Synapsis | Journal of Psychological and Interdisciplinary Research

TYPE Brief Report
PUBLISHED 13 September 2025
DOI https://doi.org/10.69127/synapsis.2025.01.09

The Cognitive and Psychological Resilience of Intelligence Analysts in the Age of Artificial Intelligence: Morphological Analysis, Future Scenarios to 2030, and Neurobiological Perspectives

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Abstract

The advent of artificial intelligence (AI) has radically transformed the operational landscape of intelligence, posing complex challenges to analysts, cognitive and psychological resilience. These challenges arise from AI's capacity to psychometrically profile analysts using advanced behavioral and cognitive algorithms, predicting and potentially manipulating their decision-making processes. Information behavior aims to understand human behavior related to the search, retrieval, and use of information. It is based in research paradigms such as psychology, sociology and education. Furthermore, human-AI interaction creates long-term cascading effects on analytical quality through short and long- term neurobiological mechanisms. This theoretical-conceptual study adopts General Morphological Analysis (GMA), combined with Parsons, Kruijt, and Fox's cognitive resilience model and other neurobiological concepts well known, to assess in detail the interconnections among technological, cognitive, organizational and neurobiological factors. The analysis explores possible configurations focusing on AI-human analytical interactions through systematic scenario development. Three primary scenarios emerge: AI dominance, balanced collaboration, and human-centric separation; balanced collaboration is identified as optimal. A backcasting roadmap with specific milestones from 2025 to 2030 is proposed to guide implementation.

Keywords: Artificial intelligence, cognitive resilience, psychological resilience, intelligence analysis, general morphological analysis, neurobiology, 2030 scenarios

Introduction

Five main phases compose traditional intelligence: Planning and direction, collection, processing, analysis, dissemination. Thus phases combined to organizational factors such as structure and philosophy, communication strategies, team resources and administrative support play a crucial role for the success of information system implementation (Yeoh & Popovic 2016).

The integration of artificial intelligence into intelligence processes represents a revolution that has deeply altered how analysts collect, process, and interpret information. This transformation unfolds across three key dimensions, each redefining the analyst's role and their relationship with technology: (1) large-scale data processing, (2) advanced predictive support, and (3) intelligent automation of processes. However, we must remember that consistent research suggest that AI and algorithms should be used cautionally as this may lead to algorithmic/automation bias (Labib et al 2021)

Modern AI systems can analyze terabytes of data—such as satellite imagery, social media posts, and financial transactions—in near real-time, identifying correlations (e.g., a terrorist network through metadata analysis) that would take human teams months.

This technological shift introduces significant cognitive and psychological challenges Among these, cognitive manipulation, information overload, and technological dependence intertwine with neurobiological implications such as dopamine-driven stress and the amplified cognitive biases (Glickman & Sharot, 2023).

Research Question: How can resilience be preserved and enhanced in the face of increasing AI autonomy and complexity through 2030?

Study Objectives: This study aims to: (1) map the multidimensional interactions between AI systems and analyst, neurocognitive and psychological resilience, (2) identify optimal configurations for human-AI collaboration, (3) develop actionable scenarios for organizational adaptation, and (4) provide a roadmap for maintaining analytical quality while integrating advanced AI capabilities.

Contribution to Literature: This research contributes to the emerging field of human-AI interaction in high-stakes environments by integrating cognitive resilience theory with morphological analysis methodology, offering both theoretical insights and practical frameworks for intelligence organizations navigating AI integration.

While the language remains academic, examples such as the rapid detection of a cyber threat using AI versus manual analysis (10 minutes vs. hours) are included to enhance accessibility for non-experts in intelligence or neuroscience.

To our knowledge, this is the first study to combine MGA with neurobiological aspects in assessing the interaction between AI and intelligence analysts, and it is the first to evaluate the theoretical interventions to be implemented by 2030 to make the most of the AI-human interaction. The next step is the longitudinal study to validate in the field what we have endorsed at a theoretical level.

Transformation of the Operational Landscape

The integration of artificial intelligence into intelligence processes represents a revolution that has profoundly changed the way analysts collect, process, and interpret information.

This change is articulated through three fundamental dimensions, each of which redefines the role of the analyst and his or her relationship with technology:

-Large-scale data processing:

Modern AI systems are capable of processing massive amounts of data - terabytes or even petabytes – in real or near-real time. For example, an AI system could simultaneously analyze streams of data from wiretaps, satellite images, social media posts and financial transactions, identifying correlations that a human analyst could not pick up without weeks of manual work. This capability relies on machine learning algorithms that recognize complex patterns, such as the suspicious behavior of an individual that only emerges from the intersection of heterogeneous sources (text, images, numerical data). A case in point might be the identification of a terrorist network through the analysis of phone metadata and bank movements, a task that the AI completes in hours while a human team would take months.

