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doi: https://dx.doi.org/10.55124/jaim.v1i2.254

SciForce

Journal of Artificial intelligence and Machine Learning

Journal homepage: www.sciforce.org

Application of the EDAS Method in Artificial Intelligence A Comprehensive Analysis

Nitesh Kumar Ramancha[1*], Satyanarayana Ballamudi[2]

[*1] Sr. SAP Consultant, SAP, TX, USA

[2] ERP Analyst / Developer Lead, TX, USA

ARTICLE INFO

Article history:
Received:20230410
Received in revised form: 20230415
Accepted: 20230422
Available online: 20230428

Keywords:
Artificial Intelligence (AI);
Machine Learning (ML);
Ethics;
Autonomy;
Explainability.
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ABSTRACT

The rapid advancement of artificial intelligence (AI) raises critical questions about its values, ethics, and societal impact. Different philosophical perspectives, including utilitarianism, Kantian ethics, and human agency, guide the debate on how AI systems should operate. AI involves creating intelligent agents that learn and make decisions to achieve specific goals. Its transformative potential spans various industries, influencing productivity, innovation, and even ethical considerations in autonomous systems. This paper explores these complexities, offering insights into AI's evolving landscape.

This research is significant as it explores the ethical, philosophical, and practical implications of artificial intelligence (AI), impacting technology, society, and human decision-making. By examining value alignment, human agency, and adaptive learning, the study advances our understanding of how AI can enhance productivity, innovation, and daily life. Additionally, addressing transparency and explain ability in AI systems is crucial for fostering trust, especially in critical domains like healthcare and security, influencing policy and future AI development.

Building information modelling (BIM), Robotics and automation, Computer vision, AI-Driven Construction Analytics, Cognitive Automation, and Visual AI Systems.

The results show that Visual AI Systems received the highest ranking, whereas Computer vision received the lowest ranking.

Visual AI Systems has the highest value for artificial intelligence according to the EDAS approach.

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*Corresponding author. e-mail: nkr112024@gmail.com

Introduction

[1] The advancement of artificial intelligence introduces significant and complex questions for technologists, humanity, and sentient beings. Chief among these is determining what values – or whose values– AI systems should embody. A perspective rooted in utilitarianism advocates designing AI technologies to maximize happiness for the largest number of people or sentient beings over time. Another approach, inspired by Kantian philosophy, argues that AI should be guided by universally applicable principles, such as fairness or goodness. Another perspective emphasizes the importance of human agency and decision-making in driving AI. In essence, artificial intelligence involves creating artificial agents that perceive their surroundings and make decisions to improve the likelihood of achieving specific goals. Within this framework, "machine learning" refers to the set of statistical and algorithmic methods used to train models to perform intelligent actions. When implemented on sufficiently advanced hardware, these methods enable models to learn from experience or from both labeled and unlabeled data, often without relying on explicit programming instructions.

The debate, which involves multiple dimensions and stakeholders, centers on whether AI-equipped machines should be allowed to perform military tasks, especially when human lives are at stake. Given the complexity of this issue, a clear operational definition the concept of AI is very important. Although there is no widely accepted definition, even among experts in computer science and engineering, a common description of AI refers to the ability of a computer system to perform tasks that typically require human intelligence, such as visual perception, speech recognition, and decision-making. However, this definition oversimplifies the concept, as what qualifies as intelligent behavior remains a matter of debate. For example, a home thermostat could be considered intelligent under this definition because it senses and regulates temperature.

This is very different from the AI used in autonomous weapons such as unmanned aerial vehicles (UAVs), which can identify and attack targets without significant human supervision—a scenario often assumed in discussions of autonomous weapons systems [2]. [3] The rapid advancement the impact of artificial intelligence is significant for both the economy and society. These advances it has the potential to change the production processes and characteristics of various types of products and services with long-term consequences for productivity, employment and competitiveness. However, beyond these immediate impacts, AI also holds the promise of transforming the innovation process itself – a process that may, if not be as influential over time, be more so. Take, for example, Atomy, a startup that uses neural networks to identify potential drug candidates and pesticides.

The company says its deep convolution neural networks can significantly outperform traditional "docking" algorithms in predicting the biological activity of candidate molecules. [4]Deep learning (DL) has recently become a powerful AI technique to tackle the challenge of extracting meaningful insights from large, unstructured datasets. After achieving significant success in computer vision, DL has expanded its applications to a variety of fields, including wireless communication, human-computer interaction, gaming, and finance. NVIDIA's Deep Learning Super Sampling (DLSS), introduced a few years ago, and is a unique innovation. This technology uses DL and other AI algorithms to improve frame rates while preserving sharp, high-quality game visuals, offering significant potential for elevating the visual experience in the met averse.

