I'm not a bot



Artificial intelligence is revolutionizing the digital landscape and transforming various aspects of the economy. Our research reveals over 400 practical applications of AI in companies and organizations across multiple industries. McKinsey Global Institute's insights and our analysis of more than 400 specific use cases highlight both the economic potential and limitations of advanced AI techniques. The value of AI lies not in the models themselves, but in how companies them to drive growth and innovation. However, it is crucial to acknowledge concerns surrounding data security, privacy, and bias when using AI techniques. Our analysis focuses on deep learning techniques that utilize artificial neural networks. These techniques have been inspired by the human brain's neural networks, and their applications in various fields. These findings suggest that AI has substantial potential across industries, but also highlights the need for further research to address limitations and develop future opportunities. Deep neural networks have emerged as a vital tool in various industries, with their connections mimicking the human brain's visual cortex organization. These convolutional neural networks (CNNs) excel at perceptual tasks and are ideal for image processing. Additionally, other AI techniques like generative adversarial networks (GANs) and reinforcement learning have shown promise but remain relatively underdeveloped compared to CNNs. GANs utilize a zero-sum game framework where two neural networks compete against each other, enabling them to mimic various data distributions, including text, speech, and images. This feature is particularly useful in generating test datasets when actual ones are scarce. Reinforcement learning, on the other hand, involves training systems using virtual rewards or punishments, allowing them to learn through trial and error, as demonstrated by Google DeepMind's success with video games like Go. In a business setting, these AI techniques can be applied to tackle real-world problems, which primarily fall into three categories: classification, continuous estimation, and clustering. Our analysis of over 400 use cases across various industries has revealed the areas where deep neural networks can create significant value, including the potential lift they offer compared to traditional analytics (Exhibit 2). However, it's essential to note that these findings might not be exhaustive and could either overestimate or underestimate or underestimate or underestimate or underestimate the potential benefits for certain sectors. The application of AI in existing use cases can significantly improve their performance. For instance, predictive maintenance can be enhanced using deep learning's ability to analyze vast amounts of data from various sensors, including microphones and cameras. This allows for early failure prediction and planned interventions, thereby reducing downtime and operating costs while improving production yield. Moreover, AI-driven logistics optimization can lead to substantial cost savings through real-time forecasts and behavioral coaching. By applying AI techniques such as continuous estimation to logistics, businesses can unlock significant value. AI can optimize delivery routes, reduction in fuel costs through sensor monitoring and real-time coaching for drivers. All can also enhance customer service by improving speech recognition in call center management, allowing for more seamless experiences and efficient processing. Deep learning analysis of audio can assess customers' emotional tone, automatically rerouting calls to human operators when necessary. In marketing and sales, AI techniques can provide personalized product recommendations by combining customer data with social media monitoring. This can lead to a two-fold increase in sales conversions. Two-thirds of AI applications are focused on improving existing analytics use cases, with deep neural networks providing significant performance boosts in 69% of cases. However, only 16% of use cases require greenfield solutions, and traditional analytics continue to be essential in industries such as insurance, pharmaceuticals, and traditional analytics continue to be essential in industries such as insurance, pharmaceuticals, and traditional analytics continue to be essential in industries such as insurance, pharmaceuticals, and traditional analytics continue to be essential in industries such as insurance, pharmaceuticals, and traditional analytics continue to be essential in industries such as insurance, pharmaceuticals, and traditional analytics continue to be essential in industries such as insurance, pharmaceuticals, and traditional analytics continue to be essential in industries such as insurance, pharmaceuticals, and traditional analytics continue to be essential in industries such as insurance, pharmaceuticals, and traditional analytics continue to be essential in industries such as insurance, pharmaceuticals, and traditional analytics continue to be essential in industries and industries are insurance, pharmaceuticals, and traditional analytics continue to be essential in industries and industries are insurance, pharmaceuticals, and traditional analytics continue to be essential in industries and insurance are insurance. labeled training data and sufficient computational resources. These methods excel at extracting patterns from complex data types such as images, video, and audio or speech. To achieve relatively good performance on classification tasks, deep-learning algorithms often need thousands of data records, sometimes millions for human-level performance. A dataset with over 10 million labeled examples is generally required to match human level performance. However, the availability of large datasets can be a challenge for many business use cases. Collecting and integrating such massive data sets while overcoming labeling challenges remains a significant hurdle. Current AI models are mostly trained through supervised