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Statistical Analytical Techniques for Intelligence Analysis

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Abstract

New quantitative analytical techniques are needed for intelligence analysis to deal with total information overload. These can draw on established methods for data analytics and complement structured analytical techniques for intelligence. Jack Duffield shows that a basic set of accessible quantitative techniques must be incorporated into new standards, primers and training for intelligence professionals. Effective implementation of statistical methods depends on a combination of robust training, cultural realignment, data-integration platforms, and clear direction and demand from policymakers.

Revolutions in Western intelligence tradecraft do not happen very often. Some are triggered by technological progress, such as the development of satellite imagery and signals collection or the emergence of online open-source and human intelligence. Others are forced by circumstances, such as the adoption of community-wide analytical standards following the systemic intelligence failures leading up to 2001–03.[1] Only very rarely do technological progress and external pressure combine to create the most urgent demand for new tradecraft. This was arguably last seen during the Second World War when the development of radar and the threat of large-scale aerial bombing forced the creation of an entirely new discipline of measurement and signature intelligence.[2] A similarly urgent demand is occurring today. Intelligence professionals now operate in an environment of total information overload which is unsuited to qualitative methods alone, and they can now routinely access advanced data analytics software and expertise e to apply qualitative methods to this challenge.

Although intelligence organisations increasingly employ data analysis methods, these have not yet been professionalised and formalised into intelligence tradecraft. Unlike structured analytical techniques, statistical analytical techniques are widely used in industry and their effectiveness is well-evidenced. There is therefore much to gain by formally adopting and implementing statistical analytical techniques into general intelligence tradecraft and training. Doing so would mitigate a growing risk of large-scale intelligence failure from information overload.

Total Information Overload

The scale of information available and its rate of growth defies comprehension: in 2024 more than 600 trillion gigabytes of data were created worldwide.[3] The challenge that this poses for intelligence analysis will only become greater, as the total amount of data is expected to have doubled by 2027 and to have tripled by 2029, as shown in Figure 1.[4] Information overload, the point where it is no longer possible to effectively use and manage all available information, has long been surpassed for both publicly available information and intelligence sources. As early as 2012, US intelligence officers stated that they were ‘drowning in data’ and unable to effectively process and analyse it.[5] Military intelligence officers estimated during the 2010s that 95% of collected imagery was never viewed, and the widespread adoption of uncrewed air systems for intelligence collection now eclipses the scale of concerns raised a decade ago. In the first 22 months following Russia’s full-scale invasion of Ukraine, full-motion video feeds from the drones of the Ukrainian Armed Forces alone contained more than 228 years of footage. Five or six terabytes of new data are being collected every day.[6] More broadly, Christopher R Moran, Joe Burton and George

[1] Richards J Heuer Jr, *Psychology of Intelligence Analysis* (Center for the Study of Intelligence, 1999); John A Gentry, ‘Has the ODNI Improved U.S. Intelligence Analysis?’, *International Journal of Intelligence and CounterIntelligence* (Vol. 28, No. 4, 2015), pp. 637–61.

[2] Jack Duffield (ed.), *Air Intelligence at War: The Official Historical Narrative of the RAF’s Air Intelligence Directorate, 1939-1945*, Revised edition (London: Air Historical Branch, 2025), pp. 113, 445.

[3] Petroc Taylor, ‘Data Growth Worldwide 2010-2028’, 2024, https://www.statista.com/statistics/871513/worldwide-data-created/, accessed 21 Apr 25.

[4] Taylor, ‘Data Growth Worldwide 2010-2028’.

[5] Sandra I Erwin, ‘Too Much Information, Not Enough Intelligence’, *National Defense* (Vol. 96, No. 702, 2012), pp. 26–28.

[6] Max Hunder, ‘Ukraine Collects Vast War Data Trove to Train AI Models’, *Reuters*, 20 December 2024.

Christou reviewed declassified information and public statements by intelligence agencies into the 2020s. They determined that the problem has become unsustainable for agencies as the ‘mounting barrage of data is too enormous to process’.[7] The unstoppable rise in the rate of new data generation means that intelligence organisations now operate in an environment of total information overload.