AI has also been used to refine game balance in a number of online multiplayer games by repeatedly training supervised learning models. This iterative process allows designers and game-testers to create an engaging virtual-reality world that is not only immersive but also creates a met averse that is as rich and dynamic as the real world. [5] The following section of this paper provides a brief summary of the key areas of artificial intelligence, providing readers with insight into the broad range of topics encompassed by the field. In addition, another section provides a comprehensive review of the literature organized around the primary categories of artificial intelligence. The review highlights several important questions with significant research implications for those interested in advancing AI studies. Successfully addressing these questions will help address some of the long-standing technical and non-technical challenges that have persisted over the past decade and continue to this day. [6] For a computer program to function For a system to act intelligently in the real world, it must have a general representation of the world in order to interpret its inputs effectively.

Designing such a system involves making fundamental decisions about the nature of knowledge and its acquisition. As a result, many traditional philosophical problems converge with the challenges of artificial intelligence. In particular, the creation of an intelligent program involves guiding decision-making by logically reasoning that a particular strategy will help achieve its goal. This process requires the formalization of key concepts central to philosophical logic, such as reason, ability, and knowledge. The first part of this paper takes a philosophical approach that naturally arises when one considers in depth the development of an intelligent machine.

It examines adequate representations of the metaphysical and epistemological world, followed by an explanation of the concepts of can, reasons, and knowing that can be designed through an interactive automated system. In addition, this paper proposes a Resolution to the philosophical problem of free will a deterministic universe and provides an approach to understanding counterfactual conditional statements. [7] Recent advances in machine learning (ML) have the potential to create AI systems that are capable of perceiving, learning, making decisions, and acting autonomously. However, these systems currently lack the ability to explain their decisions and actions to human users. This limitation is particularly important in the security domain, where there is a pressing need for intelligent, highly autonomous, and cooperative systems.

To effectively deploy these systems, explainable AI is essential, enabling users to appropriately understand, trust, and manage AI partners. In response to this need, DARPA launched the Explainable Artificial Intelligence (XAI) program in May 2017. As defined by DARPA, explainable AI refers to systems that can inform human users of their reasoning, highlight their strengths and weaknesses, and predict their future behavior. . "Explainable AI" (as opposed to alternatives such as understandable or transparent AI) underscores DARPA's focus on creating AI systems that provide meaningful and actionable explanations to enhance human understanding. [8] Artificial intelligence technologies have advanced significantly due to improvements in computer processing power and the extensive collection of big data.

However, the capabilities of existing AI systems are limited to specific cognitive tasks such as image recognition, speech recognition, and conversational responses. While these systems mimic some of the cognitive functions although inspired by the human brain, they have limited alternatives and do not reflect the full range of human brain functions. In particular, AI cannot perform full brain functions such as self-awareness, self-understanding, self-control, and self-motivation. [9] An alternative way to understand AI is to focus on the research and technology behind it, rather than the problems it can or cannot solve. Although AI is often classified as A branch of computer science it is, in fact, a multidisciplinary field. It combines elements from various fields such as statistics, linguistics, robotics, electrical engineering, mathematics, neuroscience, economics, logic, and philosophy. At a more comprehensive level, AI encompasses a set of Technologies developed through research in academia and the private sector has fueled the emergence of AI. As a result, to gain a deeper understanding of AI, it is necessary to examine the underlying technologies that enable it. [10] Differences in fundamental aspects such as architecture, Differences in speed, connectivity, scalability, and energy consumption lead to unique qualities and limitations when comparing humans and artificial intelligence.For example, our reaction times to simple stimuli are significantly slower – Humans are thousands of times slower than artificial systems. Computer systems, on the other hand, can be easily connected, allowing them to function as part of an integrated network.

This means that AI systems do not have to be treated as isolated entities that can face difficulties to cooperate or misunderstand each other. When two AI systems collaborate on a task, the chance of errors due to miscommunication is much lower (for example, in autonomous vehicles approaching an intersection). [11] Advances in Artificial intelligence (AI) algorithms, with greater access to training data, enable AI to improve or perform certain tasks that doctors currently perform.

Despite this, interest in integrating AI into healthcare among various stakeholders has not led to widespread adoption. According to many experts, one of the main reasons for this slow adoption is the lack of transparency in some AI algorithms, especially those considered “black box” models. Clinical medicine, which is largely evidence-based, relies on clear and transparent decision-making processes. Without clinically interpretable AI models, or if doctors cannot justify their decisions, patient trust in the healthcare provider may decline. To address the transparency issue, interpretable AI models have been developed. [12] A major focus of the goal of artificial intelligence research is to create adaptive AI that can perform a wide range of tasks to the adaptiveUnlike most current AI methods, which are designed for specific, narrowly defined tasks, learning systems in humans and other animals act as inspiration.

As researchers strive to create highly adaptive AI, known as artificial general intelligence (AGI), they are trying to bridge this gap there is a growing demand for tools that enable versatile experimentation across a variety of tasks. [13] Modern artificial intelligence (AI) and robotics have the ability to mimic human intelligence, enabling them to perform tasks of reasoning, learning, problem-solving, and decision-making. AI software or programs embedded in robots, computers, or related systems must have cognitive capabilities. However, many current AI and robotic systems are still in development, as further research is needed to understand how they solve tasks.