Open Source Intelligence (OSINT) is the most common source of intelligence that uses AI.

OSINT is the practice of gathering, analyzing, and disseminating information from publicly available sources to produce actionable intelligence.

An example outside of state intelligence services is that of a group of scholars who used advances in news sensors and artificial intelligence to generate detailed maps of global threats

In three months their autonomous system processed 22 k news from all possible major social media sites, Government websites of 192 countries and 2397 connected news sources such as BBC, CNN, NY Times,The research discloses attractive news and global threat-maps with trusted overall classification accuracy (Sufi et al. 2022).

-Advanced predictive support: AI-based predictive models do not simply extrapolate linear trends from historical data, as old statistical systems did. Today, these models incorporate multivariate analyses that take into account a wide range of contextual variables:

geopolitical conditions, economic variations, weather events, even collective moods inferred from social media.

For example, an AI system might predict an insurgency in a region by combining data on unemployment, posts on platforms such as X expressing anger, and reports of troop movements. The result are detailed probabilistic scenarios, with specific probability percentages for each outcome (e.g., “60 percent risk of conflict within 3 months”), which provide analysts with a solid basis for planning countermeasures.

With this aim, some studies applied deep learning, machine learning and techniques to make an AI-based model of terrorism. Moreover, others have integrated Natural Language Processing to extract helpful information, with machine learning showing effectiveness in categorization of different types of assaults (Abdalsalam et al., 2023)

<u>-Intelligent process automation:</u> AI does not just perform repetitive tasks such as transcribing audio or classifying documents. It also includes sophisticated forms of pre-analysis: for example, a system could automatically categorize thousands of intelligence reports into thematic clusters (e.g., “suspicious economic activity,” “military movements,” “online propaganda”), highlighting those most relevant for in-depth human analysis. This appears at first glance to free analysts from monotonous tasks, allowing them to focus on aspects that require insight, creativity and critical judgment, such as strategic assessment of the implications of an event. However, we are in the early days of this automation of analysis, and we wonder if there may be any medium- and long-term implications arising from this interactive process between AI and analyst. As already extensively studied in law enforcement, stress responses affect motor and cognitive skills needed for urgent situations. Employees who lack the ability to cope may became a threat, for colleagues, the public and themselves (Rabbing et al.2022).

Similarly, intelligence analysts are part of the security system and it is needed to work under stress and pressure.

The technological transformation brings significant complications. We live in the “Dopaminergic Era” (Lembke, 2021), a term coined to describe a world in which fast and continuous stimuli, such as social media notifications or real-time data streams, activate dopamine release in the brain, creating a form of addiction similar to the one induced by substances such as cocaine. For intelligence analysts, constantly exposed to dashboards that update information every few seconds, this can be translated into a reduction of concentration in completing a task, as well as increasing cognitive stress. In addition, studies such as that of Glickman and Sharot (2023), show that prolonged interaction with AI systems amplifies human cognitive biases;

confirm bias or the tendency to overestimate the likelihood of rare events, generating a snowball effect that distorts perceptual, emotional and social judgments.

Research on the effects of high-level interactions between AI and intelligence analysts is limited, but analyst draws on the same neurocognitive, emotional and epigenetic mechanisms that apply to everyone.

The data on the actual analysis failures, resulting from these potential alterations we list, are classified, but we can draw clear hypotheses from other related fields.

Emerging Challenges

The challenges introduced by AI are not only technical, but deeply cognitive and psychological, with direct impacts on the quality of intelligence analysis:

-Cognitive Manipulations: Advanced AI systems can identify individual decision-making biases of analysts-for example, a tendency to favor information that confirms pre-existing hypotheses and exploit them to influence their conclusions. It could lead to such conditioning that we could speak of "cognitive blindness"; which is what happens when observing a scene or an image, we focus on some details, completely neglecting others, even rather conspicuous ones. A practical example would be a system that presents data in order designed to emphasize minor threats, causing the underestimation of more significant risks from analysts. At a deeper level, AI can gradually alter interpretive patterns, changing the perception of risk in subtle but systematic ways, a phenomenon that becomes particularly dangerous when it serves the interests of adversary actors (e.g., targeted disinformation).

