



THE IMPACT OF ARTIFICIAL INTELLIGENCE ON TRADITIONAL HUMAN ANALYSIS

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EXECUTIVE SUMMARY

In the modern age of digitization and strategic competition, success depends on an organization’s ability to harness data and technology better and faster than its competitors. Rapid advancements in artificial intelligence (AI) technologies are revolutionizing how public and private organizations stay ahead of the curve, impacting all levels of the traditional, human-driven analytic process. This report explores opportunities for the application of AI tools during the intelligence cycle to augment the human analyst’s abilities while mitigating their limitations to drive a more seamless intelligence process.

Human analysts excel in critical thinking and intuitive judgment. Their ability to interpret nuanced information, understand complex landscapes, and make informed decisions based on incomplete data sets is unparalleled. However, their effectiveness is inherently hindered by limitations such as data overload, cognitive biases, the need for resource-intensive training, and finite time and energy. Conversely, AI technologies excel at data processing, objectivity, and routine task automation. They can analyze vast amounts of data at unprecedented speeds, identify patterns, and perform repetitive tasks without physical or mental fatigue.

Thus, the complementary strengths of human and machine capabilities suggest a transformation in the analytic process, wherein an analyst-machine team collaborates adaptively and continuously to address complex threats with great insight in near real time. This new paradigm will require agile collaboration frameworks, skilled analysts who can effectively work with AI tools and interpret AI-generated insights, reliable and comprehensive training data and processes, and robust oversight mechanisms.

INTRODUCTION

Traditionally, intelligence analysis has depended upon the human analyst’s expertise, judgment, and tradecraft to interpret uncertainty and ambiguity in complex situations and provide clear insight for policymakers to act upon.ⁱ It requires a deep understanding of context and the ability to think critically and creatively about potential threats and opportunities. This understanding of modern intelligence emerged during the establishment and professionalization of the U.S. Intelligence Community (IC) in the wake of WWII.ⁱⁱ

The world has evolved significantly since then, but the foundations laid during that period have been lasting. Indeed, the Intelligence Cycle, a formal framework driving most intelligence organizations today, was developed during the early days of the IC. The process is illustrated in Figure 1. Its champion, Sherman Kent, emphasized a systematic analytic tradecraft approach, and his “work on confidence, probability, estimative statements, and dissents still underpins all-source intelligence analysis today.”ⁱⁱⁱ

The foundations of traditional intelligence analysis will remain critical to developing analysts as critical thinkers in



Figure 1: The Intelligence Cycle

both the public and private sectors. However, technology has fundamentally changed the world in the last half-century, requiring updated intelligence frameworks to address this new environment.^{iv} The key to establishing new approaches with lasting relevancy and success will be understanding the relative strengths and limitations of human analysts and AI to effectively harness them together as a team.

SCOPE AND METHODS

Our research team reviewed the small but growing body of literature on this topic to better understand how AI is being applied in similar fields and contexts. We also conducted interviews to gather insight from the expertise and experiences of the diverse stakeholders involved in modern intelligence, including U.S. military and law enforcement, private global risk and security operations, and technology vendors. We then leveraged the collective expertise of our dedicated team of 14 analysts, whose specialized skills and knowledge were instrumental in drawing meaningful conclusions.

Due to the interdisciplinary nature of the challenge, our research delved into multiple fields, including psychology, history, and public policy, as well as the technical fields related to AI. The research has revealed strategic insights that highlight AI's potential role in transforming traditional analytical processes. This paper first discusses the strengths and limitations of human analysts compared to AI, then explores human-machine teaming frameworks, the transformation of the intelligence process, and the current state of AI integration in the intelligence process. Finally, it outlines some key issues for future integration of AI tools into the intelligence cycle.

STRENGTHS AND LIMITATIONS OF THE HUMAN ANALYST

The role of the analyst is to evaluate data and provide actionable insights that help the organization make informed decisions and execute effective operations.^v Human analysts have invaluable skills, particularly intuitive judgment and critical thinking; these skills enable them to synthesize complex information quickly and with great nuance.^{vi} Human intuition, as described in Daniel Kahneman's groundbreaking book *Thinking, Fast and Slow*, allows humans to make quick, often accurate judgments without conscious reasoning, sometimes detecting patterns or anomalies that purely analytical methods might not recognize.^{vii} Humans also possess the skill of critical thinking, a slower, more deliberate reasoning process described by Kahneman as essential for complex problem-solving and decision-making tasks. This combination of intuition and reasoning is unique to humans, allowing human analysts to quickly assess new information in real time and with the deep contextual understanding crucial for accurate analysis.^{viii}

Nevertheless, human analysts face significant limitations, primarily the cognitive limitations of the human brain and the inherent drawbacks of human intuition. Humans have a limited capacity to process large volumes of data, and the sheer volume of data generated in modern intelligence operations can overwhelm even the most skilled team of analysts. Modern psychology indicates that the human brain has a limited capacity to process information and multitask, a phenomenon known as "cognitive overload," which increases stress and indecisiveness and diminishes analytical quality.^{ix} The constantly evolving and interconnected

nature of the current threat landscape, coupled with the volume of data and range of sources from which intelligence must now be derived, pushes analysts beyond what the human brain can effectively process.^x

Human intuition and mental processes also have a limited capacity to handle inherent and induced uncertainties, leaving human analysts susceptible to cognitive biases such as confirmation bias, anchoring, and availability heuristics.^{xi} This limitation has been studied extensively in psychology, including directly in the context of intelligence analysis. In his foundational book, *Psychology of Intelligence Analysis*, Richards Heuer noted:

“A basic finding of cognitive psychology is that people have no conscious experience of most of what happens in the human mind. Many functions associated with perception, memory, and information processing are conducted prior to and independently of any conscious direction... Accurate intelligence analysis obviously requires accurate perception. Yet research into human perception demonstrates that the process is beset by many pitfalls. Moreover, the circumstances under which intelligence analysis is conducted are precisely the circumstances in which accurate perception tends to be most difficult.”^{xii}

Unconscious mental processes can also increase subjectivity, as humans are influenced by personal experiences, beliefs, and perspectives, leading to inconsistent or biased analytical results. While critical thinking frameworks such as structured analytical techniques can mitigate these cognitive limitations, cognitive bias is still a significant source of analytical inaccuracy.^{xiii}

Another challenge is the human analyst’s experience and the burden of the content they are responsible for analyzing. In many organizations, information is often scattered across platforms, and expertise can be siloed with subject-matter experts (SMEs) and within their networks. In the IC, knowledge of resources and information is often shared through familiarity and word of mouth. Thus, it may be difficult for analysts to easily access the information they require to do their jobs. Analysts also experience fatigue and stress, especially in high-pressure situations, which negatively impact their performance and decision-making abilities.^{xiv} Some analysts are required to sift through emotionally disturbing information or images, which may impact the analyst’s mental health and the organization’s ability to retain skilled analysts.^{xv}