As a result, AI machines or systems can perform tasks accurately and without errors. Furthermore, robots can perform various functions independently, without human supervision or assistance. Today's AI technologies, such as autonomous vehicles, are showing improved performance, from traffic control and speed control to fully self-driving cars, and AI systems like SIRI are showing rapid advances in this field.[14] The brain is a complex system known for its ability to learn and perform complex calculations that are critical to cognitive behavior, such as perception, cognition, and motor control. For years, scientists have been trying to replicate these capabilities in artificial intelligence (AI) systems. Until recently, when AI applications began to have a significant impact on many areas of daily life, these efforts had limited success. Machine learning algorithms are now excelling at tasks such as object and speech recognition, and have even mastered games such as chess and go, sometimes outperforming humans.

AI systems have the potential to make even more of a difference, including advances in medical diagnostics, discovering new treatments for diseases, making scientific breakthroughs, predicting financial markets and geopolitical developments, and finding valuable patterns in various types of data.[15] This research paper needs to clarify the definition of "artificial intelligence." Some AI researchers define it as any system that emulates human intelligence in any form to be "artificial intelligence," while others believe that only programs that imitate human thought processes qualify as AI. Additionally, some experts in the information systems field classify many "artificial intelligence" projects as sophisticated information systems.

Materials and Method

Alternatives:

Building Information Modeling (BIM): A digital representation of the physical and functional characteristics of a building, enabling collaboration among architects, engineers, and construction professionals throughout the project lifecycle.

Robotics and Automation: The design, creation, and use of robots and automated systems to perform tasks with minimal human intervention, enhancing productivity, accuracy, and safety in various industries.

Computer Vision: A field of artificial intelligence that enables machines to interpret and understand visual information from the world, using algorithms to analyse images and videos for tasks like object detection and recognition.

AI-Driven Construction Analytics: The application of artificial intelligence to analyze construction data, providing insights for decision-making, risk management, cost optimization, and project performance improvements.

Cognitive Automation: An advanced form of automation that uses AI techniques, such as machine learning and natural language processing, to simulate human cognitive abilities for complex problem-solving and decision-making tasks.

Visual AI Systems: Artificial intelligence systems designed to process and analyze visual data, enabling tasks like image classification, facial recognition, and scene understanding through deep learning models.

Evaluation Parameters:

Complexity: The state of having multiple interconnected parts, variables, or components, making systems or problems challenging to understand, analyze, or solve.

Aesthetics: The study and appreciation of beauty, form, and visual appeal, often applied in design, art, and architecture to create pleasing and harmonious experiences.

Sufficient Budget: An adequate allocation of financial resources required to successfully plan, execute, and complete a project without financial constraints or compromises in quality.

Regulatory Measures: Rules, laws, or guidelines established by authorities to ensure compliance with standards, safety, and ethical practices within specific industries or activities.

EDAS Method: Many chemical reactions can be monitored by observing changes in their UV-Vis spectra. When the chemical and physical reaction conditions are carefully controlled, the rate of change in the UV-Vis spectrum is directly linked to the concentration of the species involved in the reaction. Even chemically similar species often show different reaction rates, making it possible to determine their concentrations in the original mixture [16]. MOP is an optimization problem in which two or more objective functions must be optimized simultaneously. As a result, the solution consists of a set of trading points, each of which represents an equally optimal combination of objective function values. Multi-objective evolutionary algorithms well suited to this type of problem because they do not rely on the optimality of a particular form.

Their ability to explore the solution space in parallel allows for the development of an adequate model of the solution set [17]. IGO is a general approach to arbitrary search spaces that optimizes the invariant properties of a given space. When applied to the Boolean domain, the IGO method results in a weighted generalized population-based incremental learning (PBIL) algorithm that includes all previously mentioned distributional algorithms (EDAs). However, it does not include all random incremental EDAs. Other methods were explored by Shapiro and Korus, Tang, Eremeev, and Lehre, who studied EDAs that use maximum likelihood optimization. They introduced a category of EDAs that adjust their distributions solely based on current models and the existing distribution. However, these methods do not consider all random incremental EDAs [18]. To address this gap, the selection process focuses on identifying the best electrified vehicles available on the market based on entropy Estimation of Distribution Algorithms (EDAS).

The entropy method is widespread used and known for its ease of implementation. The higher the utility of a criterion, the more influential it is in the decision-making process. If alternatives have the same value for a criterion, that criterion is excluded from the evaluation, which indicates a weight of zero. The EDAS method identifies the best alternative by calculating the distance from the average solution, which distinguishes it from other MCDM methods that rely on the compromise approach logic [19]. The higher the utility of a criterion, the more important its role in the decision-making process. If alternatives have identical values for a criterion, that criterion is excluded from the evaluation, resulting in a zero weight[20]. The main function of the probabilistic model learned by EDAs is to generate new solutions, and it can also help discover previously unknown details about the structure of the problem. One factor that affects the effectiveness of using information in probabilistic models is the existence of methods for pre-processing and interpreting this information [21]. In the context of estimation of distributional algorithms (EDAs), association learning refers to the ability to identify and model relationships between variables in an optimization problem by identifying and modeling probabilistic dependencies.

