenberg (2025), CoE (2024), United Nations General Assembly (2024), European Commission (2022), Leslie et al. (2021).

The national and international AI governance efforts/acts synthesized in Table 4 of the current paper, including the US, UK, Canada, China, Japan, Singapore, Israel, India, and the EU, have been selected due to their considerable global impact and diverse AI strategies. They provide insights ranging from extensive regulatory frameworks to adaptable, sector-specific guidelines influenced by various political, economic, and cultural environments. Their role in AI innovation and their involvement in international discussions in forums as the G7, OECD, UN, highlight their crucial contribution in influencing global trends in AI governance.

The paper contends that both the OECD Recommendation on AI and the EU AI Act currently play, and may continue to play, a significant role in AI governance. Although the OECD Recommendation on AI is at the forefront and is expected to maintain its leadership in international AI governance initiatives, it remains ambiguous how likely the EU AI Act is to serve as a model for other nations to adopt comparable regulations.

The OECD's Recommendation regarding AI is recognized as the first intergovernmental standard for the governance of AI, with more than 50 countries worldwide endorsing it. The UNESCO Recommendation on AI Ethics has been accepted by all 193 Member States of UNESCO. If the Council of Europe's Convention on AI systems is ratified, it will be followed by the 46 Member States of the Council of Europe. An illustration of a relatively successful bilateral agreement is the EU-U.S. Trade and Technology Council (TTC).

Variations in legal traditions, economic frameworks, and regulatory systems make it challenging, if not impossible, to achieve full regulatory convergence. National AI policies reflect these distinctions. Nonetheless, the regulatory initiatives are still in relatively nascent phases globally. As a result, at this time, fostering and sustaining international cooperation can assist in harmonizing AI policies and regulations.

4.2. Challenges to Ethical and Responsible AI

Many businesses encounter several major challenges, particularly concerning data privacy and security. As organizations collect large amounts of data, there is a risk that such information may be misused. A significant danger for businesses integrating AI into their analytics is the failure to adequately protect customer data and stay informed about the requirements set forth in the General Data Protection Regulation (GDPR).

As the integration of (Gen)AI progresses, various ongoing challenges continue to obstruct the achievement of ethical and responsible AI. A primary concern is the bias present in training data and models (Kheya et al., 2024). AI systems often derive insights from historical data that mirror societal inequalities, resulting in discriminatory outcomes, particularly in fields such as hiring, lending, and criminal justice (Ferrara, 2024). They adjust to data, and if that data contains bias, AI algorithms will reinforce it, leading to biased decisions. This leads to serious negative consequences. AI decision-making has to be free from bias; therefore, it is essential for business to continuously identify and eliminate bias in their (Gen)AI models. Detecting

these biases is complex, and eliminating them necessitates proactive measures. Adding to this is the lack of transparency in many AI models, particularly those utilizing deep learning frameworks (Şahin et al., 2025). The so called “black box” systems make decisions that are hard to clarify, raising significant issues regarding transparency, accountability, and trust.

Munagandla et al. (2024) emphasize the importance of integrating ethical considerations into data-driven practices from the initial phases of decision-making. Patil et al. (2024) point out the necessity of finding a compromise between the creation of new ideas and the application of AI technologies. These perspectives align with those of Jackson et al. (2024), who support the adoption of a capabilities-based approach during both the analytical and implementation stages of (Gen)AI, which increasingly calls for a systematic adoption of AI technologies. According to Rane et al. (2024), the proposed solution involves developing improved methodologies that consider the ethical implications of technological advancements. This highlights, among other factors, the importance of confirming ownership of data, the demand for algorithmic transparency, and the creation of AI governance systems (Sharma et al., 2020). These steps are essential in making certain that the use of AI accomplishes its intended purposes without resulting in negative social impacts.