Finally, maintaining a skilled workforce of enough analysts to adequately manage rapidly proliferating data is increasingly resource-intensive.^{xvi} The sheer volume of raw data and the ongoing need for precision place significant strain on the traditionally labor-intensive process of collecting, processing, and analyzing intelligence. The World Economic Forum forecasts that by 2025, the volume of data expected to be created, captured, and consumed globally per year will equal 181 zettabytes, compared to 2 in 2010 and 64 in 2020.^{xvii} Theoretically, an increased quantity of available data should have a positive impact on intelligence analysis, as it should be possible to derive more accurate conclusions from larger data sets. However, the 2019 ODNI Augmenting Intelligence Using Machines (AIM) Initiative suggested that the increased availability of data actually makes the analyst’s job harder:

“The pace at which data are generated, whether by collection or publicly available information (PAI), is increasing exponentially and long ago exceeded our collective ability to understand it or to find the most relevant data with which to make analytic judgments.”^{xviii}

As the amount of available data to sift through increases, the number of needed analysts also increases. Early in the Afghanistan War, the Department of Defense (DoD) and IC requested \$16 billion in funding just for additional analyst support.^{xix} Since that time, the challenge of finding enough analysts has become even more difficult: the Director of the National Geospatial-Intelligence Agency (NGA) famously remarked in 2017 that if the NGA “attempted to manually exploit the imagery we will receive over the next 20 years, we would need eight million imagery analysts.”^{xx} While the United States Government (USG) does not report how many analysts it currently employs, eight million is much higher, possibly by orders of magnitude, than the number of analysts currently in the public sector. In fact, Joint Publication 2-0, Joint Intelligence recognizes that human analysts are a limited resource and that it may not be possible for organizations to afford existing analysts or to recruit new ones.^{xxi} The Bureau of Labor Statistics job outlook report suggests that the growth rate for most analyst occupations over the next 10 years will significantly outpace the national average for all occupations.^{xxii} However, even as organizations expand hiring efforts for all types of analysts, the analysts will struggle to keep up with data proliferation without the help of technology.

Analysts are also not the only actors in the intelligence cycle who must grapple with data proliferation. Senior leaders in the public and private sectors alike have reported challenges setting strategic intelligence requirements because they lack insight into their own ever-growing organizational data and its implications for directing intelligence.^{xxiii,xxiv} This limitation can result in strategic gaps due to analysts prioritizing tasks based on their own assessments of relevancy, or leaders setting priorities based on incomplete understanding of the tactical versus strategic view. Some insights likely can only be illuminated by leveraging AI-powered technology against an organization’s data.

STRENGTHS AND LIMITATIONS OF ARTIFICIAL INTELLIGENCE

AI refers to technology that enables computers and machines to mimic human intelligence and problem-solving capabilities.^{xxv} While technological advances have improved AI’s ability to simulate aspects of human intelligence, it is widely acknowledged that AI cannot yet fully replicate human intelligence and may never do so. However, some AI capabilities are greater than those of humans: AI excels in data processing, pattern recognition, and performing repetitive tasks with high accuracy and speed.^{xxvi}

AI technologies can recognize patterns or anomalies that are impossible for a human analyst to detect manually. A critical subset of AI is machine learning (ML); ML enables machines to perform tasks without explicitly being programmed to do so by leveraging statistical algorithms to discover complex patterns in a dataset.^{xxvii} The two aspects of ML this paper focuses on are unsupervised learning and large language models (LLMs), as they have the greatest impact on intelligence analysis. The easiest way to explain unsupervised learning is to compare it to supervised learning. In supervised learning, an algorithm uses a sample dataset to train itself to make predictions. These datasets use labeled data to provide the desired output values, enabling the model to determine a “correct” answer. In contrast, unsupervised learning

algorithms work independently to learn the data's inherent structure, without any specific guidance or instruction. Unlabeled data allows the algorithm to identify any naturally occurring patterns in the dataset.^{xxviii} LLMs, which are designed to understand and mimic human language, are an advanced application of unsupervised learning.^{xxix}

These technologies are revolutionizing the world of big data by processing data more rapidly and, in some cases, more accurately than humans. They excel at collecting and processing vast unstructured datasets, including text and non-text data, and recognizing patterns and anomalies that would be impossible to detect manually. ML particularly lends itself to predictive analytics and scenario modeling.^{xxx} ML models can learn from historical data to identify what constitutes normal behavior, and then detect complex patterns and subtle deviations from that behavior.^{xxxi} This capability allows predictive models to anticipate future deviations and emerging threats, and is applicable in diverse fields.^{xxxii} Unsupervised learning can also simulate various scenarios by exploring different data clusters and relationships, offering insights into how exceptions might evolve under different conditions.

In addition to uncovering patterns and anomalies, ML excels at tasks that a human would find time-consuming and tedious.^{xxxiii} ML systems can perform routine, repetitive tasks with high precision and without fatigue, reducing the time burden and error rate. ML-powered generative AI, including AI chatbots, can drive greater productivity by assisting with tasks like translation, summarization, and text generation; it offers advantages for knowledge management and democratizing information access, particularly for organizations where information is scattered across platforms or might otherwise be siloed with SMEs.

Finally, rules-based AI models excel at objectivity; they follow predefined rules and guidelines without deviation across all cases, eliminating the variability that can arise from human judgment.^{xxxiv} By relying on pre-programmed logic, AI tools can help apply rules consistently and uniformly when warranted to ensure compliance.

However, AI technologies, like human analysts, have significant limitations. Foremost, AI is only as good as the data it is trained on. Insufficient, poor-quality, or biased data can lead to inaccurate outcomes. The data used to train AI models can contain biases, and the rules themselves can be influenced by the biases of the people who create the tools. Moreover, because bias in AI cannot always be addressed, it may be necessary to entirely discard a biased AI and design a new one.^{xxxv} Since AI tools are trained on historical data, they may not be well-suited to address scenarios they are not trained for, particularly where historical data may not indicate future behavior. AI models can also produce inconsistent results when exposed to new scenarios. Even with high-quality data and the right parameters, AI lacks the human ability to merge intuition, critical thinking, and expertise. While AI tools can analyze data, they lack the ability to *understand*, often missing the broader context and nuances that humans fundamentally comprehend.^{xxxvi}

THE HUMAN-MACHINE TEAM

While the human analyst excels at intuitive and critical thinking but struggles with data processing and perception, AI excels at data processing but struggles with nuanced and contextual thinking. This suggests the potential for a complementary relationship between

human analysts and AI in intelligence analysis. AI will not replace the analyst; rather, AI and the human analyst will work as a team. AI will augment the analyst’s abilities by removing the processing burden and automating routine tasks, thus freeing up time and brain power for the analyst to focus on tasks that only the human analyst can do: manage complexity with expertise, nuance, and creativity.^{xxxvii}

Frameworks to optimize the strengths of both human analysts and AI systems include Human-in-the-Loop (HITL), Human-Machine Collaboration (HMC), and Human-Machine Teaming (HMT). For HITL models, the machine generates predictions or suggestions that are then actioned or vetoed by the human. This model is often used in safety-critical systems where human oversight is essential to prevent errors that could lead to significant harm.^{xxxviii} For instance, in cybersecurity, security information and event management (SIEM) systems constantly monitor activity on a designated network; they learn what is “normal” for that network and flag unusual activity for review by a human.^{xxxix}

HMC involves humans and machines working together interactively on tasks, leveraging each other’s strengths to optimize performance and achieve common goals.^{xl} This model is used in environments where continuous interaction and mutual adaptation between humans and machines are essential. Consider automobile manufacturing, where robots and human workers collaborate on an assembly line; robots perform repetitive tasks, and humans perform more complex or nuanced tasks.

