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**Lateral Thinking-Classified Perspectives for the Adoption of Artificial Intelligence: Guidance Notes for Engineering Managers**

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# Lateral Thinking-Classified Perspectives for the Adoption of Artificial Intelligence: Guidance Notes for Engineering Managers

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*Index Terms*—**Artificial Intelligence, Engineering Management, Engineering Managers, Lateral Thinking.**

*Abstract*—**Incorporating artificial intelligence (AI) into engineering practice is becoming increasingly prominent, driven by the demand for more efficient and reliable solutions to engineering challenges. Despite numerous frameworks and methodologies that showcase how AI techniques can enhance engineering workflows, there is still a notable absence of simple and generic decision-making paradigms that comprehensively facilitate the adoption of AI in engineering settings. Lateral thinking, a widely used problem-solving approach rooted in reasoning, has been extensively employed in management spheres. This paper introduces a new approach by drawing inferences from generic perspectives on the pros and cons of AI adoption, broadly classified under the six lateral thinking hats to assist engineering managers in navigating AI adoption decisions. The recommended actions inferred from these perspectives are then posited as guidance notes for engineering managers to leverage the benefits and mitigate the risks of AI adoption.**

## I. Introduction

Engineering systems and processes are inherently complex [1], [2]. Like all physical systems and processes, the complexity of engineering systems and processes tends to vary according to their statics, dynamics, and environments of operations, among several other factors. For example, an autonomous robot that is designed and developed to assist in the shelving of books in libraries and an autonomous robot that is designed and developed to assist in warehousing operations may have certain similar properties such as their degrees of freedom, number of dynamic and static parts (i.e., segments or links), and other properties [3], [4]. However, their operational environments, designated tasks, and algorithmic frameworks may set them apart in terms of complexity and range of applications. As a result of the varying degrees of complexity inherent in engineering systems, processes, and workflows, there is no universal approach to managing and improving engineering systems and processes. This is why the adoption of novel artificial intelligence (AI)-based paradigms to manage and enhance the operations of engineering systems and processes is often not a very straightforward task [5]. In many cases, there are no clear go-no-go scenarios for accelerating the making of decisions for the adoption of AI techniques in engineering contexts [5], [6].

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With a focus on engineering practice, manufacturing and industry (including construction) currently represent more than 16% and 28% of the global gross domestic product (GDP), respectively, according to estimates from the World Bank [7], [8]. So, it can be said that engineering operations and the environments in which they are performed are at the core of global economic growth and prosperity. This is why improving the efficiency and reliability of engineering operations to maximize throughput and general outcomes, and minimize time-to-market is the primary objective of the engineering sectors of contemporary societies. One of the ways this objective is being realized today is through the introduction of emerging and digital technologies (specifically, AI techniques) into engineering workflows to have AI-based and data-driven engineering systems and processes. As an example, in 2020/21, Coca Bottling Company United streamlined its order management operations with the adoption of robotic process automation (RPA) implemented on Microsoft Azure and Microsoft Power Automate [9], [10]. The continuous integration and delivery offered by RPA, using several bots that make up a master automated service agent, simplified operations and reduced the inputs from dedicated customer relationship management agents [9], [10].

Similarly to the Coca-Cola bottling case exemplified above, for many real-world cases that involve the introduction of AI techniques into engineering systems, processes, and operations, the most distinguishing factors in the resulting AI-driven engineering systems, processes, and operations are often the algorithms and analytics frameworks [5], [6], [11]. Such algorithmic and analytics frameworks have been suggested to be at the core of the cognition and intelligence that AI-based engineering systems, processes, and workflows portray [12], [13]. It should be noted that the distinction brought into effect by these frameworks is not limited to robotic and automated systems alone [6], [12], [13]. Rather, it is inherent in virtually all engineering systems and processes that are algorithmic or data-driven in one form or another. For example, edge devices such as smartphones and tablets that double as human-machine interfaces (HMIs) in industrial production and manufacturing settings tend to rely heavily on communication-efficient algorithms for the exploration, exploitation, and visualization of the data samples available to them (often from sensor nodes configured on machines and other shop floor equipment) [13].