Consistent with the insights of Jackson et al. (2024), AI plays a role in improving business capabilities, but it disrupts existing workforce structures. On the other hand, the upskilling programs, as noted by Rane et al. (2024), have achieved success, with retrained workers exhibiting a 25% rise in productivity in their new positions. The shift towards a digitized workforce, coupled with the skills gap, represents a significant challenge in the adoption of AI solutions. A further challenge is the insufficient diversity within AI development teams (Shams et al., 2025). Teams that lack diversity are more prone to neglect the potential adverse impacts of technologies on individuals from various backgrounds, resulting in design and testing blind spots. With the increasing demand for AI and data analysis, there is a pressing need for a larger pool of talent capable of implementing and managing AI-driven solutions. Employers should focus on offering training and educational opportunities that effectively prepare employees to manage the skills associated with AI-driven analytics. Ultimately, although numerous organizations and governments have established voluntary ethical frameworks for AI, the enforcement of these guidelines is still lacking (Alahmed et al., 2023). In the absence of explicit legal requirements or mechanisms for accountability within institutions, these frameworks frequently do not have the capacity to influence actual outcomes, which results in ethical issues remaining unresolved.

5. CONCLUSION

The adoption of GenAI marks a revolutionary change in the way businesses gather insights and make strategic choices. By utilizing the strengths of AI-powered algorithms, companies can go beyond established methods and implement data-informed strategies, that provide enhanced precision and flexibility. The ability to evaluate large quantities of structured and unstructured

data enables a more comprehensive analysis of market trends, consumer behaviour, and potential opportunities.

GenAI enhances both the speed and accuracy of decision-making and also encourages a more innovative and adaptable culture within companies. Businesses are able to predict market changes, recognize unfulfilled customer needs, and optimize their strategies through real-time insights. This forward-thinking strategy enables companies to maintain a competitive advantage, providing them with a significant advantage in a rapidly evolving market. Moreover, the efficiency achieved via AI-driven automation minimizes the time and resources utilized for manual data analysis, allowing companies to prioritize high-impact activities that stimulate growth and innovation. The automation of monotonous tasks, along with the valuable insights provided by AI, ensures that businesses are consistently aware of the changing market conditions. However, it is essential to articulate the potential tensions between automation based on data and the role of human agency. This could be a topic for future research.

By employing advanced algorithms, GenAI is capable of producing data patterns and simulations, providing businesses with exceptional insights and predictive capabilities. These innovations not only enhance current processes but also provide strategic insights that were once beyond reach. This transformation is essential for businesses that wish to stay competitive in a rapidly changing market. As ML and (Gen)AI continue to develop, it is essential to find a balance between leveraging their innovative potential and addressing ethical issues. By encouraging collaboration among technologists, policymakers, and stakeholders, businesses can create a future where (Gen)AI and ML align with human values, thus improving productivity and enhancing quality of life. This involves the formulation of guidelines aimed at promoting responsible data usage, addressing biases present in generated data, and guaranteeing transparency in AI-facilitated decision-making processes.

Furthermore, there is a necessity for more in-depth investigation into the implementation of GenAI within particular industry contexts. In-depth case studies and longitudinal research can offer more profound insights into the practical advantages and obstacles associated with GenAI across different fields.

Possible domains for additional research and development involve the improvement of GM architectures and training methodologies. Progress in model design, including the creation of more efficient and scalable generative algorithms, will broaden the capabilities of GenAI and enhance its relevance to complex data analytics endeavours. Investigating hybrid models that integrate GenAI with alternative analytical methods, such as (deep) reinforcement learning, could also produce groundbreaking solutions for decision-making and scenario analysis. Another area for further research refers to creating a conceptual framework (a simple visual model) linking GenAI applications to business outcomes. Prospective studies on the subject may include empirical validation of ethical frameworks.

To summarize, the ongoing advancement of GenAI offers considerable prospects for enhancing business intelligence and decision-making processes. By confronting current obstacles and investigating novel research avenues, both scholars and practitioners can play a pivotal role in fostering the creation of more advanced and ethically sound GenAI applications, thereby promoting innovation and efficiency within the realm of data analytics.

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