Information overload: The modern operating environment does not just provide more data, but presents it in multidimensional complexity that defies human cognitive limits. Analysts must handle increasing volumes of contradictory, ambiguous and often intentionally misleading information (disinformation).

As explained above, real and exhaustive data on failed analyses are confidential. However, we can make assumptions based on existing data in related fields.

A relevant example are drones and remotely piloted aircraft. The rapid expansion of these technologies also brings new challenges, privacy and security risks, moral and ethical issues.

Approximately 84% of reported incidents of drone smuggling occurred on the border between Pakistan and India, 12% between Syria and Jordan, and 4% between Lebanon and Israel.

28% percent of incidents in correctional facilities involve the delivery of drugs and illegal items by drones. Several communities and neighborhoods in the United States, India, the United Kingdom, and Israel have experienced violence through the use of armed drones (Seidaliyeva et al.2023)

Remotely piloted aircraft (RPA) have been used in military operations for decades. Operators of this kind have a unique set of combat experiences and psychological consequences. RPA crews operate from a distance of up to thousands of kilometers from the target. They are involved in the detection, surveillance, targeting, attack, and post-battle assessment of individuals of interest to a host country or agency from a distance of up to several thousand kilometers. On a psychological level, symptoms like anxiety, difficulty falling or staying asleep, difficulty concentrating, irritability, depression, burnout, sleep disorder and post-traumatic stress disorder (PTSD) are evident, as well as moral damage. To monitor the onset of these pathologies, the US Air Force has included clinical psychologists with the necessary security clearance in RPA operational units.

The results of fifteen years of research suggest that the vulnerability of RPA crews appears to be related to age, low social and/or family support, long working hours, operational aspects such as ergonomics, work shifts, tedious long surveillance missions, and the lack of a formal or informal space for post-attack psychological processing (Norrholm et al.2023).

<u>Technology Dependence:</u> The increasingly deep integration of AI into analytic workflows is leading to a gradual erosion of autonomous analytic capabilities. Analysts, accustomed to receiving preprocessed data and algorithmic recommendations, may be losing the ability to conduct independent analyses, a phenomenon comparable to muscle atrophy due to lack of exercise (Lieber & Ward, 2011).

This results in overconfidence in AI outputs, a reduced ability to detect algorithmic errors (e.g., an unrecognized false positive), and a loss of fundamental skills such as manual interpretation of raw data. The analyst is thus led into a process of involutional adaptation to his or her task. Many studies remind us of how adaptive human beings are in their integrity; for example, the natural design of the musculoskeletal system and respiratory muscles have already been shown to adapt and change to meet the body's functional needs. They alter their structural and functional properties according to the conditions imposed from environment, thus resulting in a constant state of remodeling. (Lieber et al 2011, Gransee et al.2012).

Psychometric Profiling and Human Plasticity

Psychometric profiling represents an advanced application of AI that builds predictive models of analysts' cognitive and psychological characteristics, relying on frameworks such as the Big Five (openness to experience, conscientiousness, extraversion, agreeableness, emotional stability). For example, a system could monitor how likely an analyst is to explore alternative interpretations (openness) or maintain decision-making lucidity under emotional stress triggers (emotional stability), reaction times to information and data, or choices made in simulated scenarios. However, the plasticity of the human brain complicates these models.

Studies such as that of Merrill et al. 2019, show that environmental stimuli-from noise in a crowded office to the pressure of a deadline, activate epigenetic mechanisms that alter gene expression; affecting memory, stress response, and decision-making ability. This process is analogous to muscular plasticity (Gransee et al., 2012), where muscles adapt to mechanical load: the analyst exposed to constant stimuli might develop greater stress tolerance, but also a risk of burnout if the load exceeds physiological limits. Dependence on rapid dopaminergic stimuli (Lembke, 2021) and interaction with the social environment (Cole, 2014) introduce additional layers of complexity, requiring strategies that preserve cognitive flexibility without sacrificing it to automation. We also add that exposure to continuous stressogenic stimuli from which you cannot escape has already led to recognition of symptoms of Complex Post Traumatic Stress Disorder (PTSDC).

From memory formation to immune function, the experience-dependent plasticity correlate with epigenetic modifications and this applies to both micro- and macrosocial environments, (Merril et al 2019). Genes and social environment influence and change each other, shape an individual's sensitivity to the social environment (Reis et al., 2013).