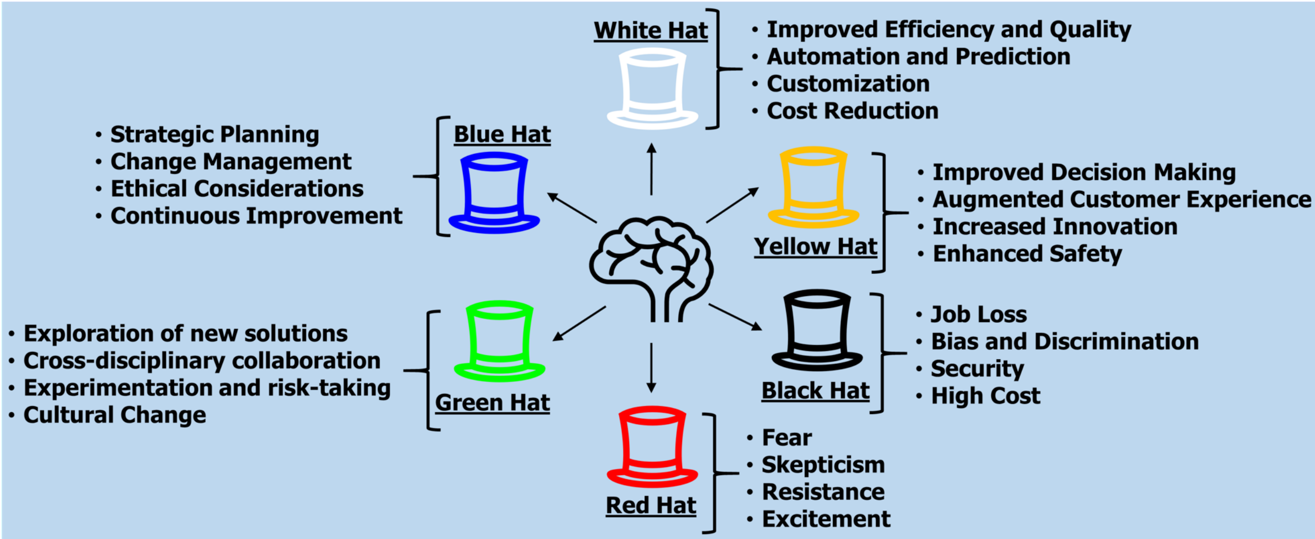


Fig. 1: Broad classification of perspectives for AI adoption using the six lateral thinking hats.

From the above-mentioned, it can be said that engineering systems, processes, and operations controlled or regulated by algorithmic, and analytics frameworks constitute the primary form in which AI is being deployed in engineering contexts [5], [14]. To lend credence to this notion, in [15], the efficiency of the operations of a wastewater treatment plant is reported to have improved significantly after an algorithmic framework involving the predictive modeling of the plant processes using an artificial neural network was introduced. Similarly, another algorithmic framework involving the adoption of CSIRO's (the Commonwealth Scientific and Industrial Research Organisation) navigation pack [16], has been used to enhance the cognition of an autonomous robot developed for radiation-informed navigation in [17]. Several other examples portraying the potential ubiquity of the application of AI techniques such as supervised learning, unsupervised learning, reinforcement learning, and deep learning techniques in engineering systems, processes, and workflows can be found in [18]–[20], and [21]. In [18]–[20], and [21], the feasibility of employing machine learning (ML) techniques for the inspection of product failures, the exploration of strategic, tactic, and operational impact levels, intrusion detection, and predictive modeling of multi-stage continuous-flow manufacturing processes has been demonstrated, respectively. Deep learning methodologies have also been demonstrated to be suitable for fault detection, analysis and classification, and descriptive, predictive, and prescriptive maintenance and analytics in recent times [11], [22]–[24].

As the applications of AI techniques continue to grow across several engineering disciplines and domains, queries bothering on the pros and cons of AI techniques are also being posed not just by engineering practitioners, but also by the society at large [25]. For example, some recent works have suggested that soon, more operational roles across businesses and organizations will become computerized because of AI's impact on the labor market [26], [27]. This is also corroborated in [28] and [29], where it is recommended that the adoption of AI-driven paradigms by businesses and organizations such as engineering firms must be accompanied by the upskilling of the workforce and guided by collaborative approaches involving a continuous and ongoing collaboration between man and machines (AI-driven systems). This recommendation is to mainly ensure that the most significant improvements are achieved when AI systems are engaged, and the displacement of employees is minimized [29]. Recent works have also portrayed AI adoption in engineering contexts as an iterative process due to the fickle interpretability and explainability of AI [30].

Generally, making decisions about engineering operations, processes and workflows is often fraught with risks and uncertainties that must be managed using the right managerial models or tools [2]. Even though AI techniques continue to assist in improving the efficiency and reliability of several engineering operations, processes, and workflows, available managerial decision-making models or tools for understanding the pros and cons associated with the adoption of AI in engineering environments and what experts make of them in engineering management are still very much embryonic [6], [31], [32]. So, for the first time, to the best of the author's knowledge, lateral thinking-informed recommended actions are provided for engineering managers, to ease and aid AI adoption in engineering contexts. To achieve this, generic perspectives on the pros and cons of AI adoption have been used to provide an appraisal of the implications of AI adoption in engineering environments, complement existing engineering decision-making and management models, and provide guidance notes for engineering managers using a lateral thinking-informed classification. In particular, the following contributions are made in this paper:

- Overview of the pros and cons of AI adoption in engineering contexts via the presentation of generic perspectives on AI adoption from the literature, broadly classified under the six lateral thinking hats (see Fig. 1).
- Guidance notes or recommended actions stemming from

the inferences drawn from the literature-informed generic perspectives on AI adoption, broadly classified under the six lateral thinking hats, to inform decision-making and planning for the adoption and implementation of AI by engineering managers.

The advantages and disadvantages of AI adoption in several disciplines (including engineering) have been discussed extensively in the literature [33]–[35]. Some of the generic advantages or pros of AI adoption according to the literature include improved efficiency and quality [36], automation and prediction [37], customization [38], cost reduction [39], improved decision making [40], enhanced customer experience [41], increased innovation and enhanced safety [42], [43]. The adoption of AI technologies has also been put forward as an excellent plinth that can facilitate strategic planning [44], efficient change management [45], discussions on ethical considerations [46], continuous improvement [47], exploration of new solutions [48], cross-disciplinary collaboration [49], experimentation and risk-taking [50], [51], and cultural change [52]. Despite the numerous pros of AI adoption, the AI adoption journey is equally fraught with cons or disadvantages that have also been discussed extensively in the literature [33]–[35]. Some of these cons or disadvantages include (but are not limited to) job loss [53], bias and discrimination [54], security [55], high cost of adoption and implementation [56], fear, skepticism, resistance and excitement among prospective users of AI technologies [57].