The information collected is represented by a probabilistic model, which is used to generate new possible solutions. [22]Since World War II, Tourism is one of the most dynamic and fastest growing sectors of the global economy. It is the fourth largest sector worldwide, or as some experts argue, the second most important industry for the export of goods and services, which is why many consider tourism to be an industry in its own right. A key characteristic that distinguishes tourism from other industries is that production and consumption occur simultaneously in different places. Another essential feature of tourism is the globalization of many production sectors and the interconnectedness of their exchange of goods and services.

This model can stimulate economic growth in developed areas while also redistributing the wealth created across different regions [23]. DLT is considered an umbrella term for databases distributed among multiple users in different locations. The second application, as the name of the technology suggests, facilitated distributed data storage via online ledgers [24]. Researchers have devoted considerable effort to identifying optimal structures for each task in order to achieve the best performance. However, computer vision tasks using CNNs can be computationally intensive, as each new task requires a unique structure. As a result, recent studies have focused on automating the process of finding the most effective structures. Over fitting in a one-shot network leads to a significant difference in network behavior during the search and evaluation phases. We confirm this by evaluating the models generated in the middle of the search process. This discrepancy between the architectures is due to the need for DARTS to retrain the newly acquired network [25].

The use of probabilistic models, especially algorithms that infer these models from data, represents a significant advance in the field of evolutionary mechanisms. Probabilistic models enable an efficient representation of the relationships between problem elements, enhancing the process of association learning. These algorithms are supported by a solid theoretical foundation in graphical model theory [26]. In contrast, evaluation of distribution algorithms (EDAs) works differently. Instead of optimizing candidate solutions, EDAs focus on learning how to generate good solutions. [27]. High-quality road infrastructure plays a key role in enabling markets to trade goods and services safely and efficiently. Roads are a central component of infrastructure projects, making national road infrastructure efforts essential to improving the quality of life in developing countries. Buildings, highways, public works, roads, water-related structures, road tunnels, railways, hydroelectric power plants, power plants, and power projects are areas of focus for project evaluation. However, challenges such as unfamiliar approaches, lack of prior knowledge, excessive testing and inspection in road construction, limited manufacturer and supplier support, and insufficient performance data contribute to inefficient cost management in road construction. Additional targets can be set to address these issues [28].

Analysis and Discussion

TABLE 1. Artificial Intelligence

	Artificial Intelligence			
	Complexity	Aesthetics	sufficient budget	Regulatory measures
Building information modeling (BIM)	3.22	120.53	562	22.05
Robotics and automation	1.71	182.97	128	84
Computer vision	0.263	101.58	987	23.1
AI-Driven Construction Analytics	0.083	198	357	80
Cognitive Automation	0.727	247.28	651	17.59
Visual AI Systems	9.58	186.41	851	98

Table 1 presents a comparative analysis of various artificial intelligence (AI) technologies across four key evaluation parameters: Complexity, Aesthetics, Sufficient Budget, and Regulatory Measures. Building Information Modeling (BIM) demonstrates moderate complexity (3.22) and a high budget requirement (562), emphasizing its need for substantial resources. Its aesthetics score (120.53) suggests a balanced visual appeal, suitable for architectural and construction applications. The regulatory impact (22.05) is relatively low, indicating fewer compliance challenges. Robotics and Automation exhibits low complexity (1.71) but demands strict regulatory measures (84), reflecting safety and ethical considerations. Despite its lower budget need (128), it achieves high aesthetic value (182.97), relevant in manufacturing and service sectors. Computer Vision stands out with minimal complexity (0.263) but requires the highest budget (987). Its moderate aesthetics (101.58) and moderate regulatory need (23.1) indicate its adaptability in diverse applications, such as security and medical imaging. AI-Driven Construction Analytics and Cognitive Automation both show low complexity but differ in budget and regulatory requirements. Cognitive Automation excels in aesthetics (247.28) but faces fewer regulatory challenges (17.59).Visual AI Systems are the most complex (9.58) and have the highest regulatory need (98), reflecting their advanced nature and potential ethical implications in applications like facial recognition.