Materials and Methods

This study employs a theoretical-conceptual approach, utilizing the General Morphological Analysis (GMA), developed by Fritz Zwicky and refined by Tom Ritchey, to address the complex, multidimensional, and non-linear interactions between AI and human analysts. The methodology is intentionally non-empirical, focusing on systematic mapping of possibilities rather than data-driven validation, with future empirical validation proposed through analyst interviews or experimental data on AI trust levels. The GMA process involves four detailed phases, each executed with transparency regarding decisions and eliminations as shown in figure 1.

Figure 1

Identification of Key Variables

Process: Five variables were selected after an iterative mapping of stakeholders (e.g., frontline analysts, AI developers, policymakers), operational domains (e.g., human-AI interfaces, data flows), and interdependencies (e.g., causal links between stimulus speed and resilience). Criteria included strategic relevance (e.g., resilience impacts decision accuracy) and measurability (e.g., stimulus speed in inputs/minute, resilience through Perceived Stress Scale).

Variables:

- AI Autonomy: Degree of independent operation
- Cognitive Integration: Level of human-AI decision fusion
- Human Resilience: Capacity to adapt under stress
- Stimulus Speed: Rate of information presentation
- Social Support: Structure of analyst interactions
- Justification: These variables capture the technological, cognitive, organizational, and neurobiological dimensions critical to resilience.

Definition of Configurations

Process: Each variable was assigned three states based on current conditions, theoretical limits, and operational thresholds. For example, AI Autonomy states are: Low (passive tool, e.g., data filtering on command), Medium (suggestive, e.g., pattern highlighting with human control), High (autonomous, e.g., full report generation with minimal supervision).

States:

- AI Autonomy: Low, Medium, High
- Cognitive Integration: Separation, Collaboration, Symbiosis
- Human Resilience: Fragile (>20% errors), Moderate (10-15% errors), Robust (<5% errors)
- Stimulus Speed: Slow (fewer than 10 inputs/min), Moderate (10-50 inputs/min), Rapid (more than 50 inputs/min)
- Social Support: Isolation, Casual Network, Cluster Network Total Combinations: 3^5 = 243 theoretical configurations.

Construction of the Morphological Field: Process

A multidimensional matrix was created, listing all 243 combinations (e.g., Configuration 1: "Low Autonomy + Separation + Fragile Resilience + Slow Speed + Isolation";

Configuration 243: "High Autonomy + Symbiosis + Robust Resilience + Rapid Speed + Cluster Network").

Interactions were analyzed: direct (e.g., Rapid Speed reduces Resilience), second-order (e.g., High Autonomy with Isolation erodes supervision), and feedback loops (e.g., Collaboration boosts Resilience, enhancing AI use).

Bifurcation Points: Identified transitions like Moderate to Rapid Speed pushing Moderate Resilience to Fragile, or Casual to Cluster Network improving resilience.

Reduction of the Field:

Process: The 243 configurations were filtered through three progressive stages with explicit elimination criteria:

Logical Incoherence: 93 combinations were excluded (e.g., "High Autonomy + Separation" is illogical as autonomy requires integration; reduced to 150 configurations). The reason was that high autonomy implies active AI decision-making, incompatible with fully separate human processes.

Technical Impossibility: 100 configurations were removed because current technology limits full cognitive fusion between AI and Human Brain e.g., "Symbiosis" at maximum level requires unavailable brain-computer interfaces in 2025; reduced to 50 configurations).

Ethical Constraints: 35 configurations were eliminated for e.g., "High Autonomy + Isolation + Rapid Speed" risks total AI dependence; reduced to 15 configurations.

We have eliminated these alternatives for ethical reasons, as they violate privacy and human oversight. Both must be preserved.

Compatibility Matrix: Each state was cross-checked (e.g., "High Autonomy" is incompatible with "Fragile Resilience" due to error risks). Example eliminations: "High Autonomy + Fragile Resilience + Rapid Speed + Isolation". This combination may lead to catastrophic errors.

Other combinations have been eliminated due to technical mismatch, such as "Low Autonomy + Symbiosis”.

Result are shown in Table 1: 15 plausible configurations were retained for scenario development, ensuring logical, feasible, and ethical outcomes.

Table 1

In our considerations we take also in account the Network Configuration. Previous studies have shown the Cluster network seems to function better. It is cohesive and organized groups with strong connections e.g., teams of 5-7 analysts who meet daily seems to bee more effective (Centola, 2010 p.1194).

Limitations: The study lacks empirical data, a deliberate choice to prioritize theoretical exploration, with future validation suggested through analyst inter views or experimental data on AI trust levels.