learning, which relies on human labeling and categorization of the underlying data. Emerging techniques like reinforcement learning, and "one-shot learning, and training, datasets at scale while avoiding overfitting and underfitting issues. Linking data across customer segments and channels is crucial to create value from AI. Neural AI techniques excel in analyzing image, video, and audio data due to their ability to handle high dimensionality. These networks can learn to represent various features through multiple layers, enabling them to tackle complex tasks like facial recognition with ease. As conditions change rapidly, training data must be frequently updated to maintain model accuracy. In many cases, models need refreshing at least once a month, while daily refreshes are required in almost one-guarter of instances. This is particularly crucial in sectors like marketing, sales, supply chain management, and manufacturing. AI has the potential to generate between \$3.5 trillion annually across nine business functions in 19 industries. This accounts for approximately 40% of the overall \$9.5 trillion annually across nine business functions in 19 industries. This accounts for approximately 40% of the overall \$9.5 trillion annually across nine business functions in 19 industries. This accounts for approximately 40% of the overall \$9.5 trillion annually across nine business functions in 19 industries. This accounts for approximately 40% of the overall \$9.5 trillion annually across nine business functions in 19 industries. is estimated to range from one to nine percent of 2016 revenue. The specific use cases, data availability, and regulatory constraints significantly impact this potential value impacts from AI come from both top-line-oriented functions like marketing and sales and bottom-line-oriented operational functions, such as consumer retail and high tech, tend to benefit more from AI applications in marketing and sales. E-commerce platforms are particularly well-suited for AI as they can easily collect customer data and personalize promotions, prices, and products dynamically in real-time. Our use cases highlight three sectors where AI's impact is significant: In retail, the most valuable potential area for AI lies within marketing and sales, specifically in pricing and promotion management and customer service management. Using customer data to tailor individual offers daily can increase incremental sales by one to two percent through causal drivers of demand rather than prior outcomes. This results in a potential five percent reduction in inventory costs and revenue increases of two to three percent. In banking, AI has significant value potential in marketing and sales, similar to its role in retail. However, due to the importance of assessing and managing risk in banking, AI's value is much higher in areas like loan underwriting and fraud detection. AI in Banking Sector Faces Challenges The use of artificial intelligence (AI) is gaining traction in the banking sector, with companies investing heavily in its development and implementation. However, despite its potential benefits, only about 20 percent of AI-aware companies are currently utilizing its technologies on a large scale. Several limitations need to be addressed to unlock the full value of AI in banking. Firstly, data labeling is a significant challenge due to the manual nature of this task, which often requires human intervention for supervised learning. New techniques such as reinforcement learning and in-stream supervision aim to address this issue by automating data labeling during natural usage. Obtaining sufficient and comprehensive data sets is another hurdle. For many business use cases, creating or acquiring large datasets can be difficult, especially in industries with limited data availability, like healthcare. Explaining AI-generated results in human terms is also a challenge. Companies need to provide clear explanations for complex models, which is particularly important in regulated industries such as healthcare and automotive. Moreover, AI models struggle with generalizability, requiring companies to commit resources to train new models even for similar use cases. Transfer learning offers a promising solution to this issue by applying existing knowledge to distinct activities. The risk of bias in data and algorithms poses another significant challenge. Biases can be introduced when training data is not representative of the larger population, as seen in facial recognition models developed by predominantly white AI developers. The malicious use of AI highlights security threats such as hacking and hyper-personalized disinformation campaigns. Organizations planning to adopt deep learning capabilities must weigh their options, considering in-house development, outsourcing, or leveraging existing capabilities must weigh their options, considering in-house development, outsourcing, or leveraging existing capabilities must weigh their options, considering in-house development, outsourcing, or leveraging existing capabilities. human interfaces. Key challenges include creating and defining data, building infrastructure, and implementing governance processes. Organisations must also develop digital maturity and overcome the "last mile" problem of making sure AI insights drive behavioural change within their people and processes. The demand for AI experts far outstrips supply, with competition from tech giants fierce. All business cases can be elusive, especially when data and techniques are new or complex, and the value is unclear. Some use cases may not justify the cost, such as using facial recognition in airlines due to privacy concerns. Other scenarios involve immature data types, volumes, or techniques where the potential value is unknown. In some areas, like healthcare, AI could unlock significant economic value by broadening precision in diagnoses and medical procedures. However, this would require flawless technical execution and addressing legal concerns such as