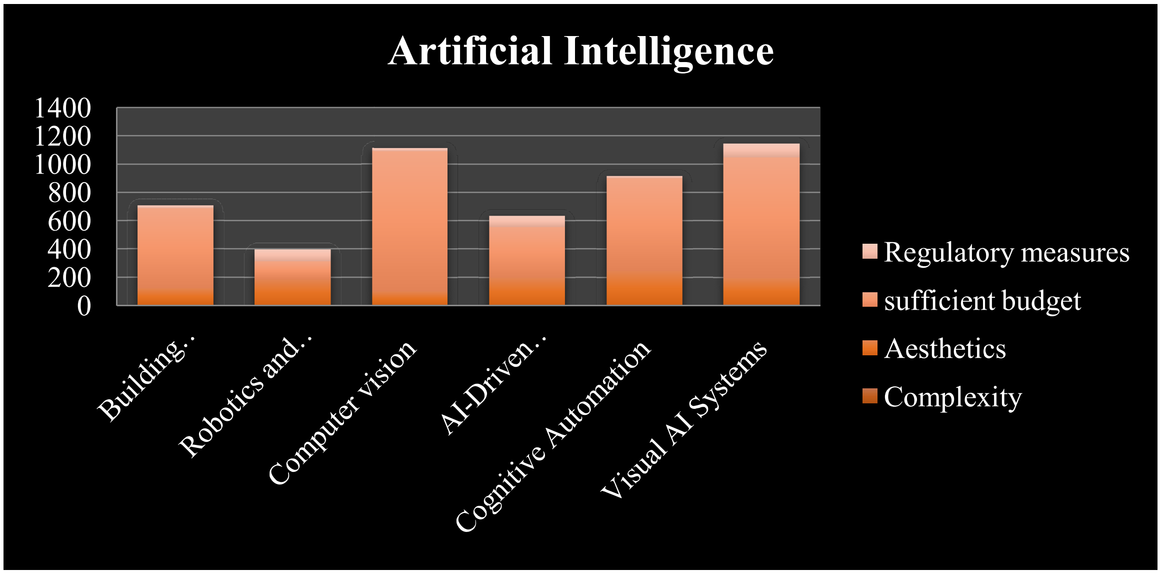

FIGURE 1. Artificial Intelligence

Figure 1 compares six artificial intelligence (AI) technologies—Building Information Modelling (BIM), Robotics and Automation, Computer Vision, AI-Driven Construction Analytics, Cognitive Automation, and Visual AI Systems—using four criteria: Complexity, Aesthetics, Sufficient Budget, and Regulatory Measures. Building Information Modelling (BIM) shows moderate complexity (3.22) and requires a significant budget (562), reflecting its resource-intensive nature. Its aesthetics score (120.53) indicates balanced visual appeal, while its regulatory measures (22.05) are relatively low, suggesting manageable compliance challenges. Robotics and Automation is less complex (1.71) but demands stringent regulatory compliance (84) due to safety and ethical concerns. It requires a lower budget (128) but achieves high aesthetics (182.97), suitable for automated manufacturing and service applications. Computer Vision has the least complexity (0.263) but the highest budget requirement (987), reflecting its reliance on advanced hardware. It scores moderately in aesthetics (101.58) and faces moderate regulatory needs (23.1), showing versatility in diverse fields like security and healthcare.AI-Driven Construction Analytics and Cognitive Automation both show low complexity but vary in budget and aesthetics. Cognitive Automation scores highest in aesthetics (247.28) but faces minimal regulatory challenges (17.59).Visual AI Systems are the most complex (9.58) and have the highest regulatory requirements (98), indicating ethical considerations in advanced applications like facial recognition.

TABLE 2. Positive Distance from Average (PDA)

	Positive Distance from Average (PDA)			
Building information modeling (BIM)	0.239813	0	0.04638	0.5925972
Robotics and automation	0	0.058885	0.782805	0
Computer vision	0	0	0	0.573197
AI-Driven Construction Analytics	0	0.145866	0.394231	0
Cognitive Automation	0	0.43106	0	0.6750015
Visual AI Systems	2.688635	0.078793	0	0

Table 2 presents the Positive Distance from Average (PDA) for six AI technologiesBuilding Information Modeling (BIM), Robotics and Automation, Computer Vision, AI-Driven Construction Analytics, Cognitive Automation, and Visual AI Systemsacross four criteria. A higher PDA value indicates better-than-average performance in that category.Building Information Modeling (BIM) shows moderate PDA in complexity (0.239813) and regulatory measures (0.5925972), highlighting its balanced approach in these areas. However, it scores zero in aesthetics and budget, indicating average performance in visual appeal and cost efficiency.Robotics and Automation excels in budget (0.782805), showing cost-effectiveness, but its zero PDA in complexity and regulatory measures suggest no significant advantage over other technologies in these areas.Computer Vision shows no PDA advantage except in regulatory measures (0.573197), reflecting its compliance efficiency despite high costs and average aesthetics.AI-Driven Construction Analytics shows moderate PDA in aesthetics (0.145866) and budget (0.394231), highlighting its cost-efficiency and appealing design, but zero in complexity and regulatory measures.Cognitive Automation stands out in aesthetics (0.43106) and regulatory measures (0.6750015), emphasizing its visual appeal and minimal compliance challenges.Visual AI Systems exhibits a high PDA in complexity (2.688635), indicating significant sophistication, but zero in other areas, reflecting high complexity with average cost and compliance needs.