As shown in Fig. 1, the above findings about the cons and pros of AI adoption from the literature have been broadly classified under the six lateral thinking hats to provide generic perspectives that highlight the pros and cons of AI adoption. This broad classification directly stems from the traditional definitions of each lateral thinking hat [58], [59], and it is elucidated later in Section III. It should be noted that such a classification is reported for the first-time in this paper as a tool for the inferential formulation of recommended actions in the form of guidance notes for engineering managers in their AI adoption journey. The remainder of the paper is organized as follows: an overview of the concept of lateral thinking is presented in Section II, the lateral thinking-classified perspectives for the adoption of AI in engineering contexts and guidance notes inferred from them are detailed in Section III, and the concluding remarks are provided in Section IV.

## II. Lateral Thinking

Lateral thinking was first proposed by Edward de Bono as a methodology for ideation and creativity that disrupts the conventional linear approach to solving problems [60]. As opposed to traditional vertical and horizontal thinking approaches for problem solving and idea generation, lateral thinking involves the adoption of indirect, inconspicuous, and creative ways to logically and inventively gain insights and radical new perspectives that aid in finding innovative solutions to a broad class of real-world problems [58], [60]. Since its proposition, lateral thinking has been widely adopted in several disciplines, making it a very popular multidisciplinary approach to problem solving, idea generation, and robust design and development in both technical and non-technical fields [59]–[63]. In [61], lateral thinking is put forward as a practical approach for enhancing the capacity and proficiency of product development teams, when faced with uncontrollable variations in technological infrastructure and sophistication that may impact new product development projects. Some of the other areas of practice in which lateral thinking appears to be lending a hand in terms of assessment and decision-making include (but are not limited) to economics [62], public management [62], general management [59], and leadership [63]. These works and several other works all point to the fact that lateral thinking is a very generic and robust methodology that can be utilized to address new decision-making conundrums, such as the adoption of AI-driven technologies in engineering contexts. As an example, in [59], the generality and robustness of lateral thinking are revealed through its integration with an existing managerial decision model (decision theory model) to have a new tool for managerial decision-making.

Using the definitions and connotations of lateral thinking put forward in the literature [60]–[63], a lateral thinking-based approach is proposed as a practical way of evaluating the benefits, risks and challenges of the adoption of AI-based paradigms in engineering environments. As revealed in Fig. 1 and detailed later in Section III, the proposed lateral thinking-based approach premises on action steps inferred from generic perspectives on the pros and cons of AI adoption in the literature that are broadly classified under the six lateral thinking hats (also proposed by Edward de Bono [58]) in this work. This methodology anchors on the use of inferential reasoning to tailor the wider implications (i.e., pros and cons) of AI adoption to the context of engineering practice. A similar use of inferential reasoning as carried out in this paper has been exemplified in [6], where guidance notes or recommended actions, inferred from generic political, economic, socio-cultural and technological considerations of AI adoption, have been proposed to aid engineering managers in navigating the AI adoption process. To do this effectively and uniquely in this paper, the six lateral thinking hats have been meticulously employed to classify generic perspectives on the pros and cons of AI adoption (see Fig. 1). Against the backdrop of this classification, recommended actions in the form of guidance notes are then formulated inferentially, and posited to aid engineering managers in their decision-making in the context of AI adoption (see Section III). It should be noted that the inference-based recommended actions or guidance notes in this work have not been previously reported in the literature to the best of the author's knowledge.

## III. Lateral Thinking-Classified Perspectives

As discussed already, lateral thinking is an effective approach to problem solving that is not like the conventional logical or linear technique [60]. It mostly entails approaching issues from drastically different angles, which enables original and creative approaches to problem solving and understanding, by thinking beyond the box [59]. Because of its potential ability to compel engineering managers to examine various viewpoints and solutions to problems, lateral thinking can play