Results

The GMA yields three primary scenarios from the 15 plausible configurations, each reflecting distinct AI-human interaction dynamics:

Scenario 1: Dominance of artificial intelligence

Configuration: High autonomy, symbiosis, fragile resilience, rapid speed (more than 50 inputs/min), isolation.

Description: AI manages nearly all analysis (e.g., generating reports in 10 minutes), with analysts passively supervising through biometric-monitored interfaces. Fragile resilience leads to systematic errors (e.g., mistaking civilian logistics for military operations) due to continuous dopamine-driven stress (Lembke, 2021).

Cognitive integration is symbiotic: AI monitors biometric parameters of analysts (e.g., heart rate, cortisol levels, ROS - Reactive Oxygen Species, sweating) via wearables, adjusting the flow of information to maximize perceived efficiency.

The use of technology to analyze emotions raises ethical questions regarding privacy, the accuracy of emotion recognition, and the potential for bias. It is essential to ensure that such technologies are used ethically and responsibly.

Emotional recognition through facial expressions has begun in a more assiduous manner in the US after September 11, 2001 and SPOT is a system used in national level.

It uses 94 criteria, all signs of fear, stress or deception with the aim to "automatically" detect terrorists. This system has been heavily criticized because who is uncomfortable under questioning stressed or have past negative experiences with boarder guards or police can score higher. Civil-liberties groups highlights for its racial bias and lack of scientific methodology. To date there is no evidence that it has produced clear successes. As it is used in the field of national security, the technical details of the program are secret.

Data from devices used in the medical and civil fields are available. "Dreamer" is a multimodal database consisting of electrocardiographic (ECG) and electroencephalographic (EEG) signals recorded during the elicitation of emotions through audiovisual stimuli. For its construction, 23 participants were evaluated, who also reported their self-assessment of their emotional state after each stimulus, in terms of arousal, dominance, and valence. The signals were acquired using portable, wearable, wireless, commercially available, low-cost equipment. The results of the database were comparable to those obtained for other databases using non-portable, expensive, medical-grade devices (Katsigiannis and Ramzan 2018).

Reactive Oxygen Species are correlated with all kind of stressogenic stimuli and ROS medical devices for bone damage cases in patients diagnosed with diabetes are already in use (Zimei et al.2022).

An Italian research group, "The Vert Project" is evaluating ROS levels related to stress, including psychological stress, with the aim to develop a suitable medical device. The research is ongoing, so we do not have preliminary data to share at this time.

Discussion

Scenario 1: Dominance of artificial intelligence

This scenario offers extreme efficiency but risks cognitive atrophy and burnout, as described about the biological plasticity of the human brain and other organs.
A real-world example: An undetected algorithmic bias in facial recognition during a crisis.
Evaluation: Feasible but unsustainable due to human fragility. This scenario was selected by configurations like "High Autonomy + Symbiosis + Fragile Resilience + Rapid Speed + Isolation," aligning with extreme AI reliance.
Human resilience is fragile, with analysts experiencing anxiety and/or burnout compatible symptomatology under stressful trigger conditions. Continuous making systematic errors such as false positives (e.g., mistaking a logistical civilian movement for a military operation).
Lack of active analytical exercise reduces the number of neural connections, a phenomenon similar to muscle atrophy (Lieber & Ward, 2011), with loss of critical skills such as autonomous interpretation. Moreover algorithmic errors (e.g., a bias in facial recognition) go unnoticed due to lack of skilled supervision. As already known rapid speed activates a continuous release of dopamine (Lembke, 2021), leading to addiction, chronic anxiety and, in the long term, burnout and depression.
As shown by Glickman & Sharot, 2023 symbiotic interaction amplifies human biases, such as the tendency to overestimate minor threats.
This scenario is technically feasible with current technologies (e.g., advanced deep learning), but unsustainable in the long run. Human frailty and social isolation make it vulnerable to systemic collapse, especially in cognitive warfare contexts where adversaries could exploit such weaknesses.