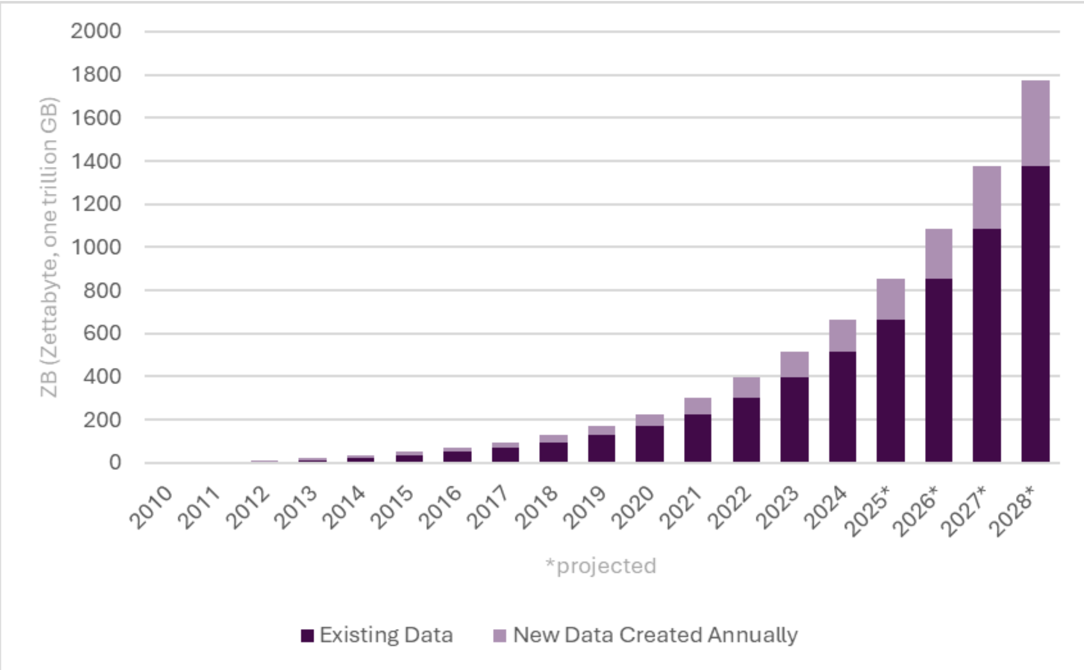

Figure 1 - Total Amount of Data in the Global Information Environment over Time (Wright, 2024; Taylor, 2024)

For decades, intelligence organisations have recognised the challenge of coping with large volumes of information.[8] The issue was traditionally managed by focusing collection on highly assured, targeted subsets of data such as agents with close access and high-value communications channels, and further refining large datasets with selectors and keywords. The need to confront information overload in intelligence was delayed by the counterterrorism intelligence priorities that characterised the early 21st century. These saw intelligence organisations focus on small human networks with poor counterintelligence practice, greatly narrowing the scope of required data. However, careful curation is no longer sufficient to manage even well-selected sources for today’s intelligence problems. With the return to state threats and full-scale warfighting as intelligence priorities, comprehensive operational intelligence pictures at the scale of countries and continents are now required instead of deep studies of individuals. Such studies necessitate a much broader intelligence base that now makes total information overload unavoidable.[9]

Scholars are increasingly aware of the need for intelligence professionals to adapt to total information overload. Damien Van Puyvelde, Stephen Coulthart and M Shahriar Hossain explored its impact across the

[7] Christopher R Moran, Joe Burton and George Christou, ‘The US Intelligence Community, Global Security, and AI: From Secret Intelligence to Smart Spying’, *Journal of Global Security Studies* (Vol. 8, No. 2, 2023), p. 489.
[8] Douglas Porch and James J Wirtz, ‘Surprise and Intelligence Failure’, *Strategic Insights* (Vol. 1, No. 7, 2002).
[9] Jack Duffield, ‘Analytic Standards in the Context of Military Intelligence’, *Air and Space Operations Review* (Vol. 3, No. 1, 2024), pp. 35–49, 41–42.