TABLE I: White Hat Viewpoint of Lateral Thinking

| Some perspectives | Recommended actions |
|---|---|
| 1) Improved efficiency and quality | • Find inefficiencies and bottlenecks in engineering processes and workflows that can be solved through AI adoption, that is areas where AI technologies can improve performance, quality, or speed.<br>• Streamline workflows, cut waste, and boost efficiency to optimize operations and procedures by integrating AI into supply chain coordination, machine monitoring, and control, and the design and testing of new goods and services.<br>• Maximize the potential to use AI for fault detection and correction, standard compliance, feedback, recommendation, product quality inspection and verification to improve the quality of goods and services, problem diagnosis and resolution, and customer happiness.<br>• Harness AI-driven solutions to implement enterprise-wide asset management that assist to minimize downtime and lags in engineering operations and procedures by tracking, optimizing, and maintaining assets across multiple facilities across the enterprise. |
| 2) Automation and prediction | • Employ robotic process automation tools, ML algorithms, and intelligent process automation platforms to automate mundane tasks like data entry, documentation, and quality control to greatly lower operational costs related to labor, errors, and inefficiencies.<br>• Use predictive maintenance strategies that rank maintenance activities based on the probability and impact of potential failures, reducing downtime and enhancing asset lifespan to lower unplanned maintenance costs, prolong equipment lifespans, and increase operational dependability.<br>• Build predictive models that predict demand, distribute resources efficiently, and spot opportunities for process improvement by examining data, producing forecasts, and offering suggestions based on various scenarios and objectives.<br>• Build strong data infrastructure to enable automation and prediction initiatives by gathering and combining data from a variety of sources such as sensors, industrial Internet of Things (IIoT) devices, and operational systems. |
| 3) Customization | • Use AI-driven manufacturing and production processes to enable mass customization of products at scale to support the design, production, and delivery of products that meet individual customer preferences and specifications efficiently and effectively.<br>• Employ AI-assisted customer relationship management (CRM) systems to facilitate customized interactions and engagement with customers throughout the life cycle of products to better grasp customer needs, preferences, and behavior, and deliver personalized solutions, advice, and support.<br>• Promote customization to enable the development of customized or customer-centric final products based on end users' wants, preferences, and feedback.<br>• Orchestrate product creation for particular markets, demographics, or people, to improve client retention and loyalty. |
| 4) Cost reduction | • Apply AI-based energy management solutions to improve energy usage and cut energy costs in engineering facilities by analyzing energy consumption patterns, finding inefficiencies, and proposing strategies for energy saving and optimization.<br>• Examine historical purchasing data, supplier performance metrics, and market trends to find opportunities for cost reduction and efficiency enhancement using AI-driven supply chain management tools that optimize inventory levels.<br>• Use AI-powered procurement platforms that analyze vendor data, negotiate terms, and manage contracts efficiently and effectively, to automate vendor selection, negotiation, and contract management processes.<br>• Employ AI for cost forecasting and budget optimization to boost cost predictability and ensure efficient allocation of financial resources. |

a very vital role in the making of decisions about AI adoption in engineering contexts. Specifically, if established AI adoption assessment procedures (e.g., following the recommended guidelines in [6]) are employed by engineering managers in their AI adoption and integration journey, the examination of generic perspectives on the pros and cons of AI adoption, broadly classified under the six lateral thinking hats [58], can further assist in finding novel opportunities and approaches that they might not have thought of previously. These generic perspectives, and their broad classification under the six lateral thinking hats, informing the guidance notes posited in this work, are discussed as follows:

### A. White Hat Viewpoint

The white hat viewpoint of lateral thinking can serve as a guiding principle for evaluating the potential benefits and advantages of implementing AI in several engineering contexts because of the objectivity, neutrality and impartiality that it orchestrates in decision making [58]. Specifically, when employed, it can empower engineering managers to collect and employ factual data and knowledge relevant to potential AI adoption, enabling informed decision-making and efficient assessment of AI's applicability in their industries. Such analytical approach could take on the form of a thorough investigation into crucial factors or perspectives associated with AI integration in engineering settings. These factors may encompass various aspects such as increased output and process efficiency, enhanced product and service quality, utilization of advanced predictive maintenance techniques, customization capabilities for tailored products, automation enhancements, and opportunities for cost reduction [36]–[39].

In addition to the perspectives mentioned above, the white hat viewpoint of lateral thinking also has the potential to equip engineering managers with insights into how AI could revolutionize their operations, optimize resource allocation, and streamline workflows by meticulously examining the

TABLE II: Yellow Hat Viewpoint of Lateral Thinking

| Some perspectives | Recommended actions |
|---|---|
| 1) Improved decision making | • Employ AI technologies to analyze massive amounts of data from sensors, devices, and historical records to support the application of ML algorithms to discover patterns, trends, and insights within the data, enabling data-driven decision-making.<br>• Design decision support systems that utilize AI technologies to offer timely insights and suggestions to decision-makers, empowering them to make decisions that reduce risk and increase the chance for success.<br>• Employ AI-based scheduling and resource allocation tools that adaptively change plans and schedules in line with changing circumstances or restrictions to ensure the improvement of processes and optimum allocation of resources.<br>• Utilize AI-enabled analytics to forecast performance, expenses, and risks and streamline design, testing, and validation processes through early detection of deviations from anticipated performance metrics and stressing of potential challenges or prospects for improvement. |
| 2) Augmented customer experience | • Utilize AI technologies to personalize customer interactions and adjust design solutions to individual needs and preferences by deploying AI-based recommendation engines, chatbots, and virtual assistants to provide personalized product recommendations, troubleshooting aid, and support services.<br>• Adopt omnichannel communication strategies that facilitate smooth interactions across multiple channels, such as email, chat, social media, and voice assistants by integrating AI-powered communication tools and platforms that simplify customer interactions, lower response times, and improve accessibility.<br>• Undertake customer data analysis to increase customer happiness and loyalty and cultivate proactive support and recommendations for customers to ensure the tailoring of goods and services to the preferences, requirements, and comments of customers on an as-needed basis.<br>• Use AI-powered analytics and predictive modeling to identify opportunities for proactive customer engagement and relationship-building that anticipate customer needs and preferences based on historical data and behavioral patterns. |
| 3) Increased innovation | • Free up time for higher-value work by promoting innovative concepts, designs, and solutions via design exploration and the use of generative design methodologies.<br>• Use automation to perform all risky and routine tasks to the maximum extent feasible, to reduce human exposure to danger, increase efficiency and accuracy, and save time and resources.<br>• Cultivate a culture of versatility and resilience, where engineering teams are empowered to adjust to evolving market conditions, technological progress, and customer expectations using AI techniques.<br>• Motivate open communication, knowledge transfer, and innovative thinking to generate new insights and explore novel approaches to engineering challenges, considering AI-driven paradigms. |
| 4) Enhanced Safety | • Design sturdy and consistent safety standards and practices that integrate AI systems, confirming they conform to safety regulations and benchmarks.<br>• Perform comprehensive risk assessments and evaluations to detect possible safety threats and dangers related to engineering procedures and processes, and assess how AI solutions can be incorporated to reduce these risks and improve safety.<br>• Execute complete training and education plans to equip the engineering workforce with the knowledge and skills required to efficiently use AI for safety improvement.<br>• Employ AI-oriented analytics and monitoring tools such as smart sensors, alarms, and instructions to assess safety performance metrics, identify potential safety challenges, project safety risks, predict and prevent mishaps, injuries, and damages. |