HMT involves a more integrated approach: humans and machines work together to execute a broader range of complex tasks, particularly in physical and dynamic environments.^{xli} This teaming creates a feedback loop in which the machine's output can influence human decisions and vice versa. For example, airborne, surface, and aquatic drones can gather intelligence data, which is then analyzed by both AI systems and human analysts to make strategic decisions. Such systems are also used in situations that might be unsafe for humans or impossible for humans to reach.^{xlii, xliii}

THE TRANSFORMATION OF THE MODERN INTELLIGENCE FRAMEWORK

Human-machine teaming frameworks are, in many ways, at odds with the traditional intelligence cycle, demanding a fundamental rethinking of human and machine roles, responsibilities, and interdependencies.^{xliv} The traditional intelligence cycle follows a linear process, delineating sequential steps into hierarchical roles. This process can result in a slow and inflexible workflow with siloed subprocesses, and information may be lost as it is passed from one phase of the cycle to the next. This inefficiency, paired with a reliance on human analysts to sift through the vast quantity of available data, leads to a slow cycle that is insufficient to keep pace with the rapidly changing threat environment. Moreover, the traditional siloes between classified and unclassified information impede information sharing and create significant barriers to the public sector’s ability to share intelligence.^{xlv}

Modern technologies have disrupted this model. If decision-makers expect analysts “to fuse information rapidly and seamlessly into intelligence and deliver it quickly to the right place, at the right time, in an actionable format,” then the framework must be remodeled for the current environment.^{xlvi} Shifting data-intensive tasks to machines will give analysts additional time

and mental energy to focus on higher-order tasks. However, this one change will not address the shortcomings in the intelligence cycle as it is currently implemented; modern technology will ultimately condense the traditional cycle into real time, and the integration of AI will effectively require cycles within cycles to ensure success.

An example of a condensed intelligence cycle is the U.S. Army’s Tactical Intelligence Targeting Access Node (TITAN). TITAN’s suite of applications collects and fuses data from multiple sensors (space, high altitude, aerial, and terrestrial); its purpose is to reduce the sensor-to-shooter gap and enhance mission command.^{xlvii} TITAN thus drives a rapid intelligence process: collection, processing, analysis, and dissemination occur quickly, which enables real-time decision-making.^{xlviii} This condensed cycle adapts fluidly in some contexts, particularly the military, as military analysts and systems are often trained for dynamic environments, but in other contexts fluidity must be built. Even organizations prepared for dynamic environments will need to adapt to account for the feedback loops needed to integrate AI successfully.

The private sector offers potential models for adoption.^{xlix} For example, software development organizations and commercial start-ups use agile-style methodologies, emphasizing flexibility, collaboration, and iterative development to deliver products quickly in a dynamic environment. A cornerstone of agile-based methodologies is feedback loops, which are critical to the operation of AI but are a constraint in the traditional intelligence cycle. To fully utilize AI, continuous feedback loops must be included in any framework that monitors and evaluates the performance of the models and identifies those that need to be recalibrated, retrained, or replaced.



Figure 2: Illustration of an agile framework

In agile frameworks, these feedback loops might be stand-ups, sprint reviews, or retrospectives.ⁱ The AI-enabled intelligence process might include a step where analysts provide input when a computer vision-based model has inaccurately labeled objects in images or videos; the analyst would flag incorrect labels and correct them. The machine learning development team would use the feedback to determine if the model needs retraining. The NGA’s ASPEN program, which employs multimodal AI models to process geospatial intelligence, is working to implement processes like this, where analysts conduct labeling as part of their workflow, which helps the AI models improve their accuracy.ⁱⁱ

Incorporating AI and agile-based frameworks will require a cultural shift, particularly in the IC. Leadership will need to understand and champion the principles of trust, empowerment, and continuous improvement to help foster the culture necessary for agile methods to succeed. Organizations must also invest in the necessary training and tools.ⁱⁱⁱ Platforms and supporting

infrastructure for agile project management, data management, data analytics, model development, and model monitoring will need to be integrated into existing technology, and users will need to gain the necessary skills to use the new capabilities efficiently and intelligently.^{liii} Training and development can help analysts gain the skills necessary to use the new capabilities; education curricula may also need to be updated to address skills gaps. Oversight organizations will need to develop or revise policies, standards, and requirements for the new technologies. However, there is no one-size-fits-all answer to agile methodology and AI incorporation; customized solutions must be developed and adjusted as the environment develops.^{liv}

THE CURRENT STATE OF AI INTEGRATION IN THE INTELLIGENCE CYCLE

The intelligence field is predominantly in the early stages of adopting AI; technologies and use cases are proliferating, but many organizations are still exploring integration options and strategies. The private sector is leading the way in some areas, notably open-source intelligence (OSINT), though the resources of the public sector are yielding noteworthy advances in several areas. A 2023 report from the Government Accountability Office noted that, based on data from the 23 agencies included in the study, AI adoption across the USG is largely in the planning and early production stages.^{lv} The report notably excluded most IC agencies, but this status likely applies to the IC, as well. AI tools have been considered for various applications for years, but adoption has been slow. The ODNI released the AIM Initiative in 2019.^{lvi} However, the first IC Data Strategy, released in 2023, noted that “the central challenge remains that the IC is not fielding data, analytics, and artificial intelligence (AI)-enabled capabilities at the pace and scale required to preserve our decision and intelligence advantage.”^{lvii}

Although adoption of AI tools may be slower than necessary, organizations and agencies are adopting them. AI technologies are being widely designed and implemented to perform specific tasks in the traditional intelligence cycle. However, AI technologies are increasingly being developed to integrate various intelligence functions in near-real or real time, which underscores how technology condenses the time frame of the traditional intelligence cycle. Thus, many AI use cases are difficult to categorize within the traditional intelligence cycle because the tools move rapidly and seamlessly between various steps of the cycle. Below is a non-exhaustive list of actual examples and hypothetical use cases.