TABLE 3. Negative Distance from Average (NDA)

	Negative Distance from Average (NDA)			
Building information modeling (BIM)	0	0.302468	0	0
Robotics and automation	0.34159	0	0	0.5520108
Computer vision	0.898736	0.412136	0.674774	0
AI-Driven Construction Analytics	0.968042	0	0	0.4781056
Cognitive Automation	0.72008	0	0.104638	0
Visual AI Systems	0	0	0.444005	0.8106793

Table 3 presents the Negative Distance from Average (NDA)for six AI technologies Building Information Modeling (BIM), Robotics and Automation, Computer Vision, AI-Driven Construction Analytics, Cognitive Automation, and Visual AI Systems across four criteria. A higher NDA value indicates a performance below the average in that category. Building Information Modeling (BIM) shows a negative deviation in aesthetics (0.302468), indicating less visual appeal compared to other technologies, but performs at or above average in complexity, budget, and regulatory measures. Robotics and Automation has a notable NDA in complexity (0.34159) and regulatory measures (0.5520108), suggesting it is more complicated and faces greater compliance challenges, despite performing well in aesthetics and budget. Computer Vision shows significant NDA in complexity (0.898736), aesthetics (0.412136), and budget (0.674774), indicating challenges in simplicity, design appeal, and cost efficiency, though it performs adequately in regulatory measures.AI-Driven Construction Analytics demonstrates high NDA in complexity (0.968042) and regulatory measures (0.4781056), reflecting challenges in implementation complexity and compliance, while maintaining average aesthetics and budget. Cognitive Automation shows negative deviation in complexity (0.72008) and budget (0.104638), indicating complexity and cost challenges, while excelling in aesthetics and regulatory measures. Visual AI Systems has high NDA in budget (0.444005) and regulatory measures (0.8106793), indicating cost inefficiency and compliance challenges, but performs well in complexity and aesthetics.

TABLE 4. Weight

	Weight			
Building information modeling (BIM)	0.25	0.25	0.25	0.25
Robotics and automation	0.25	0.25	0.25	0.25
Computer vision	0.25	0.25	0.25	0.25
AI-Driven Construction Analytics	0.25	0.25	0.25	0.25
Cognitive Automation	0.25	0.25	0.25	0.25
Visual AI Systems	0.25	0.25	0.25	0.25

Table 4 presents the Weight Distribution for six AI technologies Building Information Modeling (BIM), Robotics and Automation, Computer Vision, AI-Driven Construction Analytics, Cognitive Automation, and Visual AI Systems across four criteria: Complexity, Aesthetics, Sufficient Budget, and Regulatory Measures. Each category is assigned an equal weight of 0.25 for all technologies, indicating that the evaluation criteria are considered equally important. This balanced weighting approach suggests a neutral perspective, where no single criterion disproportionately influences the overall assessment. This uniform distribution ensures that the evaluation remains unbiased and comprehensive, allowing for a fair comparison among all six AI technologies. It also highlights a strategic decision to treat complexity, aesthetics, budget, and regulatory compliance as equally critical to the successful implementation and performance of these AI solutions in construction and related industries. The equal weights also imply that stakeholders are expected to value operational challenges, visual appeal, financial feasibility, and compliance equally when making strategic decisions. This approach ensures a holistic evaluation of each technology's impact, facilitating balanced decision-making processes in the adoption of AI-driven solutions.

TABLE 5.Weighted PDA, SPi

	Weighted PDA				SPi
Building information modeling (BIM)	0.059953	0	0.011595	0.148149	0.219697
Robotics and automation	0	0.0147212	0.195701	0	0.210423
Computer vision	0	0	0	0.143299	0.143299
AI-Driven Construction Analytics	0	0.0364666	0.098558	0	0.135024
Cognitive Automation	0	0.107765	0	0.16875	0.276515
Visual AI Systems	0.672159	0.0196982	0	0	0.691857

Table 5 presents the Weighted Positive Distance from Average (PDA) and the resulting Strategic Priority Index (SPi) for six AI technologies: Building Information Modeling (BIM), Robotics and Automation, Computer Vision, AI-Driven Construction Analytics, Cognitive Automation, and Visual AI Systems. Visual AI Systems show the highest SPi (0.691857), indicating the most strategic advantage due to strong performance in Complexity (0.672159). This suggests it is highly innovative but may require significant expertise to implement. Cognitive Automation follows with anSPi of 0.276515, driven by a balance of Aesthetics and Regulatory Measures. BIM and Robotics and Automation show moderate SPi values (0.219697 and 0.210423, respectively), reflecting balanced contributions from budget and aesthetics. Computer Vision and AI-Driven Construction Analytics have the lowest SPi (0.143299 and 0.135024), indicating a lesser strategic advantage, possibly due to lower positive deviations from the average across all criteria.