factors mentioned above. In other words, it can foster a culture of evidence-based decision-making, empowering engineering managers to navigate the challenges of AI deployment with precision. In this way, a strategic AI implementation guided by rigorous data collection, interpretation, and analysis led by engineering managers, can make engineering environments to become more innovative, efficient, and competitive in today's rapidly evolving, technology-driven landscape. Findings in the literature corroborate these perspectives [36]–[39]. Summarized guidance notes for engineering managers inferred from these perspectives broadly classified under the white hat viewpoint of lateral thinking in this work, are posited in Table I.

### B. Yellow Hat Viewpoint

The yellow hat viewpoint of lateral thinking can advocate for engineering managers and their workforce to redirect their focus toward identifying potential advantages and opportunities within any given scenario, according to its logical positivism premise [58]. By fostering positivity and optimism, this viewpoint can highlight the implications of AI implementation in engineering settings, prompting engineering managers to explore the benefits. Thus, the yellow hat viewpoint of lateral thinking can prove to be a valuable tool in envisioning the advantages of integrating AI in engineering systems, processes and operations. As a result, engineering managers can harness the many benefits of AI integration by embracing this viewpoint. These benefits include (but are not limited to) enhanced productivity and process optimization, the generation of innovative solutions, and the adoption of cutting-edge technologies [40]–[43].

By harnessing the yellow hat viewpoint of lateral thinking, engineering managers are more likely to envision how AI can enhance overall quality control, minimize downtime, and streamline production lines. This viewpoint can also motivate engineering managers to strategize by considering the long-term implications of AI implementation, including the empowerment of their workforce with new skills, cultivation

TABLE III: Black Hat Viewpoint of Lateral Thinking

| Some perspectives | Recommended actions |
|---|---|
| 1) Job loss | • Examine the possibilities of establishing new jobs and positions that make use of AI technologies and enhance the knowledge and talents of the current workforce or staff members.<br>• Give top priority to the creation and application of AI technologies that are human-centric, and augment rather than entirely replace human skills.<br>• Assign resources to thorough retraining and upskilling initiatives designed to furnish employees with the competencies required to adjust to evolving job functions and capitalize on emerging prospects in the AI-enabled workplace.<br>• Offer aid and guidance to employees as they navigate transitions to alternative roles or career trajectories within the organization, prompted by the integration of AI technologies. |
| 2) Bias and discrimination | • Ensure that the datasets used to train AI models are balanced, diverse, representative, and free from biases.<br>• Make algorithmic fairness and transparency the main goals in creating and using AI systems by applying algorithms and methods that reduce bias and unfairness in AI-driven decision-making processes.<br>• Encourage inclusivity and diversity in AI development teams to reduce prejudice and advance equity in AI systems.<br>• Put into practice laws, guidelines, and moral principles that encourage equity, responsibility, and openness in the use of AI. |
| 3) Security | • Use strong data protection methods (such as encrypting data to keep it safe when moving or storing, limiting data access to authorized users only, and removing or hiding data identifiers to protect privacy) to safeguard confidential information used in AI systems.<br>• Perform frequent vulnerability scans and penetration testing to find and fix potential security flaws (such as software, hardware, or network issues that could be exploited by hackers) in AI systems.<br>• Establish clear policies and procedures for handling sensitive data to guarantee accountability, equity, and openness.<br>• Use incident response procedures and constant monitoring to quickly identify and address security concerns. |
| 4) High cost | • Perform a comprehensive cost-benefit analysis to measure the potential return on investment of AI adoption by estimating the direct and indirect expenses related to AI implementation, such as hardware, software, training, maintenance, and staff costs.<br>• Determine areas where process optimization and efficiency gains can help lower the overall cost of adopting AI.<br>• Examine prospects for cooperation and alliances with technology providers, academic institutions, and business associates to pool resources, knowledge, and expenses related to the implementation of AI.<br>• Leverage available platforms, frameworks, and open-source tools to speed up AI creation and adoption, lowering the demand for expensive tailor-made solutions. |

of an innovative organizational culture, and staying ahead of technological advancements. In this way, the opportunities for growth and success and inspiring teams and stakeholders in engineering organizations to embrace change proactively are reinforced. This can ultimately catalyze organizational transformation, encouraging teams to leverage AI to its full potential. Recent works in the literature corroborate these perspectives [40]–[43]. Guidance notes for engineering managers, inferred from these perspectives broadly classified under the yellow hat viewpoint of lateral thinking in this work, are suggested in Table II.