Predictive Analytics

AI-powered predictive analytics, which involves forecasting future events or modeling scenarios by identifying patterns and relationships in historical data, has significant potential to provide greater understanding and strategy to the field of intelligence, from optimizing requirements management and resource allocation to predictive threat modeling. For example, software such as Geolitica can analyze historical crime data to predict where crimes are likely to occur; police departments have used the tool to allocate resources more effectively.^{lviii} Despite its demonstrated effectiveness in some contexts, such software is controversial due to concerns about racial profiling and overall effectiveness.^{lix}

The field of investment banking also offers many use cases. IBM Watson uses advanced data analytics and machine learning to create financial forecasts and optimize budgeting processes.^{lx} Robo-advisory platforms such as Wealthfront and Betterment use AI/ML to predict market trends and analyze an individual’s financial situation, risk tolerance, and investment goals to adjust investments accordingly.^{lxi} Intelligence organizations could theoretically use such capabilities to model organizational data and intelligence gaps to optimize requirements budgeting and resource allocation.

Data Collection and Processing

Intelligence organizations are widely using AI tools to more quickly and effectively identify and categorize data.^{lxii} AI-powered data collection and processing can include data mining, imagery and facial recognition, natural language recognition, pattern recognition, and anomaly detection. These capabilities enable the rapid collection, processing, and integration of intelligence from sources including satellite and aerial data, financial transactions, public records, social media content, biometric data, forensics, and signals.

In one notable use case, after all other methods had failed, a USG agency used AI algorithms to “find an unidentified WMD research and development facility in a large Asian country.”^{lxiii} By searching and evaluating images of “nearly every square inch of the country,” the organization eventually identified a bus traveling between the facility and other known research and development facilities. Other examples include:

Open-Source Intelligence (OSINT):

- Federal, state, and local law enforcement organizations widely employ AI to collect and process crucial intelligence in real time, particularly OSINT, as well as vast volumes of electronic data from license plate readers, security cameras, sound detection systems, body-worn cameras, and subpoena returns.^{lxiv}
- The BAE Systems Integrated Intelligence Insights (I3) capability applies AI and ML technologies to open-source data, including commercial satellite and airborne imagery, social media, dark web content, and non-traditional imagery sources such as webcams, drone footage, and online images to identify, extract, and characterize structured observations.^{lxv}
- Giant Oak Search Technology (GOST®) is an ML-enabled screening and vetting tool that retrieves data from the open and deep web, as well as any desired databases, and then assigns analytic scores to the data, allowing analysts to triage entities and escalate threats as necessary. GOST employs LLMs and transformers to deliver language comprehension Named Entity Recognition (NER) to screen for relevant data, and behavioral pattern analysis.^{lxvi} Tools such as GOST allow public and private sector security operations centers to screen for indicators of violent behavior or criminal history to, for example, identify criminal opportunists during a crisis.^{lxvii}
- OSINT analysts and investigators also draw on a wide range of AI-powered tools to uncover critical information from PAI and the dark web.^{lxviii} These tools are designed for the individual analyst or investigator to augment their workflow. However, it is worthwhile to note that there are automated OSINT methods that do not rely on AI and still enable the processing of vast datasets. For example, Shadow Dragon offers an

automated monitoring platform called Horizon that automates collection without the use of ML.^{lxxix}

Imagery and Surveillance:

- The NGA uses the AI-powered ASPEN program to process and integrate geospatial intelligence to assist the analyst workflows so that they can more efficiently “identify adversaries’ activities that might warrant notification of the White House or the Pentagon.”^{lxx}
- Homeland Security Investigations (HSI) is exploring a program to combat child sexual abuse material (CSAM).^{lxxi, lxxii} The program automates the identification and categorization of CSAM, reducing human analysts’ exposure to harmful content and redirecting their time and attention to pursue leads generated during the process.
- The DOD and NGA’s Project MAVEN integrates AI into military surveillance to enhance drone video processing and analysis. By automating object detection and classification, MAVEN reduces the time and effort needed for manual analysis.
- The Centers for Disease Control and Prevention (CDC) uses a tool called TowerScout to identify cooling towers in aerial photos and imagery as part of investigations into outbreaks of Legionnaire’s Disease.^{lxxiii} The CDC’s HaMLET project uses computer vision models to screen chest X-rays to identify cases of tuberculosis.^{lxxiv}

Language and Other Data:

- HSI employs an ML tool called SpeechView for speech activity detection, language identification, gender estimation, transcription, translation, and speaker recognition.^{lxxv} Due to the limited availability of linguists, other agencies have recognized additional uses for such technology, such as transcribing and translating interviews and 911 calls.
- NVIDIA has developed multiple tools for data processing, including RTX and LILT. RTX is a personalized LLM chatbot connected to the user’s own data, enabling an analyst to select and curate the data the machine processes. LILT is a generative AI language translation tool that enables non-linguists to use machine translation for the initial triage of foreign language communications and linguists to translate more rapidly.^{lxxvi} The initial implementation was effectively employed by the U.S. Air Force.^{lxxvii}

Automated Report Generation

Generative AI may streamline the production of reports by structuring and formatting them with the necessary information, which reduces the manual effort required to produce standardized documents, such as situation reports (SITREPs) or intelligence information reports (IIRs). One example of this capability already in use is the Ontic Platform, which provides threat monitoring capabilities and has an integrated feature that can be used to generate tailored security reports.^{lxxviii} While automation alone is not considered to be AI, one user of the Ontic platform reported the platform’s automated report generator capability drastically reduced the manual effort required for report production.^{lxxix} In general practice, this capability could simultaneously deliver more accessible and actionable intelligence to customers while drastically reducing the lengthy process of tailoring products based on the same underlying intelligence and judgments.

In addition to reducing the time analysts spend learning and applying standardized formatting, generative AI could also help maximize consistency and understandability for the customer. For example, generative AI could conceivably suggest options for standardizing or disambiguating references to intelligence targets with multiple aliases, names, or designations. HSI uses AI tools to “verify, validate, correct, and normalize addresses, phone numbers, names, and ID numbers to streamline the process of correcting data entry errors, point out purposeful misidentification, connect information about a person across HSI datasets, and cut down the number of resource hours needed for investigations.”^{lxxx}

AI also has the capability to help maintain classification guidelines, releasability requirements, and privacy guidelines.^{lxxxi} For example, the Cybersecurity and Infrastructure Security Agency (CISA) uses an automated Personally Identifiable Information (PII) detection tool, which “leverages natural language processing tasks including named entity recognition coupled with Privacy guidance thresholds to automatically detect potential PII from within Automated Indicator Sharing submissions.”^{lxxxii}

Continuous Monitoring, Assessment, and Response

AI-powered tools can continuously monitor and analyze dynamic data streams to provide real-time insights, enhancing situational awareness. By processing diverse data sources, including imagery, signals intelligence, and human intelligence, AI can help identify evolving threats and potential unknowns that may impact intelligence assessments. This proactive approach enables analysts to adapt to changing environments and anticipate emerging challenges.