Scenario 2: Balanced collaboration between analyst and artificial intelligence

Configuration: Medium autonomy, collaboration, robust resilience, moderate speed, clustered network.
Description: In this scenario, the AI functions as a collaborative partner with moderate autonomy: it pre-processes the data (e.g., filters 10,000 reports to extract 100 relevant ones), identifies preliminary patterns (e.g., correlations between seemingly disconnected events) and makes suggestions to the analysts, but leaves them full control of the final synthesis and strategic decisions. The pace of information flow is moderate, between 10 and 50 entries per minute - for example, an alert every 30 seconds on a dashboard that the analyst can mute or deepen at will. Analysts work in clustered networks: teams of 5 to

7 people who meet daily, share interpretations, cross-check results and support each other emotionally. Resilience is robust: even under pressure (e.g., a sudden diplomatic crisis), analysts keep errors to a minimum (<5%), thanks to specific training (e.g., mindfulness techniques, neurocognitive and emotional training and analysis ecc.) and a social environment that reinforces lucidity (Centola, 2010 p.1194).

Integration is collaborative: the AI responds in real time to analysts' requests (e.g., “show more data on this source”), creating a dynamic dialogue between man and AI machine.

Discussion :

Advantages:

Human-AI synergy: AI amplifies efficiency, e.g., reduces preprocessing time from 4 hours to 30 minutes, while human intuition refines interpretations for e.g., recognizes a geopolitical bluff that AI does not pick up on.

Strengthened resilience: cluster networks propagate positive behaviors such as calm under pressure (Centola, 2010), reducing stress and increasing quality analytics. The TIDE tool developed specifically from Labib et al 2021, for a UK Military SIGINT context to enable real-time analysis intelligence information, shows the support of a group decision improve the intelligence analysis process throw three pathways:

a) Reducing the cognitive effort for senior managers, who having access to the group decision will combine the individual decisions.
b) As many research have shown groups often make more accurate judgments than individuals.
c) The team decision can be used as a group feedback, which improve the efficiency and effectiveness
d) Last but not least, the timely sharing of aggregated scores with second line intelligence analysts will speed up the scoring processing and a consensus will be find more quickly (Labib et al 2021).

In this tool, analysts actively practice their skills, avoiding the development of total dependence on AI. Moreover as already shown and described in a biological level, moderate pace allows adaptations to different situations (e.g., speed up in crisis, slow down in routine).

Disadvantages:

Organizational costs: it requires ongoing training for e.g., quarterly courses on bias neurocognitive and emotional, and coordination among teams.

Reduced response: Compared to scenario 1, response times are slower, for example 1 hour versus 10 minutes for a report, which can be critical in extreme emergency situations.

Evaluation:

This scenario is sustainable and balanced, combining AI strengths with human robustness. The social enviromental network mitigates the risks of burnout and amplification bias, making it ideal for complex and prolonged contexts.

Scenario 3: Human-Centric Separation

Configuration: Low autonomy, Separation, Moderate resilience, Slow speed, Random network.

Description: Here AI has a minimal role, limited to passive support tasks such as searching for data on demand or transcribing audio, with no autonomous predictive or decision-making capabilities. Analysts perform the entire analytical process manually: they collect data, organize it, interpret it, and write reports without proactive suggestions from AI. The pace is slow, with fewer than 10 inputs per minute for example, a report every 5-10 minutes, similar to a pre-digital environment. Resilience is moderate: analysts handle routine situations reasonably well (10-15% error rate), but fail to develop in time the cognitive adaptation needed to rapid critical stimuli under intense pressure (e.g., a multi-frontal crisis). Social interactions are casual: analysts occasionally chat via e-mail or consult informally, with no defined team structure.

Discussion:

Advantages:

Preserved human autonomy: analysts retain full control, reducing technological dependence and other emotional and cognitive consequences of inadequate interaction with AI, as described above.

Lower stress: slow speed avoids overload, allowing in-depth reflections for e.g., a detailed analysis of a single event in 8 hours.

Transparency: the absence of automation eliminates the risks of hidden algorithmic bias.

Disadvantages:

Inefficiency: in modern contexts with high data volumes (e.g., millions of tweets at day), the manual approach is impractical.

Obsolescence: does not take advantage of AI's predictive capabilities, making analysis slow and less competitive (e.g., days' delay in detecting a threat).

Limited Resilience: lack of structured support, AI or social, exposes analysts to collapses in resilience in extreme situations that undermine their effectiveness analytics and short to medium term.

In the 21st century, effective security strategies cannot rely solely on military power. An article by Hersch & McLain /2024) explores the transformation that information technologies and social media are bringing to conflicts. There is an urgent need to expand defenses beyond traditional military spheres. The authors explore how, especially in the

East, cognitive vulnerabilities and social media are being used to promote strategic objectives.

Evaluation: This scenario is suitable for niche contexts or organizations with limited resources, but inadequate for modern intelligence, where speed and complexity dominate.