### C. Black Hat Viewpoint

The black hat viewpoint of lateral thinking can provide a crucial framework for examining the drawbacks inherent in any given situation due to its natural inclination or leaning on logical negativism [58]. Its application to the adoption of AI in engineering settings can reveal the risks and challenges associated with such an effort. Foremost among these could be the potential for job displacement, as AI systems increasingly automate tasks once performed by human workers, leading to workforce restructuring and unemployment [53]. In addition to this, the inherent biases in AI-driven systems may also present a serious ethical dilemma, potentially reinforcing or exacerbating social injustices due to their reliance on biased training data [54]. The security flaws in AI systems can also further elevate concerns about data privacy and confidentiality, leaving engineering organizations' susceptible to hacking and cyberattacks [55]. A significant financial investment may also be required for the successful implementation of AI systems, encompassing costs related to technology procurement, establishment of data storage infrastructure, and extensive employee training programs [56]. This financial burden, coupled with uncertainties regarding long-term return on investment, necessitates careful cost-benefit analysis and strategic planning to mitigate any potential financial risks associated with AI adoption in engineering contexts [56].

By exploring these perspectives that have been established in the literature [53]–[56], the black hat viewpoint of lateral thinking can assist engineering managers in identifying and confronting the issues bothering on these perspectives proactively. This may entail adopting a risk-reduction approach and formulating robust plans to navigate the complexities of AI integration while safeguarding against unfavorable outcomes. Consequently, summarized guidance notes for engineering managers, inferred from these perspectives and broadly classified under the black hat viewpoint of lateral thinking in this work, are put forward in Table III.

TABLE IV: Red Hat Viewpoint of Lateral Thinking

| Some perspectives | Recommended actions |
|---|---|
| 1) Fear | • Develop extensive training and education initiatives for engineers, technicians, technologists, and other AI adoption stakeholders.<br>• Ensure that the training and education initiatives developed for the workforce are centered on demystifying AI technologies, outlining their advantages for engineering workflows as well as their capabilities and limitations.<br>• Encourage open lines of communication and teamwork throughout the AI adoption process between engineers, technicians, technologists, AI specialists, and other team members.<br>• Create unambiguous routes for information, updates, and perspectives regarding AI projects. |
| 2) Skepticism | • Initiate pilot projects that demonstrate the useful applications of AI in engineering settings.<br>• Gather information and inputs during the pilot phase of all AI projects to evaluate how AI solutions affect key performance metrics and pinpoint areas that require more optimization.<br>• Establish credibility and trust by giving ethical and transparent considerations top priority when adopting AI.<br>• Effectively apprise stakeholders of the aims, potential, and constraints of AI technologies, stressing their complementary role in enhancing human knowledge rather than its total substitution. |
| 3) Resistance | • Involve important stakeholders such as engineers, technicians, technologists, managers, and other pertinent workforce from the outset of the AI adoption process.<br>• Schedule frequent meetings, workshops, and feedback sessions to address the reasons for adopting AI, its possible advantages, and any worries or objections voiced by the stakeholders and workforce.<br>• Provide practical training sessions, tutorials, and educational materials that are suited to the various roles and demands of the many stakeholders.<br>• Create a network of internal champions or mentors that can offer peer-to-peer support and best practices for incorporating AI into engineering systems, processes and operations. |
| 4) Excitement | • Set reasonable expectations regarding the potential and constraints of AI technologies to moderate excitement.<br>• Stress that AI is not a panacea that will quickly cure every issue, but rather a tool to improve human capabilities.<br>• Inspire experimentation, creativity, and learning to foster a culture of continual progress and development.<br>• Establish mechanisms for gathering feedback and insights from frontline workers regarding the practical challenges and opportunities of AI adoption. |

### D. Red Hat Viewpoint

With a focus on the human aspect of AI integration in engineering contexts, the red hat viewpoint of lateral thinking can prompt the exploration of emotions, impulses, and instinctual responses within the decision-making process [58]. When AI is introduced into established workflows, concerns about job redundancy may arise, triggering various emotional reactions among the workforce [53]. For instance, engineering teams may fret over the potential impact of AI on their roles, fearing automation could render their jobs obsolete or diminish the value of their skills [53], [57]. Additionally, past negative experiences with technology adoption may also fuel skepticism among operational staff, further complicating the acceptance of AI initiatives [57], [64].

Despite these apprehensions, there remains an opportunity to cultivate hope and enthusiasm as employees recognize the transformative potential of AI adoption [64]. Therefore, engineering managers, in a way, bear the responsibility of fostering excitement and garnering support across all organizational levels by transparently outlining the anticipated benefits of AI integration. These benefits may encompass enhanced customer experiences, heightened productivity, and increased creativity [40]–[42]. When engineering managers take a proactive approach to managing emotions to foster transparency and collaboration during the AI adoption journey, employees become more inclined to viewing AI as a catalyst for opportunity rather than a source of apprehension. In other words, by acknowledging and addressing the spectrum of emotional responses elicited by AI adoption, a supportive environment conducive to effective integration and the realization of engineering teams' potential for innovation and growth can be fostered by engineering managers. As a result, guidance notes for engineering managers, inferentially drawn from these perspectives and broadly classified under the red hat viewpoint of lateral thinking in this work, are proposed in Table IV.