TABLE 6.Weighted NDA, SNi

	Weighted NDA				SNi
Building information modeling (BIM)	0	0.0756171	0	0	0.075617
Robotics and automation	0.085398	0	0	0.138003	0.2234
Computer vision	0.224684	0.1030339	0.168693	0	0.496411
AI-Driven Construction Analytics	0.242011	0	0	0.119526	0.361537
Cognitive Automation	0.18002	0	0.02616	0	0.206179
Visual AI Systems	0	0	0.111001	0.20267	0.313671

Table 6 presents the Weighted Negative Distance from Average (NDA) and the corresponding Strategic Negative Index (SNi) for six AI technologies: Building Information Modeling (BIM), Robotics and Automation, Computer Vision, AI-Driven Construction Analytics, Cognitive Automation, and Visual AI Systems. Computer Vision shows the highest SNi (0.496411), indicating the greatest strategic disadvantage due to significant negative deviations in Complexity, Aesthetics, and Sufficient Budget. This suggests challenges in cost efficiency and design integration. AI-Driven Construction Analytics follows with anSNi of 0.361537, impacted mainly by negative performance in Complexity and Regulatory Measures. Visual AI Systems and Robotics and Automation also show moderate negative impacts, with SNi values of 0.313671 and 0.2234, respectively. Their challenges are linked to Regulatory Measures and Complexity. Conversely, BIM has the lowest SNi (0.075617), reflecting minimal strategic disadvantage, particularly in Complexity and Budget. Cognitive Automation also shows relatively low SNi (0.206179), indicating balanced performance with minor drawbacks in Complexity.

TABLE 7.NSPi, NSPi, ASi

	NSPi	NSPi	ASi
Building information modeling (BIM)	0.317548	0.8476726	0.58261
Robotics and automation	0.304142	0.5499695	0.427056
Computer vision	0.207123	0	0.103561
AI-Driven Construction Analytics	0.195162	0.2716989	0.233431
Cognitive Automation	0.399671	0.5846602	0.492166
Visual AI Systems	1	0.3681229	0.684061

Table 7 presents the Normalized Strategic Positive Index (NS Pi), Normalized Strategic Negative Index (NS Ni), and Aggregate Strategic Index (ASi) for six AI technologies: Building Information Modeling (BIM), Robotics and Automation, Computer Vision, AI-Driven Construction Analytics, Cognitive Automation, and Visual AI Systems.

Visual AI Systems demonstrates the highest NS Pi (1), reflecting a strong strategic advantage, particularly in Complexity and Aesthetics. It also maintains a moderate NS Ni (0.368), resulting in the highest ASi (0.684), indicating overall strategic leadership. BIM follows with a high NS Pi (0.318) and the second-highest ASi (0.583),showing robust strategic positioning with minimal negative impacts. Cognitive Automation shows balanced performance with a moderate NS Pi (0.400) and NS Ni (0.585), leading to a solid ASi (0.492), reflecting competitive stability. In contrast, Robotics and Automation and AI-Driven Construction Analytics exhibit lower ASi values (0.427 and 0.233, respectively), suggesting strategic disadvantages due to higher NS Ni values. Computer Vision performs the weakest with the lowest NS Pi (0.207) and ASi (0.104), largely due to significant negative deviations in Complexity and Budget. This analysis underscores Visual AI Systems as the most strategically advantageous, while Computer Vision faces the most strategic challenges.

TABLE 8. Rank

	Rank
Building information modeling (BIM)	2
Robotics and automation	4
Computer vision	6
AI-Driven Construction Analytics	5
Cognitive Automation	3
Visual AI Systems	1

Table 8 ranks six AI technologies based on their Aggregate Strategic Index (ASi), highlighting their overall strategic performance. Visual AI Systems secures the top rank (Rank 1), reflecting its superior strategic advantage driven by high Complexity and Aesthetics scores, along with effective budget utilization and regulatory alignment. This positions it as the most strategically valuable AI technology. Building Information Modeling (BIM) holds Rank 2, showcasing strong strategic stability due to its balanced performance across all evaluated factors, particularly in Complexity and Budget. Cognitive Automation is ranked 3rd, demonstrating competitive positioning with a good mix of strategic strengths and manageable weaknesses. Robotics and Automation ranks 4th due to moderate strategic benefits but faces challenges in budget efficiency and regulatory measures. AI-Driven Construction Analytics follows at Rank 5, reflecting strategic potential but hindered by higher negative deviations, particularly in Complexity. Computer Vision ranks the lowest (Rank 6), primarily due to significant strategic drawbacks, especially in Complexity and Budget. This analysis reveals Visual AI Systems and BIM as strategically leading technologies, while Computer Vision lags behind, necessitating strategic improvements for better competitiveness.