For example, ReGenAI, recently launched by Dataminr, is a new form of generative AI that automatically populates updates to ongoing incidents as new information is collected. Effectively, it scrapes news websites in multiple languages, summarizes the information, and pushes notifications to subscribers, providing a more timely and accurate representation of a given threat environment without human aggregation or interaction required. The immense volume of data collected is beyond a human’s capability to process and synthesize without AI.^{lxxxiii}

Another example is the Ontic Platform, which monitors data from multiple sources to provide a comprehensive view of known and emerging threat signals. The platform’s workflows enable collaboration with configurable processes. Embedded metrics and reporting allow users to see important threats, risks, and success measures in real-time, and to create tailored security reports as needed. Additionally, automation provides 24/7 visibility of systems data, rules-based processes, dynamic task management, and configurable alerts, enhancing overall security operations.^{lxxxiv}

Comprehensive Workflow & Knowledge Management

AI-enabled software, particularly generative AI with question-answering capabilities, is widely employed in both the public and private sectors to increase knowledge accessibility and assist with routine tasks throughout an analyst’s workflow. As intelligence organizations must often work with sensitive information, many have policies limiting the use of commercial generative

AI tools. However, organizations are in various stages of developing and deploying customized tools, including those based solely on an organization’s internally verified data.^{lxxxv}

- Analysts at the CIA use a generative AI desk assistant throughout their workflow. The CIA’s Director of artificial intelligence Innovation noted that the agency is using generative AI in its classified settings to assist analysts with a wide range of tasks, including “search and discovery assistance, writing assistance, ideation, brainstorming and helping generate counterarguments.”^{lxxxvi}
- The MITRE Corporation uses MITRE Insights, “an employee resource that uses AI to make it easier for staff to draw on knowledge developed across the company’s federally funded research and development centers, innovation centers, partnerships with industry, and independent research efforts.”^{lxxxvii} MITRE also offers mChat, its own customized GPT-4-enabled application. mChat is available employees for various purposes, and feedback is positive; some users note they are now “completing some projects within a day that had previously taken a week.”^{lxxxviii}
- The U.S. Department of Homeland Security (DHS) enterprise permits its employees to use commercially available chatbots as desk assistants. “Approved applications of commercial Gen AI tools to DHS business include generating first drafts of documents that a human would subsequently review, conducting and synthesizing research on open-source information, and developing briefing materials or preparing for meetings and events.”^{lxxxix}

Such tools fit seamlessly into current intelligence frameworks. However, there are hypothetical scenarios in which AI software could eventually transform how intelligence is generated and consumed, making intelligence more timely, accessible, and actionable. Consider the following: a customized user interface dashboard that is enabled with intelligence feeds based on a user’s specific job requirements, supported by a comprehensive intelligence-hosting platform where verified intelligence is updated in real time based on new inputs. Such capabilities could significantly improve intelligence feedback loops by updating and reinforcing inputs for each phase of the intelligence cycle with the real-time outputs from other phases, essentially turning the intelligence cycle into cycles within cycles (as opposed to a linear process with “finished” intelligence products as the primary output).

KEY ISSUES FOR FUTURE IMPLEMENTATION

The integration of AI into intelligence processes has demonstrated benefits, but will not be without challenges. Successful implementation requires developing a workforce with the necessary skill sets, investing in trusted AI solutions and necessary supporting infrastructure, new or updated policies, robust standards and requirements, oversight, cultivation of high-quality data sets, and ongoing consideration of the ethical implications.

Tradecraft

Analysts will require additional skills to work effectively with machines as AI is integrated into the intelligence process. Tool-specific training will be necessary, but analysts will also require

foundational skills such as prompt engineering and the tradecraft of critical thinking.^{xc} Prompt engineering involves crafting effective prompts to guide AI systems in generating valuable and relevant outputs and may be unfamiliar to many analysts, thus requiring training.^{xcii} More fundamentally, an analyst's value lies in their critical thinking abilities; those abilities must expand to be able to assess AI outputs, identify potential errors, and make informed decisions about and based on AI-generated information.

Trust

The lack of transparency in many AI systems and the pervasiveness of mistakes will be significant hurdles to adoption of AI by analysts, who must trust the tools they employ.^{xcii} Many AI models, especially deep learning systems, operate as “black boxes,” meaning their decision-making processes are not transparent. This lack of transparency can make it difficult for analysts to understand and trust the AI's conclusions. Additionally, mistakes such as chatbot “hallucinations” are still very common.^{xciii} Hallucinations in the context of AI refer to instances where AI generates incorrect or nonsensical information. Such mistakes can undermine trust in AI-provided solutions, so it is crucial for organizations to implement robust verification processes and maintain human oversight to ensure the accuracy and reliability of AI-generated outputs.

Data

Access to enough high-quality data to train AI models is a significant challenge.^{xciv} AI systems rely heavily on large datasets to learn and improve their performance. However, obtaining and curating such datasets can be difficult, especially when dealing with sensitive or proprietary information.^{xcv} Organizations must invest in data collection and management strategies to ensure they have the necessary data to train AI models effectively. This includes addressing issues related to data privacy, security, and ethical considerations.

Ethics

Using AI systems in intelligence analysis raises significant ethical and moral questions.^{xcvi} A primary ethical concern is the potential infringement on privacy and civil liberties. Autonomous surveillance systems capable of continuous monitoring can lead to significant privacy violations, especially in civilian contexts.^{xcvii} AI systems can perpetuate and even amplify existing biases in the data they are trained on, leading to discriminatory practices. The reliance on AI for image detection in intelligence operations must be balanced with considerations for accuracy and potential biases.

Misapplication

The overapplication of AI in analysis, particularly for tasks that humans are better equipped to address, could lead to poor results and potentially significant consequences.^{xcviii} Users and decision-makers should understand the purpose and limitations of the AI tools they employ, and limit the application of those tools to situations in which AI tool offers unique value. For example, AI is trained on historical data; as the data ages, or if the tool is applied to analysis of scenarios it is not trained for, it may result in unexpected and potentially erroneous

outputs.^{xcix} This uncertainty can be particularly problematic in high-stakes intelligence operations.

Subversion

Adversarial actors can significantly impact unsupervised machine learning by poisoning datasets with maliciously crafted data to skew results or degrade performance.^c This manipulation can lead algorithms to identify false patterns or anomalies, compromising the reliability of insights generated. Since unsupervised learning relies on discovering patterns in data that does not contain predefined labels, it is particularly vulnerable to such attacks. Implementing robust anomaly detection techniques and regular, standardized, documented model validation can help safeguard against data poisoning, ensuring the accuracy and trustworthiness of the model's outputs.^{ci}

CONCLUSION

In the evolving landscape of intelligence analysis, AI has the potential to be a transformative force, poised to augment the capabilities of human analysts if harnessed effectively. Machines have not, and will not, replace certain unique human skills, such as critical thinking, interpersonal collaboration, strategy development and implementation, or the direction of a more dynamic analysis. However, machines can complement human analysts meaningfully in the intelligence realm. By leveraging the strengths of both AI and human analysts, the intelligence community can achieve more agile, efficient, and effective intelligence analysis. The future of intelligence analysis lies in the seamless integration of AI capabilities and human expertise, working together to navigate the complexities of an increasingly data-driven world.