intelligence cycle, correctly predicting that it would dramatically change how intelligence organisations must operate.[10] Christopher Eldridge, Christopher Hobbs and Matthew Moran raise concerns that improperly managed data-driven intelligence analysis risked elevating large-scale correlation at the expense of meaningful analysis.[11] Kevin Lim laments the lack of conceptual thought linking data-driven approaches to strategic intelligence.[12] This intersects with other literature, including that of Mark Phythian and Belinda Canton who both advocate active management of uncertainty from incomplete intelligence pictures, and proponents of Bayesian statistics in intelligence, tracing lineage back to Jack Zlotnick.[13] The consensus is that intelligence organisations have not yet adapted to the demands of large-scale data in analytical tasks.

Faced with this unavoidable challenge, practitioners are increasingly turning to AI as a potential solution to total information overload. US Director of National Intelligence Tulsi Gabbard testified in late 2025 that large language models (LLMs) are already in use for bulk data processing across the US Intelligence Community.[14] The use of LLMs beyond analysis – for example, in the processing step of the intelligence cycle to handle vast unstructured data sources, or in the collection step to optimise the allocation of intelligence resources – is likely to be widespread, controlled and often well-suited to the purpose. For analytical tasks, however, the black-box nature of LLMs make them a poor fit as a replacement for analytical techniques. For such techniques, reproducibility and transparency are both important principles in their own right, and are essential for objectivity. This is the conclusion of Miah Hammond-Errey and the research participants in her study, who see this as a key limiting factor.[15] AI will almost inevitably form part of the future analytical workflows of intelligence organisations. It will likely augment the work of individual analysts by acting as a copilot, provide capabilities such as retrieval-augmented generation, and summarise and identify flaws in assessments. However, it is not a silver bullet for the challenge of total information overload. For that purpose, human-led analysis will remain central, requiring a new body of general analytical tradecraft.

The Need for New Tradecraft

Total information overload forces intelligence communities to shift their analytical tradecraft from primarily qualitative analysis to a split process. This sees quantitative analysis enriching large quantities of data into high-value information, and qualitative analysis increasing the rigour and scope of this insight in a mutually reinforcing cycle. Existing qualitative analytical tradecraft – such as structured analytical techniques – are

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[10] Damien Van Puyvelde, Stephen Coulthart and M Shahriar Hossain, 'Beyond the Buzzword: Big Data and National Security Decision-making', *International Affairs* (Vol. 93, No. 6, 2017), pp. 1397–1416, 1399.

[11] Christopher Eldridge, Christopher Hobbs and Matthew Moran, 'Fusing Algorithms and Analysts: Open-source Intelligence in the Age of "Big Data"', *Intelligence and National Security* (Vol. 33, No. 3, 2018), pp. 391–406.

[12] Kevjn Lim, 'Big Data and Strategic Intelligence', *Intelligence and National Security* (Vol. 31, No. 4, 2016), pp. 619–35, 620–21.

[13] Mark Phythian, 'Policing Uncertainty: Intelligence, Security and Risk', *Intelligence and National Security* (Vol. 27, No. 2, 2012), pp. 187–205, 204; Belinda Canton, 'The Active Management of Uncertainty', *International Journal of Intelligence and CounterIntelligence* (Vol. 21, No. 3, 2008), pp. 487–518, 488–89; Jack Zlotnick, 'Bayes' Theorem for Intelligence Analysis', *Studies in Intelligence* (Vol. 16, No. 2, 1972), pp. 43–52.

[14] David Klepper, 'Gabbard Says AI is Speeding up Intel Work, Including the Release of the JFK Assassination Files', *The Independent*, 10 June 2025.