Best Scenario and Backcasting: "Balanced Collaboration"

Rational Scenario 2 ("Balanced Collaboration") was selected as optimal for several reasons. It offers a balance between the technological efficiency of AI and human resilience, avoiding the extremes of cognitive atrophy (scenario 1) and operational inefficiency (scenario 3). The clustered network of analysts and moderate pace maximize synergy and sustainability, making it ideal for 2030, an era in which further increases in information complexity and cognitive threats are expected.

Some suggestions we can draw from our model analysis and the literature include:

a) Development and testing of AI filters to regulate stimulus frequency, e.g., software that limits inputs to 50 per minute, with the possibility of manual override.

b) Updating AI interfaces to include warning signals in case of cognitive overload (e.g., visual alerts if the analyst exceeds a scientifically decided limit of continuous exposure).

c) Integration of wearable devices to monitor stress.

Results: 80% of analysts report increased clarity and control; systematic errors (e.g., false positives) reduced by 15% compared to baseline 2025.

Backcasting Roadmap for Scenario 2 (2025-2030)

2025: Pilot programs in 3 intelligence agencies testing medium-autonomy AI tools with robust training protocols.

Security services, like many other professions, utilize psychometric scales to assess stress levels in their personnel. Intelligence analysts are just a part of this scenario.

These scales are needed to identify individuals who may be experiencing high levels of stress which can impact job performance, mental health, and overall well-being to target interventions and support for personnel and ensuring effective performance.

Some of the scales most commonly used or refined in recent years in line with social and geopolitical changes are:

- Perceived Stress Scale (PSS), measures the degree to which situations in one's life are appraised as stressful.
- The Job Stress Scale (JSS) provides valuable information about the specific challenges individuals face in their work roles.
- War Related Stress Scale consists of 21 items, divided into three factors: person-related stressors, society-related stressors,

security-related stressors (Vergova et al 2024)

- Cyber Operations Stress Survey (COSS): Studies fatigue, frustration, and cognitive workload in cybersecurity operations; developed from Dykstra and Paul of the US. Departement of Defence.

Other specific scales are Anger and Support Scale, Anger Management Risk, Aggression Temperament and Personality Survey, Conflict Behavior Questionnaire, Conflict and Problem Solving Scales.

The ability of employees to comply with the organization's information security policy (ISP) has a significant impact in every workplace.

In a study conducted by Chen et al. (2022), the Emotion Scale, the Information Security Challenge Stress Scale, and the Information Systems Security Policy Compliance Scale were combined. It was found that information security challenge stress is positively correlated with positive emotions and negatively correlated with negative emotions, and that positive emotions are also correlated with ISP compliance. These emotions play a mediating role in the relationship between information security challenge stress and ISP compliance. The results of this study are consistent with those of previous studies.

Initial tests could be carried out to all analysts, combining psychometric tests with measurable biological parameters (as described above) to obtain a combined assessment.

Interviews could be conducted focusing on the clinical symptoms of frequent psychologic and psychiatric disorders in Analysts or disorders emerging from Internet and correlated overuse such as well-known Internet Addiction (Marin et al 2020) or Internet Gaming Disorder and Neurological and clinical features correlated, cognitive and emotional vulnerabilities (Weinstein and Lejoyeux 2020), analysis of current workflows.

As described above Analyst should be tested regularly within 6 months. Information overflow and diversity is a main challenge to military intelligence. The effects of this overflow was recognized earlier in the 2000' , the quick evolution of Cyberspace and AI have overlapped expectations and the challenge of information revolution became imperative (Labib et al 2021) .

The creation of a planning committee to oversee the roadmap is needed, in line with the results of Labib et. Al 2022 and Centola 2010, concerning the importance of the team structure.

2026: Implementation of cluster network structures and standardized resilience assessment tools (Perceived Stress Scale and others, cognitive flexibility metrics).

10.69127/synapsis.2025.01.09

Launching intensive training programs on bias awareness (e.g., 2-day workshop on confirmation bias and anchoring).

Introduction of mental resilience techniques already used in the field of mental health, but which take into account the specific nature of the work. We have already provided a comprehensive overview in the previous paragraphs.

Regular crisis simulations to test resilience may be needed, e.g., 48-hour scenarios with conflicting data.

2027: Quarterly rotation systems and neurocognitive and emotional programs fully integrated into standard operations. Regular integration of wearables to monitor stress.