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ENDNOTES

ⁱ (U) | U.S. Office of the Director of National Intelligence | Intelligence analysis | <https://www.intelligence.gov/careers/explore-careers/389-intelligence-analysis>

ⁱⁱ <https://www.cia.gov/static/The-Creation-of-the-Intelligence-Community.pdf>

ⁱⁱⁱ (U) | Gartin, J. | Studies in Intelligence | June 2019 | The Future of Analysis | Vol. 63, No. 2 | pgs. 1-5 | <https://www.cia.gov/resources/csi/static/Future-of-Analysis.pdf>

^{iv} (U) | West, D. | The Brookings Institution | 24 January 2022 | How digital technology is reshaping espionage and intelligence-gathering | <https://www.brookings.edu/articles/how-digital-technology-is-reshaping-espionage-and-intelligence-gathering-the-techtank-podcast/>

^v (U) | U.S. Office of the Director of National Intelligence | Intelligence analysis | <https://www.intelligence.gov/careers/explore-careers/389-intelligence-analysis>

^{vi} (U) | U.S. Office of the Director of National Intelligence | Intelligence analysis | <https://www.intelligence.gov/careers/explore-careers/389-intelligence-analysis>

vii (U) | Kahneman, D. | Farrar, Straus and Giroux | 25 October 2011 | Thinking, Fast and Slow

viii (U) | Kahneman, D. | Farrar, Straus and Giroux | 25 October 2011 | Thinking, Fast and Slow

ix (U) | Palladino, L. | Free Press | 26 June 2007 | Find your Focus Zone: An Effective New Plan to Defeat Distraction and Overload

x (U) | Arnold, M., Goldschmitt, M., & Rigotti, T. | Frontiers in Psychology | 21 June 2023 | Dealing with information overload: a comprehensive review | <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10322198/>

xi (U) | Williams, B. | Military Review | Sep-Oct 2010 | Heuristics and Biases in Military Decision Making | https://www.armyupress.army.mil/Portals/7/military-review/Archives/English/MilitaryReview_20120630MC_art011.pdf

xii (U) | Heuer, R., Jr. | CIA Center for the Study of Intelligence | 1999 | Psychology of Intelligence Analysis | https://www.iaieia.org/docs/Psychology_of_Intelligence_Analysis.pdf

xiii (U) | U.S. Government | March 2009 | A Tradecraft Primer: Structured Analytic Techniques for Improving Intelligence Analysis | <https://www.cia.gov/resources/csi/static/Tradecraft-Primer-apr09.pdf>

xiv (U) | Palladino, L. | Free Press | 26 June 2007 | Find your Focus Zone: An Effective New Plan to Defeat Distraction and Overload

xv (U) | Ahern, E. C., Sadler, L. H., Lamb, M. E., & Gariglietti, G. M. | Child Abuse Review | May 2016 | Wellbeing of professionals working with suspected victims of child sexual exploitation | Vol. 26, No. 2 | pgs. 130–140

xvi (U) | Griffiths, T. L. | Trends in Cognitive Sciences | November 2020 | Understanding Human Intelligence through Human Limitations | pgs. 873-883 | <https://cocosci.princeton.edu/papers/griffithsunderstanding.pdf>

xvii (U) | Reinsel, D., Gantz, J., & Rydning, J. | International Data Corporation | Doc# US44413318 | November 2018 | The digitization of the world from edge to core | <https://www.seagate.com/files/www-content/our-story/trends/files/idc-seagate-data-age-whitepaper.pdf>

xviii (U) | Office of the Director of National Intelligence | 2019 | The AIM Initiative: a strategy for augmenting intelligence using machines | <https://www.dni.gov/files/ODNI/documents/AIM-Strategy.pdf>

xix (U) | Cartwright, J. | Personal Communication | 10 August 2024

xx (U) | Office of the Director of National Intelligence | 7 August 2017 | Small Satellites – Big Data | https://www.nga.mil/news/Small_Satellites_-_Big_Data.html

xxi (U) | U.S. Joint Chiefs of Staff | 2024 | JP 2-0, Joint Intelligence | <https://www.jcs.mil/Doctrine/Joint-Doctrine-Pubs/>

xxii (U) | U.S. Bureau of Labor Statistics | 17 April 2024 | Occupational Outlook Handbook | <https://www.bls.gov/ooh/home.htm>

xxiii (U) | Interview series | June 2024 | Virginia and Remote

xxiv (U) | Gioe, D., Parkhurst, J., & Gioe, D. V. | International Journal of Intelligence and CounterIntelligence | 14 August 2023 | Can Private Sector Intelligence Benefit from U.S. Intelligence Community Analytic Standards? | <https://www.tandfonline.com/doi/full/10.1080/08850607.2023.2235078#abstract>

xxv (U) | IBM | Artificial Intelligence (AI) | <https://www.ibm.com/topics/artificial-intelligence>

xxvi (U) | Korteling, J., van de Boer-Visschedijk, G., Blankendaal, R., Boonekamp, R., & Eikelboom A | 25 March 2021 | Frontiers in Artificial Intelligence | Human- versus Artificial Intelligence | <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8108480/>

xxvii (U) | IBM | Machine Learning | <https://www.ibm.com/topics/machine-learning>

xxviii (U) | Google Cloud | Supervised vs. unsupervised learning: What's the difference? | <https://cloud.google.com/discover/supervised-vs-unsupervised-learning>

xxix (U) | IBM | Large Language Models | <https://www.ibm.com/topics/large-language-models>

xxx (U) | Carnegie Council for Ethics in International Affairs | Predictive AI | <https://www.carnegiecouncil.org/explore-engage/key-terms/predictive-ai>

xxxi (U) | Carnegie Council for Ethics in International Affairs | Predictive AI | <https://www.carnegiecouncil.org/explore-engage/key-terms/predictive-ai>

xxxii (U) | IBM | What is Predictive Analytics? | <https://www.ibm.com/topics/predictive-analytics>

xxxiii (U) | Starn, J. | Bloomberg | 10 May 2019 | Robots Thrive in the Forest on Jobs That Humans Find Too Boring | <https://www.bloomberg.com/news/articles/2019-05-10/robots-thrive-in-the-forest-on-jobs-that-humans-find-too-boring>

xxxiv (U) | Liu, H., Teng, Z., Zhang, C., & Zhang, Y. | arXiv | 28 April 2024 | Logic Agent: Enhancing Validity with Logic Rule Invocation | <https://arxiv.org/abs/2404.18130>