[15] Miah Hammond-Errey, 'Big Data, Emerging Technologies and the Characteristics of "Good Intelligence"', *Intelligence and National Security* (Vol. 39, No. 4, 2024), pp. 657–76, 669–70.

not invalidated. Rather, it is supplemented by statistical analysis that allows analysts to easily draw from a much wider intelligence base when providing assessments. For example, intelligence outputs from statistical methods may be post-processed using structured validation techniques, or initial hypothesis-generation methods may be used to inform statistical analysis – this is then returned to structured forms for further evaluation.

Such a paradigm shift in analytical methods is the only practical solution to the challenge of making assessments based on overwhelming quantities of data. This was realised several years ago in industries – such as banking, healthcare, insurance, securities and investment services, and telecommunications – that were exposed to large amounts of data and faced competitive pressure.[16] The explosion of interest in statistical methods in response to information overload was captured by the 'big data' zeitgeist of the mid- to late 2010s.[17] The term describes the increasing volume, variety and velocity of data, all of which echo the issues of total information overload facing intelligence organisations.[18] Various scholars and commentators described big data as revolutionary to industry. Its widespread adoption has since validated this view. In fact, the usage of the term has declined as the associated philosophy and practice became increasingly normalised, as visualised in Figure 2.[19]

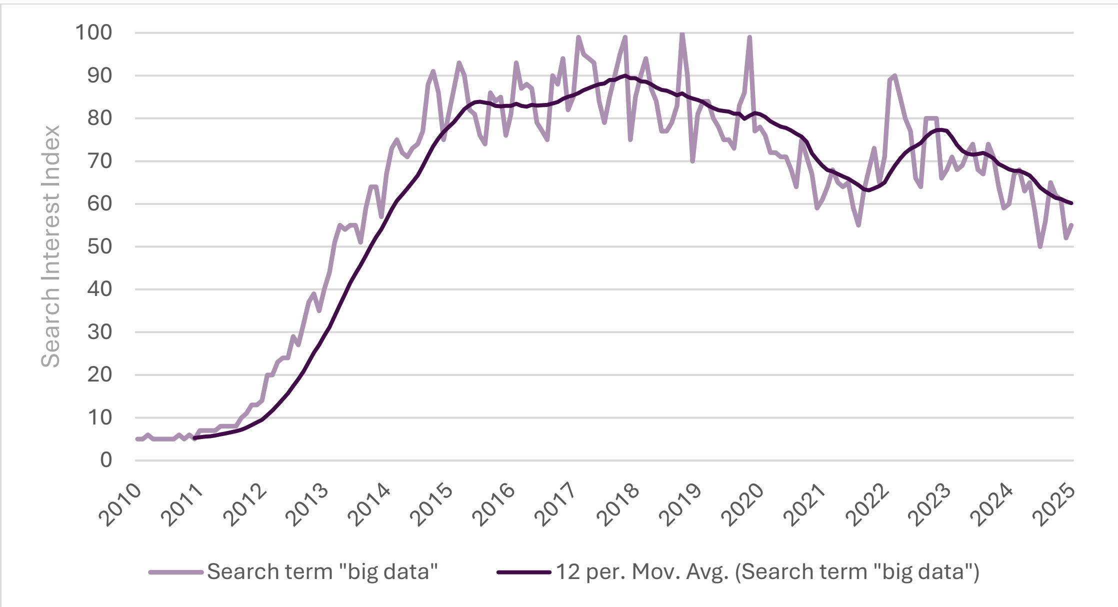

Figure 1 - Search Interest in Big Data on Google Search over Time (Google, 2025)

Intelligence organisations face a different set of challenges from many of the sectors listed above. The adoption of new approaches has been understandably delayed by such challenges – the most prominent of

[16] Fabio Arena and Giovanni Pau, 'An Overview of Big Data Analysis', *Bulletin of Electrical Engineering and Informatics* (Vol. 9, No. 4, 2020), pp. 1646–53, 1646.
[17] Harry E Pence, 'What is Big Data and Why is it Important?', *Journal of Educational Technology Systems* (Vol. 43, No. 2, 2014), pp. 159–71, 169.
[18] Francis X Diebold, 'On the Origin(s) and Development of the Term "Big Data"', PIER Working Paper 12-037, 2012, p. 3.
[19] Matthew Jones, 'What We Talk About When We Talk About (Big) Data', *Journal of Strategic Information Systems* (Vol. 28, No. 1, 2019), pp. 3–16, 5.