### E. Green Hat Viewpoint

The green hat viewpoint of lateral thinking can be utilized to delve into innovative solutions and potentials, fostering a culture of innovation either directly or indirectly, owing to its strong emphasis on innovation, creativity, and transcending traditional limits [58]. When it comes to integrating AI into engineering contexts, this viewpoint can prompt engineering managers to brainstorm and explore unconventional and innovative AI applications that could prove practical and advantageous for their workforce and to their systems, operations, and processes. Through this brainstorming and exploration process, engineering managers can ignite the investigation of alternative solutions that go beyond the conventional or evident ones. Consequently, AI ceases to be viewed solely as a tool for process enhancement; rather, it emerges as a catalyst for reimagining the fundamental approaches and executions of engineering tasks and operations [38], [48], [50].

Engineering practice typically adopts a multidisciplinary approach to problem-solving [65], albeit traditionally focusing more on the interplay of various engineering disciplines rather

TABLE V: Green Hat Viewpoint of Lateral Thinking

| Some perspectives | Recommended actions |
|---|---|
| 1) Exploration of new solutions | • Promote transparent communication, foster knowledge exchange, and cultivate creative thinking to ignite fresh concepts and unearth innovative strategies for tackling engineering hurdles.<br>• Adopt agile and iterative methodologies in project management and product development to facilitate the exploration of innovative ideas through an emphasis on rapid prototyping, experimentation, and feedback-driven iteration.<br>• Avoid limitations imposed by traditional uses of AI by thinking of novel ways AI technology can transform processes, optimize designs, or enhance decision-making.<br>• Prioritize the use of generative designs (designs that are automatically generated by algorithms based on predefined criteria and constraints) and digital twins (virtual representations of real-world resources or systems that can be used to track, mimic, and improve their functionality). |
| 2) Cross-disciplinary collaboration | • Dismantle compartmentalization within teams to leverage the combined strengths of AI and engineering proficiency, fueling innovation and the pursuit of novel ideas.<br>• Encourage teamwork among engineers, data scientists, domain specialists, and relevant stakeholders to harness a range of viewpoints and skills when exploring novel concepts enabled by AI integration.<br>• Establish multidisciplinary teams or innovation centers where professionals from various fields collaborate, brainstorm, experiment, and refine inventive solutions together.<br>• Ensure that AI initiatives are in harmony with the overarching goals and objectives of the organization, fostering a collective sense of purpose that inspires collaboration. |
| 3) Experimentation and risk-taking | • Encourage the development of a culture that values taking chances and experimenting.<br>• Allow staff members to experiment with novel concepts and cutting-edge methods without worrying about failing.<br>• Establish specialized sandbox environments or test beds tailored for engineers and other stakeholders to conduct experiments with AI technologies within a secure and regulated framework.<br>• Foster collaborative efforts across functional teams within the above settings to facilitate the cooperation of engineers, data scientists, and domain experts in validating assumptions, testing hypotheses, and refining solutions iteratively. |
| 4) Cultural change | • Demonstrate unwavering support for the adoption of AI by actively promoting cultural transformation and outlining the strategic value of AI.<br>• Provide a clear explanation of how AI supports the objectives and core values of the organization, highlighting its ability to boost innovation, efficiency, and competitiveness.<br>• Encourage experimentation, risk-taking, and learning from mistakes by cultivating a growth mindset.<br>• Acknowledge and reward groups and individuals who support efforts to adopt AI, highlighting the significance of cultural change and collective success within the organization. |

than incorporating non-engineering disciplines [66]. The green hat viewpoint of lateral thinking can also open avenues for engineering managers to collaborate across disciplines, including non-engineering ones like cognitive science and sociology as recently demonstrated in [67]. Such collaborations can facilitate the design and development of AI systems tailored to optimize not only the technical aspects of operations and processes but also to consider human-centric factors such as usability, safety, and ethical implications [29], [46], [67]. Embracing such a transition can encourage the willingness to experiment and take risks in exploring AI techniques, recognizing that failures can yield significant insights and discoveries. Some suggested actions inferred from these perspectives that are broadly classified under the green hat viewpoint of lateral thinking in this work, are posited in Table V, as guidance notes for engineering managers.

### *F. Blue Hat*

The blue hat viewpoint of lateral thinking can empower engineering managers to assume the role of an orchestrator, guiding the thought process and providing a coherent direction pertinent to the complexities of integrating AI in engineering settings, because of its intrinsic overarching premise [58]. To effectively oversee AI initiatives, engineering managers need to adopt a strategic stance, prioritizing the development of detailed and well-conceived strategic plans, as suggested in [6], [68], [69]. More specifically, since ensuring the seamless integration of AI technology necessitates a meticulous evaluation of organizational objectives, resource allocation, and risk management strategies, the critical role of fostering efficient change management and underscoring the imperative for comprehensive impact analyses to assess the ramifications of AI adoption by engineering managers, can be brought to bear via the blue hat viewpoint of lateral thinking.