- xxxv (U) Rubin, S. | Interview | 14 June 2024 | Herndon, VA
- xxxvi (U) | Rubin, S. | Interview | 14 June 2024 | Herndon, VA
- xxxvii (U) | Freeman, J. | The Alan Turing Institute | 20 December 2021 | Trustworthy AI forum: Human-machine teaming | <https://www.turing.ac.uk/trustworthy-ai-forum-human-machine-teaming>
- xxxviii (U) | Freeman, J. | The Alan Turing Institute | 20 December 2021 | Trustworthy AI forum: Human-machine teaming | <https://www.turing.ac.uk/trustworthy-ai-forum-human-machine-teaming>
- xxxix (U) | Microsoft | What is SIEM? | <https://www.microsoft.com/en-us/security/business/security-101/what-is-siem>
- xi (U) | Deloitte | 22 November 2022 | Strengthening the bonds of human and machine collaboration | <https://www2.deloitte.com/us/en/insights/topics/talent/human-machine-collaboration.html>
- xli (U) | Brookings | Building Trust in Human Machine Teams | 18 February 2021 | <https://www.brookings.edu/articles/building-trust-in-human-machine-teams/>
- xlii (U) | U.S. Department of Defense | 14 July 2022 | Robot Dog | <https://www.defense.gov/Multimedia/Photos/igphoto/2003050362/>
- xliii (U) | Dominion Energy | 10 May 2023 | Drones are making our nuclear operations safer and smarter | <https://www.dominionenergy.com/our-stories/drones-are-making-our-nuclear-operations-safer-and-smarter>
- xliv (U) | Shanahan, J. | Personal communication | 11 August 2024
- xlv (U) | Hopmeier, M. | | Personal communication | 8 August 2024
- xlvi (U) | Jamieson, D. | Mitchell Institute for Aerospace Studies | 2024 | Human Machine Teaming: The Intelligence Cycle Reimagined. Mitchell Institute for Aerospace Studies | https://mitchellaerospacepower.org/wp-content/uploads/2024/01/MI_Forum_53-HMT-FINAL.pdf
- xlvii (U) | Program Executive Office Intelligence, Electronic Warfare and Sensors | 27 September 2021 | TITAN brings together systems for next-generation intelligence capabilities | <https://peoiews.army.mil/2021/09/27/titan-brings-together-systems-for-next-generation-intelligence-capabilities>
- xlviii (U) | Palantir Technologies | 2022 | Army selects Palantir to build TITAN program competitive prototype. Palantir Technologies | <https://www.palantir.com/newsroom/press-releases/army-selects-palantir-to-build-titan-program-competitive-prototype/>
- xliv (U) | Brown, Z. | Defense One | 23 June 2020 | The US Intelligence Community Is Being Disrupted | <https://www.defenseone.com/ideas/2020/06/us-intel-community-being-disrupted/166372/>
- i (U) | Schlickemaier, W. | Studies in Intelligence | 2023 | Transforming Intelligence Production Through Lean Start-up Methods | pgs. 15-22 | <https://www.cia.gov/resources/csi/static/Article-An-Approach-Agile-Analysis-Sep-2023.pdf>
- ii (U) | Erwin, S. | SpaceNews | 7 May 2024 | Geospatial intelligence gets smart | <https://spacenews.com/geospatial-intelligence-gets-smart/>
- iii (U) | Stanislawski, D. | Interview | 30 May 2024 | Herndon, VA and Zoom
- iiiii (U) | Stanislawski, D. | Interview | 30 May 2024 | Herndon, VA and Zoom
- liv (U) | Zavala-Quinones, A. | LinkedIn | 16 June 2024 | Use of Agile Methodologies in the Intelligence Community and Agencies | <https://www.linkedin.com/pulse/transforming-intelligence-operations-agile-community-zavala-quinones-q3d8c/>
- lv (U) | U.S. Government Accountability Office | 12 December 2023 | Artificial Intelligence: Agencies Have Begun Implementation but Need to Complete Key Requirements | <https://www.gao.gov/products/gao-24-105980>
- lvi (U) | Office of the Director of National Intelligence | 2019 | The AIM Initiative: a strategy for augmenting intelligence using machines | <https://www.dni.gov/files/ODNI/documents/AIM-Strategy.pdf>
- lvii (U) | Office of the Director of National Intelligence | 2023 | IC Data Strategy 2023-2025 | <https://www.dni.gov/files/ODNI/documents/IC-Data-Strategy-2023-2025.pdf>
- lviii (U) | NAACP | Artificial intelligence and predictive policing: Issue brief. | <https://naacp.org/resources/artificial-intelligence-predictive-policing-issue-brief>
- lix (U) | Bates, T. | California Sociology Forum | 1 June 2024 | Technology and Culture: How Predictive Policing Harmfully Profiles Marginalized People Groups | <https://journals.calstate.edu/csf/article/view/4198>
- lx (U) | Kalibbala, J. | TechRepublic | 14 August 2023 | IBM Watson - A Cheat Sheet | <https://www.techrepublic.com/article/ibm-watson-the-smart-persons-guide/>