which is that intelligence organisations almost always have a less complete picture of the situation. They lack crucial details – such as market information or customer data – against which to act. As such, they must adjust their methods in light of the permanent risk of significantly incomplete information.[20] In addition, the variety of intelligence sources are far greater than those faced by industry.[21] The subjects of this information are also often attempting to conceal or deceive their activities and intentions, and new intelligence problems often necessitate dramatic reprioritisations of analytical effort. These factors imperil detailed long-term coverage of any single subject area. This active uncertainty remains the driving factor in cyclical models of intelligence, where organisations must work actively to collect new information to resolve gaps as they are identified. Cross-cueing of intelligence collection is well-established tradecraft where information environments grow too dense, most notably in the use of other sources to cue satellite imagery. However, this paradigm breaks down when information overload also affects the ability to select initial sources for subsequent cross-cueing.[22] While it is more difficult for intelligence organisations to adopt new quantitative approaches, the core underlying statistical processes that are required do not vary significantly from those already widely used in industry.

This necessary revolution in analytical tradecraft is not yet part of core procedure in intelligence as it is in some commercial sectors such as finance.[23] Instead, statistical methods for analysis of data are largely unacknowledged by existing intelligence tradecraft. In the US, Intelligence Community Directive 203, which sets out analytic standards for the US Intelligence Community, makes no reference to statistical techniques or quantitative methods. Instead, it focuses on directing that intelligence is communicated through qualitative analysis and judgement supported by 'tables, flow charts, images' and clear communication of uncertainty and confidence levels.[24] Likewise, the UK's Professional Head of Intelligence Assessment's Analytical Standards and Professional Standards for All-Source Intelligence Analysis make no reference to these concepts, although the latest edition of Joint Doctrine Publication 2-00 does belatedly introduce 'big data' to UK military intelligence doctrine.[25]

While current analytical tradecraft and standards make no mention of statistical methods, neither do they rule out their use. They simply reflect an institutional focus on strategic assessment. This itself derives from the major strategic intelligence failures of Western intelligence at the turn of the century, and the tradecraft of an era before the scale of information available to intelligence organisations became overwhelming.[26]

[20] Thomas E Copeland, 'Intelligence Failure Theory', *Oxford Research Encyclopedia of International Studies* (Oxford: Oxford University Press, 2010).
[21] Neil Couch and Bill Robins, 'Big Data for Defence and Security', *RUSI Occasional Papers*, September 2013, p. 6.
[22] See Chapter IV, 'Collection Synergy', in Permanent Select Committee on Intelligence, 'IC21: Intelligence Community in the 21st Century', Staff Study, US House of Representatives, 1996.
[23] Van Puyvelde, Coulthart and Hossain, 'Beyond the Buzzword'.
[24] Office of the Director of National Intelligence, 'Analytic Standards', Intelligence Community Directive 203, 2007, pp. 3–6.
[25] Professional Head of Intelligence Assessment (PHIA), 'Professional Development Framework for All-source Intelligence Assessment', January 2019, https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1146217/2019-01_PHIA_PDF_First_Edition_Electronic_Distribution_v1.1__1_.pdf accessed 30 Aug 23; Ministry of Defence, 'Intelligence, Counter-intelligence and Security Support to Joint Operations', Joint Doctrine Publication 2-00, 4th edition, August 2023, p. 20.
[26] Duffield, 'Analytic Standards in the Context of Military Intelligence', pp. 38–39.

So, while new tradecraft is required, it does not immediately invalidate existing high-level guidance and directives for intelligence analysis. Instead, new tradecraft can build on existing processes by adding assured tools for quantitative analysis and by training intelligence professionals in their safe and effective use. This can be supported by clarifications and new underpinning standards which are specific to statistical methods.