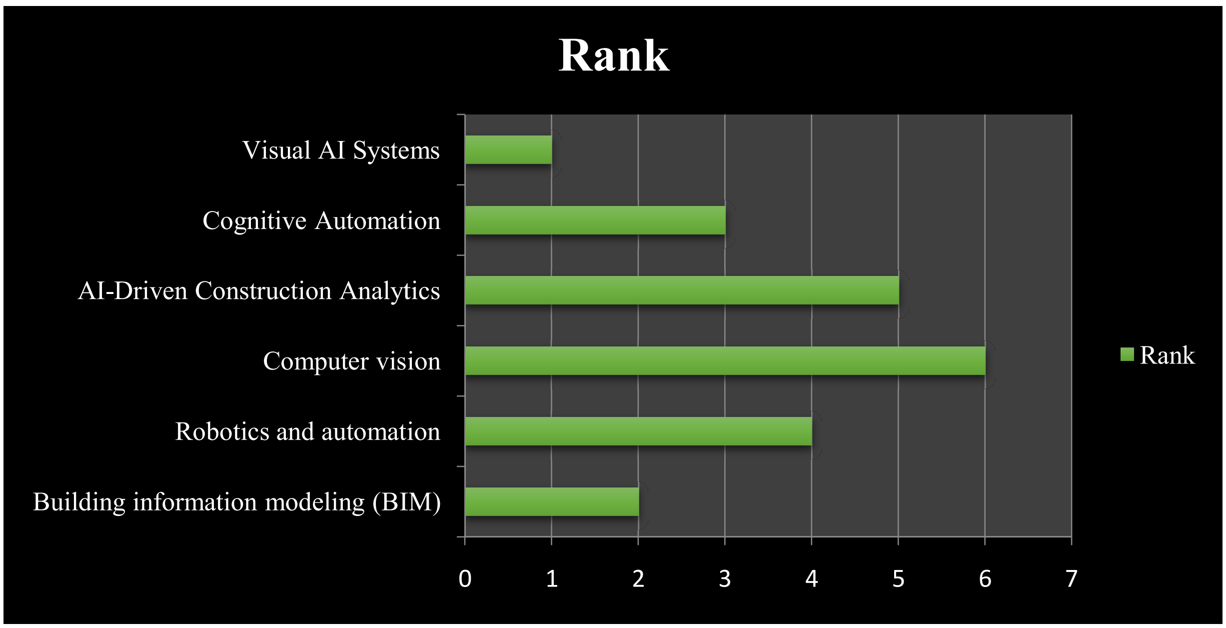

FIGURE 2. Rank

Figure 2 presents the strategic ranking of six AI technologies, emphasizing their overall effectiveness and potential impact. Visual AI Systems claims the top position (Rank 1), underscoring its high strategic value. This superiority likely stems from its exceptional performance in Complexity and Aesthetics, along with efficient budget allocation and favorable regulatory adaptability. Its dominance highlights its strong influence and competitive edge in AI applications.Building Information Modeling (BIM) secures Rank 2, reflecting its balanced strategic contributions, particularly in Budget and Complexity. This suggests its robust integration in construction projects, promoting efficiency and precision. Cognitive Automation is positioned at Rank 3, showcasing its strategic relevance through intelligent decision-making and process optimization. Robotics and Automation ranks 4th, indicating moderate strategic impact but facing challenges related to regulatory measures. AI-Driven Construction Analytics is at Rank 5, showing potential in data-driven insights but hindered by limitations in Complexity and Regulatory Adaptation.

Computer Vision is ranked the lowest (Rank 6), highlighting strategic constraints, particularly in budget efficiency and adaptability. This ranking emphasizes the strategic leadership of Visual AI Systems and BIM, while indicating improvement areas for Computer Vision to enhance its strategic impact.

Conclusion

The rapid advancements in artificial intelligence (AI) present significant opportunities and challenges for humanity. AI's potential to transform industries, enhance productivity, and revolutionize decision-making processes is undeniable.

However, these advancements also raise complex ethical questions, particularly concerning the values that AI systems should embody. As explored, perspectives range from utilitarian approaches that seek to maximize overall happiness to Kantian philosophies emphasizing universal principles like fairness and justice. Additionally, the debate on human agency highlights the importance of maintaining human control over AI-driven decisions, especially in high-stakes areas such as military applications. The evolution of machine learning, deep learning, and neural networks has propelled AI's capabilities, enabling complex tasks like visual perception, speech recognition, and autonomous decision-making.

These technologies are reshaping sectors like healthcare, construction, gaming, and finance, demonstrating AI's versatility and transformative power. For example, the application of AI-driven construction analytics optimizes project performance, while deep learning innovations like NVIDIA's DLSS enhance virtual experiences. However, the limited explain ability of some AI models, particularly black-box systems, poses challenges to transparency and trust, especially in critical fields like healthcare. The journey towards artificial general intelligence (AGI) underscores the ambition to develop adaptive AI systems capable of performing a wide range of tasks.

However, current AI systems remain task-specific, lacking human-like cognitive abilities such as self-awareness, reasoning, and emotional intelligence. The interdisciplinary nature of AI research, encompassing statistics, linguistics, robotics, neuroscience, and philosophy, further illustrates its complexity. As AI systems become more integrated into society, addressing regulatory measures, ethical standards, and budgetary constraints becomes essential to ensure responsible development and deployment. The philosophical implications of AI, including debates on free will, determinism, and knowledge representation, highlight the convergence of traditional philosophy with contemporary technology. Moreover, the societal impact of AI on employment, productivity, and competitiveness requires a balanced approach to harness its benefits while mitigating potential risks. As AI continues to evolve, a comprehensive understanding of its underlying technologies, ethical considerations, and societal implications is crucial. By fostering transparent, fair, and accountable AI systems, society can navigate the complexities of this transformative technology, ensuring its positive impact on humanity's future.

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