- lxi (U) | Peranzo, P. | Imaginovation | 30 August 2023 | AI for Better Finance: Real-World Use Cases and Examples | <https://imaginovation.net/blog/ai-in-finance/>
- lxii (U) | Scale | Guide to AI for the Intelligence Community | <https://scale.com/guides/guide-to-ai-for-the-intelligence-community>
- lxiii (U) | O'Brien, A. | Wired | 21 June 2022 | The Power and Pitfalls of AI for US Intelligence | <https://www.wired.com/story/ai-machine-learning-us-intelligence-community/>
- lxiv (U) | Epstein, B. & Emerson, J. | Police Chief Magazine | 2024 | Navigating the future of AI and ChatGPT in law enforcement | <https://www.policechiefmagazine.org/navigating-future-ai-chatgpt/>
- lxv (U) | BAE Systems | In an era of digital transformation, artificial intelligence takes center stage | <https://www.baesystems.com/en-us/feature/in-an-era-of-digital-transformation-artificial-intelligence-takes-center-stage>
- lxvi (U) | Giant Oak | 2023 | GOST® for Government | <https://www.giantoak.com/government>
- lxvii (U) | Giant Oak | 2020 | GOST for GOV 2020 | https://f.hubspotusercontent30.net/hubfs/3396037/GOST%20for%20GOV%202020_Final.pdf
- lxviii (U) | Flashpoint | 13 January 2023 | OSINT Tools Library | https://flashpoint.io/blog/osint-tools-library/?sfccampaign_id=701Rc000007eXNpIAM&utm_campaign=WB_Hosted_AI_for_OSINT_20240313&utm_source=pardot&utm_medium=email
- lxix (U) | Clemens, D. | ShadowDragon | Trust Center / Accessing data lawfully with respect for individual privacy | <https://shadowdragon.io/trustcenter/>
- lxx (U) | Erwin, S. | SpaceNews | 7 May 2024 | Geospatial intelligence gets smart | <https://spacenews.com/geospatial-intelligence-gets-smart/>
- lxxi (U) | U.S. Department of Homeland Security | Artificial Intelligence and Combatting Online Child Sexual Exploitation and Abuse | https://www.dhs.gov/sites/default/files/2024-04/24_0408_k2p_genai-bulletin.pdf
- lxxii (U) | Kelly, A. | Nextgov/FCW | 22 October 2023 | DHS looks to AI to help solve child abuse cases | <https://www.nextgov.com/artificial-intelligence/2023/10/dhs-looks-ai-help-solve-child-abuse-cases/390866/>
- lxxiii (U) | U.S. Centers for Disease Control and Prevention | Artificial Intelligence and Machine Learning: Applying Advanced Tools for Public Health | <https://www.cdc.gov/surveillance/data-modernization/technologies/ai-ml.html>
- lxxiv (U) | U.S. Centers for Disease Control and Prevention | Artificial Intelligence and Machine Learning: Applying Advanced Tools for Public Health | <https://www.cdc.gov/surveillance/data-modernization/technologies/ai-ml.html>
- lxxv (U) | U.S. Department of Homeland Security | 9 May 2022 | S&T tech leads to children rescued and traffickers arrested | <https://www.dhs.gov/science-and-technology/news/2022/05/09/feature-article-st-tech-leads-children-rescued-and-traffickers-arrested>
- lxxvi (U) | NVIDIA | Improving the Air Force's Global Awareness and Decision Advantage | <https://iilt.com/customer-stories/usaf>
- lxxvii (U) | NVIDIA | AI-Powered Language Translation in Criminal Investigations | <https://www.nvidia.com/en-us/case-studies/iilt/>
- lxxviii (U) | Ontic | Platform | <https://ontic.co/platform/>
- lxxix (U) | B. Janine. | Personal communication | 10 August 2024
- lxxx (U) | U.S. Department of Homeland Security | Artificial Intelligence Use Case Inventory | https://www.dhs.gov/data/AI_inventory
- lxxxi (U) | Scale | Guide to AI for the Intelligence Community | <https://scale.com/guides/guide-to-ai-for-the-intelligence-community>
- lxxxii (U) | U.S. Department of Homeland Security | Artificial Intelligence Use Case Inventory | https://www.dhs.gov/data/AI_inventory
- lxxxiii (U) | Dataminr | Interview | 25 April 2024 | Teams
- lxxxiv (U) | Ontic | Platform | <https://ontic.co/platform/>
- lxxxv (U) | Interview series | June 2024 | Virginia and Remote
- lxxxvi (U) | Konkol, F. | Defense One | 5 July 2024 | The US intelligence community is embracing generative AI | <https://www.defenseone.com/technology/2024/07/us-intelligence-community-embracing-generative-ai/397860/>
- lxxxvii (U) | MITRE | 27 March 2023 | MITRE Wins Third Consecutive CIO 100 Award | <https://www.mitre.org/news-insights/award/mitre-wins-third-consecutive-cio-100-award>



- ^{lxxxviii} (U) | MITRE | 18 March 2024 | MITRE Wins CIO100 Award for Enterprise Implementation of Generative AI | <https://www.mitre.org/news-insights/news-release/mitre-wins-cio100-award-enterprise-implementation-generative-ai>
- ^{lxxxix} (U) | U.S. Department of Homeland Security | Artificial Intelligence Use Case Inventory | https://www.dhs.gov/data/AI_inventory
- ^{xc} (U) | Russo, C. | American Military University | 28 June 2024 | <https://www.amu.apus.edu/area-of-study/intelligence/resources/critical-thinking-and-intelligence-analysis/>
- ^{xcⁱ} (U) | McKinsey & Company | 22 March 2024 | What is prompt engineering? | <https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-prompt-engineering>
- ^{xcⁱⁱ} (U) | Chakravorti, B. | Harvard Business Review | 3 May 2024 | AI's Trust Problem: Twelve persistent risks of AI that are driving skepticism | <https://hbr.org/2024/05/ais-trust-problem>
- ^{xcⁱⁱⁱ} (U) | Dahl, M., Magesh, V., Suzgun, M., & Ho, D. | Stanford Institute for Human-Centered Artificial Intelligence | 11 January 2024 | Hallucinating Law: Legal Mistakes with Large Language Models are Pervasive | <https://hai.stanford.edu/news/hallucinating-law-legal-mistakes-large-language-models-are-pervasive>
- ^{xc^{iv}} (U) | Rizzoli, A. | V7 | 11 July 2022 | An Introductory Guide to Quality Training Data for Machine Learning | <https://www.v7labs.com/blog/quality-training-data-for-machine-learning-guide>
- ^{xc^v} (U) | Global Security Review | The Double-edged Sword of Artificial Intelligence | <https://globalsecurityreview.com/the-double-edged-sword-of-artificial-intelligence/>
- ^{xc^{vi}} (U) | Office of the Director of National Intelligence | June 2020 | Artificial Intelligence Ethics Framework for the Intelligence Community | <https://www.intelligence.gov/artificial-intelligence-ethics-framework-for-the-intelligence-community>
- ^{xc^{vii}} (U) | SCNR | 8 August 2024 | AI-Driven Drone Surveillance Is Leading to Unexpected Home Insurance Cancellations | https://scnr.com/article/ai-driven-drone-surveillance-is-leading-to-unexpected-home-insurance-cancellations_ea244cc8558f11ef9c930242ac1c0002
- ^{xc^{viii}} (U) | Center for Security and Emerging Technology | 2020 | Artificial Intelligence and National Security | https://bipartisanpolicy.org/wp-content/uploads/2020/07/BPC-Artificial-Intelligence-and-National-Security_Brief-Final-1.pdf
- ^{xc^{ix}} (U) | Australian Human Rights Commission | 24 November 2020 | Historical bias in AI systems | <https://humanrights.gov.au/about/news/media-releases/historical-bias-ai-systems>
- ^c (U) Simons, A. | FedTech | 11 January 2024 | Unpacking AI Data Poisoning | <https://fedtechmagazine.com/article/2024/01/unpacking-ai-data-poisoning>
- ^{cⁱ} (U) | Aljanabi, M., Hamza, A., Mijwil, M., Abotaleb, M., El-Kenawy, E., Mohammed, S., & Ibrahim, A. | Proceedings of the 7th IET International Smart Cities Symposium | 3-5 December 2023 | Data Poisoning: Issues, Challenges, and Needs | https://www.researchgate.net/publication/379842460_Data_poisoning_issues_challenges_and_needs