Technological progress also drives the need for new tradecraft for statistical techniques. First, industrial-grade platforms for data integration and data analysis make high-quality data analytics tools from the commercial sector available to their respective intelligence communities.[27] Technical capabilities and infrastructure now exist for large workforces to conduct statistical analysis across vast datasets. Second, the talent pool of data analysts is rapidly growing, with 48% of UK businesses recruiting for roles requiring data skills and a 34% projected growth rate for data science roles from 2024–34 in the US.[28] It is therefore increasingly likely that a recruited intelligence analyst will have data analysis skills, and that a given decision-maker will expect data-driven insight from their analysts.

Available evidence from open sources suggests that Western intelligence organisations already incorporate statistical methods into their work in some capacity. There are active recruitment programmes for data analysts at MI5 and GCHQ in the UK, and data science is listed as a dedicated career field in the US Intelligence Community with a wide range of job descriptions specifically referencing analysing large volumes of data.[29] However, the evidence of current use of quantitative analysis in intelligence organisations stands in stark contrast to the lack of approved tradecraft or acknowledgement of statistical techniques in Western intelligence standards. This introduces a significant risk that data analysis methods are being employed without agreed tradecraft.

The absence of best practice, guidance for the production and consumption of quantitative analysis, and mechanisms for standards and assurance all markedly increase the risk of intelligence failure. There are a variety of vectors for this failure. These include: analysts misapplying statistical methods, unknowingly leading to incorrect assessments; those responsible for quality control lacking the expertise to rigorously critique intelligence outputs; and customers drawing incorrect conclusions from quantitative information. All of these issues, and the growing risk of intelligence failure that results, can be overcome by establishing formal tradecraft for statistical analytical techniques.

[27] Van Puyvelde, Coulthart and Hossain, 'Beyond the Buzzword', p. 1413.

[28] Josh Fearns, Lydia Harriss and Clare Lally, 'Data Science Skills in the UK Workforce', UK Parliament POSTnote 697, 28 June 2023, p. 12; Bureau of Labor Statistics, 'Data Scientists', 2025, https://www.bls.gov/ooh/math/data-scientists.htm, accessed 5 Sep 25

[29] MI5, 'Intelligence and Data Analyst Development Programme', 2025, https://www.mi5.gov.uk/careers/opportunities/intelligence-and-data-analyst-development-programme-idadp, accessed 4 Sep 25; GCHQ, 'Intelligence Data Analyst Ref. 3544', 2025, https://www.gchq-careers.co.uk/jobs/intelligence-data-analyst-ref-3544.html, accessed 4 Sep 25; USAJobs, 'Intelligence Community Career Fields', 2025, https://www.intelligencecareers.gov/career-fields, accessed 4 Sep 25.

Statistical Analytical Techniques

Statistical analytical techniques, which will perhaps inevitably bear the acronym STATss, can mirror the structured analytical techniques (SATs) that are now ubiquitous in Western intelligence tradecraft for qualitative methods. Statistical analytical techniques can fulfil a similar function for quantitative methods. They can leverage the existing oversight and assurance framework created for SATs to meet the need for new tradecraft for statistical analysis.

Statistical analytical techniques can formalise the use of quantitative methods for intelligence analysis and apply them in an intelligence context, with guidance tailored to their use against intelligence problems. This is already well-established for SATs. Documents such as the CIA's 'Tradecraft Primer for Structured Analytic Techniques', the Defense Intelligence Agency's similarly named primer, and the UK's 'Quick Wins for Busy Analysts' are now achingly familiar to a generation of Western intelligence professionals.[30] Each tradecraft primer formally adopts a subset of the techniques subsequently laid out in Richards J Heuer Jr and Randolph H Pherson's *Structured Analytic Techniques for Intelligence Analysis*, which is publicly available as a textbook.[31] Only about a quarter of the SATs included in Pherson and Heuer's textbook are contained in tradecraft primers, with adoption focusing on relatively simple techniques with wide utility. The implementation of similar tradecraft primers detailing endorsed statistical analytical techniques can be achieved relatively easily. It can build on widely available textbooks and manuals for data analysis.