Engineering managers can mitigate resistance to change and cultivate a unified vision for the organization's AI-driven future by fostering a culture of transparency and communication [70]. It should be noted that addressing potential ethical concerns when it comes to AI adoption generally requires vigilant and effective management of the ethical implications of AI adoption [46]. This entails upholding principles of fairness, assuming accountability, and fostering transparency throughout the AI adoption journey to guide decision-making processes and safeguard against ethical lapses [46], [54], [55], [57]. The blue hat viewpoint of lateral thinking can also aid in emphasizing the importance of ongoing improvement, advocating for continuous evaluation and oversight of AI adoption initiatives to ensure alignment with organizational objectives and desired outcomes, as required for AI adoption [6], [68], [69]. This allows engineering managers to harness the transformative potential of AI-driven systems and technologies by continuously refining their approaches to AI integration,

TABLE VI: Blue Hat Viewpoint of Lateral Thinking

| Some perspectives | Recommended actions |
|---|---|
| 1) Strategic planning | • Develop clear strategic plans for possible AI adoption and ensure that they are in line with the organization's vision, purpose, and goals.<br>• Break down the AI adoption process into manageable phases, prioritize high-impact initiatives with achievable milestones, and allocate resources such as funds, expertise, and technological infrastructure to facilitate the successful execution of the devised AI implementation strategy.<br>• Specify the parameters, goals, and anticipated results of adopting and implementing AI in addition to the necessary resources, schedules, and benchmarks.<br>• Perform an in-depth needs assessment to pinpoint the domains and operations within engineering processes and workflows where AI can deliver the greatest value and influence, and develop a clear road map based on the findings of the needs assessment. |
| 2) Change management | • Obtain buy-in from all relevant stakeholders and the workforce through strategic and tactical engagements and meetings, such as presentations and demonstrations.<br>• Facilitate organization-wide impact assessments of AI adoption, with an emphasis on the stakeholders and workforce who will be impacted by the change.<br>• Determine the possible advantages, dangers, and difficulties of adopting AI as well as the level of readiness or preparedness, resistance, and support of stakeholders and staff.<br>• Create a governance structure and change management framework to direct the adoption and use of AI. |
| 3) Ethical considerations | • Ensure adherence to the norms, values, and guidelines of the organization and the society at large by assessing the ethical consequences of adopting AI through an evaluation of the ethical aspects of adopting AI, including security, privacy, responsibility, and justice.<br>• Create and implement ethical rules, and monitoring and audit systems to ensure AI technologies are used responsibly within engineering systems, processes, and workflows.<br>• Provide oversight and ethical governance frameworks to direct the responsible application of AI technologies.<br>• Ensure that AI systems are built to take into consideration a variety of user demands and preferences by incorporating inclusive and varied design techniques into the development and application of AI technology. |
| 4) Continuous improvement | • Evaluate and track the use of AI, making sure that the intended outcomes are realized and that the systems and solutions used are updated and enhanced regularly.<br>• Assess the effectiveness, value, and impact of AI deployment in addition to the prospects for learning, innovation, and feedback.<br>• Dedicate funds to continuing research and development projects that will enhance AI capabilities.<br>• Establish a culture of lifelong learning and skill building for the workforce or staff members participating in the deployment of AI. |

embracing an innovative and adaptable mindset. Summarized guidance notes for engineering managers, inferred from the above perspectives that have been broadly classified under the blue hat viewpoint of lateral thinking in this work, are posited in Table VI.

## IV. Conclusions

One of the challenges that engineering managers face in today's fast-paced world of digital and emerging technologies is how to decide whether to adopt and integrate AI technology in their systems, processes, and operations. This is because engineering systems, processes, and operations are often complex and involve many factors and uncertainties. So, engineering managers need simple and generic management models or frameworks that can highlight the crucial but hidden facets of AI adoption in engineering settings to facilitate this decision-making process. This work posits a new approach to help engineering managers who wish to make well-informed choices on the use of AI in engineering settings. The method is predicated on lateral thinking, a creative method of problem solving that makes it easier to look at a problem from multiple perspectives. Using inferences drawn from generic perspectives on the pros and cons of AI adoption that have been broadly classified under the six lateral thinking hats, this work recommends specific actions that engineering managers can take to leverage the benefits and mitigate the risks of AI adoption in engineering settings.

In typical engineering settings, where line management responsibilities fall on engineering managers, who are often also the directors of technical operations, the potential adoption of AI technologies to retrofit or completely overhaul current engineering operations, processes, and systems can be assessed by these managers. They will subsequently pass the outcomes of their appraisal to the executive or other relevant higher administrative authorities within their organizations. To adopt the approach outlined in this work, engineering managers can conduct brainstorming sessions to broadly review the pros and cons of potential AI-driven changes. These sessions will need to utilize inquiries and inferences formed in clusters of think tanks for each lateral thinking approach, matched with Tables I to VI in each cluster. Also, these think tanks should, as much as possible, represent all stakeholders involved in the AI-driven transition.

The perspectives from all think tank clusters above can then be weighed against the overarching goal of AI adoption to arrive at a definitive go/no-go scenario based on the cumulative duality of outcomes for each perspective. If a ”no” is the definitive outcome, the current AI adoption proposal can be shelved until additional information becomes available to offset the ”no” outcome through another brainstorming session. It can be expected that several iterative brainstorming sessions will be required until a "no" becomes a "go," depending on the complexity of the AI adoption being proposed. Otherwise, the AI adoption proposition is further evaluated in terms of its potential impact, risks, and costs to ensure its feasibility, allowing sufficient margins for both success and failure before implementation. This suggested approach for the practical adoption of the propositions in this work will be validated through real-world case studies, with outcomes to be disseminated in a planned future research article.

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