malpractice insurance and societal regulations, especially those related to personally identifiable information. The storage and use of personal information is particularly crucial in sectors such as banking, healthcare, pharmaceuticals, and social services. To address societal concerns, businesses must adapt their data-driven businesses must adapt the data-driven businesses adapt the data-driven businesses adapt the data-driven businesses adapt the data-driven businesses adapt the data-d for tailored approaches. For stakeholders, the key lies not in the AI technology, having a deep understanding of end markets is vital. While focusing on high-potential areas is tempting, combining data analysis with competitor landscape insights, internal strengths, and customer relationships can lead to more informed investment decisions. Technical guidance comes from mapping problem types and techniques to sectors and functions of value. Adopting AI in operations often begins with small-scale experiments. Before scaling up, businesses must prioritize their initiatives, focusing on the most valuable use cases and deploying the necessary analytical techniques. This requires understanding both theoretical potential and practical scalability, driven by a company's skills, capabilities, and data. Efforts to acquire and organize data (the "first mile") and integrate AI models into workflows (the "last mile") are critical, with previous research indicating significant investment in these areas. Policy makers must strike a balance between supporting AI technology development and addressing concerns around its use. Managing risks from nefarious actors is crucial for successful adoption of artificial intelligence (AI). The benefits of AI include higher labor productivity, economic growth, and societal prosperity. Governments can support AI development through research funding and training programs to nurture AI talent. Open data initiatives and common data standards can facilitate private innovation. However, AI raises new policy challenges that may require innovative solutions. Despite the challenges, the goal should be to encourage beneficial and safe AI use, rather than constraining its adoption. The latest McKinsey Global Survey reveals the rapid growth of generative AI (gen AI) tools. One-third of respondents say their organizations are using gen AI regularly in at least one business function. AI has become a priority for company leaders, with nearly one-quarter of C-suite executives personally using gen AI tools. The survey shows that early adopters have already embedded AI capabilities and are exploring gen AI tools, adoption grows, respondents expect significant workforce changes, including cuts and large reskilling efforts to address shifting talent needs. While gen AI may drive the adoption of other AI tools, adoption remains concentrated within a few business functions. Seventy-nine percent of respondents have been exposed to generative AI is consistent across seniority levels but higher among technology sector employees and those in North America. A third of respondents report their organizations are already using generative AI in at least one function, with 60 percent of organizations with AI adoption plan to increase investment in AI due to generative AI, and 28 percent have generative AI on their board's agenda. The primary business functions using these tools are marketing and sales, product development, and service operations, which aligns with areas where AI is commonly used. Three-quarters of respondents expect generative AI to significantly impact their industry's competition within three years, particularly in knowledge-based industries such as technology, finance, and education. However, few companies have established policies for governing the use of generative AI, with only 21 percent of respondents reporting AI adoption having such policies in place. This lack of preparedness may leave organizations vulnerable to potential risks associated with generative AI. Companies are prioritizing mitigating the risk of inaccuracy with generative AI (gen AI), which is cited more frequently than cybersecurity and regulatory compliance risks. Only 32% of respondents say their organizations are addressing this issue, a smaller percentage compared to those who mitigate cybersecurity risks. Most companies are not addressing AI-related risks overall. Others are struggling with the fundamental aspects of adopting AI, with high performers frequently citing issues related to models and tools, such as monitoring performance and retraining models. In contrast, other organizations face challenges in setting a clear AI vision that links to business value or securing sufficient resources. The findings highlight that even topperforming organizations have not fully mastered best practices for AI adoption, including machine learning operations approaches. For instance, only 35% of high performer respondents report assembling existing components rather than reinventing them, which is a more significant share than the 19% of other organizations who do so. Many specialized technologies and practices are necessary to adopt transformative AI use cases that deliver significant benefits while ensuring safety. One area where high performers excel but have room for growth is in live-model operations, with 25% of respondents reporting full system monitoring and instant alert setup, compared to 12% of other organizations. Most businesses see no significant improvement from previous survey on using AI, yet still optimistic about future gains. Many companies have already started seeing revenue growth from implementing AI in various businesses areas and plan to invest more in it next year. The majority of respondents reported an increase in AI-related revenues across different departments that utilize AI technology. Furthermore, over two-thirds expect their organization's AI spending to rise significantly within the next three years.

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