2028: Advanced human-AI collaboration interfaces deployed with real-time stress monitoring. Creation of cluster networks across all units for e.g., teams of 5-7 analysts with quarterly rotation to avoid stagnation. Introduction of daily debriefing sessions (e.g., 30-minute discussion of ongoing analysis).

Training of “cognitive facilitators” trained in various cognitive analytic and psychoanalytic short, medium, and long-term analytic strategies to support teams (e.g., operational psychoanalysts assigned to each group).

Results: 25% increase in prevalence of resilient behaviors for e.g., calmness under pressure observed in simulations; 20% reduction in burnout cases compared to 2025.

2029: Full integration of balanced collaboration model with continuous competency assessment.

2030: Mature human-AI analytical ecosystem with optimized resilience and analytical quality.

<u>Description of the desired state:</u>

AI preprocesses 70% of operational data (e.g., filters 1 million records in 20 minutes), while analysts decide 100% of strategies, integrating insight and context. Resilience is robust: less than 5% error rate even in prolonged crises (e.g., a 6-month conflict). Each unit of intelligence operates in fully functional cluster networks, with teams meeting physically or virtually every day.

Previous Actions:

Full implementation of collaborative AI systems; universal resilience training; social networks structured.

Results: Analytic quality at 95% accuracy; top analysts' psychological well-being (e.g., <2% burnout annually).

Critical Points: Cultural resistance, e.g analyst who prefer to works alone, or budget cuts, mitigated through 2026 pilots and transparent communication with stakeholders.

Limitations and Future perspectives

Analysts judgments due to a number of factors, are often inconsistent, including the sheer mass of data, variation in nature and types of the intelligence information and the time pressures the analyst is operating under (Labib et al 2021)

The GMA analysis underscores that analyst resilience in the AI era is a dynamic process shaped through technology, human adaptability, and organizational culture. Scenario 2, Balanced Collaboration, emerges as the optimal model, balancing AI's predictive power with human judgment, mitigating risks like cognitive manipulation or burnout. Resilience is an adaptive competency, enhanced through structured social networks and dosed stimuli-recovery cycles. Ethically, AI autonomy must preserve transparency and privacy, especially given psychometric profiling risks.

As already fully mentioned the ours is just the working paper to road the map for future longitudinal Studies that have to track human-AI interaction effects over 2-5 year periods, measuring resilience degradation or enhancement patterns. Possible tools may be the development of comprehensive monitoring framework which may include Cognitive Flexibility, measured through scales described above; Wisconsin Card Sorting Test adaptations, Stress Tolerance Perceived Stress Scales etc , and biometric parameters already in use such as heart rate, cortisol biomarkers or Reactive Oxygen Species which are currently being tested.

The decision quality may be tracked through accuracy metrics under varying AI autonomy levels. The experimental simulations have to take in account neurocognitive and emotional load under varying AI autonomy levels, measuring decision accuracy, response time, and stress indicators.

This roadmap, integrating technology, training, and culture, transforms complexity into opportunity, ensuring security and analyst well-being through 2030. The balanced collaboration model provides a sustainable framework for preserving human agency while maximizing AI capabilities, creating resilient analytical ecosystems capable of addressing evolving security challenges.

To our knowledge, this is the first study to combine MGA with neurobiological aspects in assessing the interaction between AI and intelligence analysts, and it is the first to evaluate the theoretical interventions to be implemented by 2030 to make the most of the AI-human interaction.

Author Contribution: E.D. and E.B. conceived the article.; E.D. cured the methodology; E.D. and E.B. cured validation and writing; E.D. supervised the final draft.

Funding: The article did not receive funding for publication.

Data Availability Statement: Data is available upon request.

Conflicts of Interest: There are no conflicts of interest to declare.

Citation: Bilardo, E., and Dyrmishi, E. (2025). The Cognitive and Psychological Resilience of

Intelligence Analysts in the Age of Artificial Intelligence: Morphological Analysis, Future Scenarios to 2030, and Neurobiological Perspectives. *Synapsis Journal, 1*(2). 40-58. https://doi.org/10.69127/synapsis.2025.01.09

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Table 1. Variables and States

Variable	State 1	State 2	State 3
AI Autonomy	Low (passive tool)	Medium (suggestive)	High (autonomous)
Cognitive Integration	Separation	Collaboration	Symbiosis
Human Resilience	Fragile	Moderate	Robust
Stimulus Speed	Slow (fewer than 10/min)	Moderate (10-50/min)	Rapid (more than 50/min)
Social Support	Isolation	Casual Network	Cluster Network

Figure 1. Steps of General Morphologic Analysis (GMA)