Unlike SATs, all statistical analytical techniques require mathematical understanding to both apply and assure. Professionals generally agree that some mathematical knowledge is necessary for data-focused roles, and that a good understanding of and comfort with mathematical concepts is vital. That said, the current level of mathematics in academic preparation for data-focused roles is generally higher than practitioners need.[32] UK government guidance is that a degree in a mathematical or scientific subject is a prerequisite for data analysis work. This further corroborates the view that a baseline mathematical education is becoming increasingly important for intelligence practitioner roles. While some intelligence organisations already screen for these skills, others – particularly in the UK – do not. This presents a choice between raising entry standards or extending professional training to include dedicated mathematics and statistics courses.[33]

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[30] US Government, *A Tradecraft Primer: Structured Analytic Techniques for Improving Intelligence Analysis* (Washington, DC: US Government, 2009); Directorate of Analysis, 'A Tradecraft Primer: Structured Analytic Techniques for Improving Intelligence Analysis', 1st edition, Defense Intelligence Agency, 2008; Defence Intelligence, 'Quick Wins for Busy Analysts', Ministry of Defence, 2013.

[31] Richards J Heuer Jr and Randolph H Pherson, *Structured Analytic Techniques for Intelligence Analysis* (Washington, DC: CQ Press, 2021).

[32] Deniz Akdur, 'The Analysis of Mathematical Skills Used in the Software Industry', *Turkish Journal of Mathematics and Computer Science* (Vol. 12, No. 2, 2020), pp. 92–100.

[33] GCHQ, 'Intelligence Data Analyst Ref. 3544'; RAF, 'Intelligence Analyst', 2025, https://www.gchq-careers.co.uk/jobs/intelligence-data-analyst-ref-3544.html, accessed 4 Sep 25.

The most important characteristic of statistical analytical techniques for organisations is that, unlike SATs, their efficacy is largely not doubted. On their introduction, intelligence professionals generally viewed SATs with suspicion. They were viewed as faddish and unsupported by clear evidence of their utility.[34] Now that their use is variously encouraged or mandated by intelligence organisations, an increasing number of studies have determined that they have mixed utility – they provide tangible benefits without being a panacea.[35] This stands in stark contrast to statistical analytical techniques which are widely adopted by industry. Academic and economic evidence has proven that they are useful in solving the challenges of total information overload.[36] There is therefore a very strong case for the rapid adoption of statistical analytical techniques by intelligence organisations.

The selection of a core set of techniques to incorporate into assured tradecraft is a nebulous task. Much like SATs, these techniques should not be the most advanced or comprehensive. Rather, they should form an accessible baseline of widely applicable tools. Given the sometimes deep mathematical skill required to employ statistical methods, there is also a strong argument in favour of focusing on less complex techniques. This can reduce the scope for error and widen their usability with follow-on effects for reducing intelligence failure. Plausible candidates are drawn from well-established textbooks and widely supported in currently available data-integration platforms. Of these, only Bayesian methods have ever featured prominently in intelligence literature, including studies which have fused them with SATs to considerable effect.[37] Table 1 details a core set of techniques that can form a strong baseline for a Statistical analytical techniques primer for intelligence analysis.

[34] Stephen Marrin, 'Intelligence Analysis: Structured Methods or Intuition?', *American Intelligence Journal* (Vol. 25, No. 1, 2007), p. 10.

[35] Stephen J Coulthart, 'An Evidence-Based Evaluation of 12 Core Structured Analytic Techniques', *International Journal of Intelligence and CounterIntelligence* (Vol. 30, No. 2, 2017), pp. 368–91, 369.

[36] Dazhi Chong and Hui Shi, 'Big Data Analytics: A Literature Review', *Journal of Management Analytics* (Vol. 2, No. 3, 2015), pp. 175–201; Chun-Wei Tsai et al., 'Big Data Analytics: A Survey', *Journal of Big Data* (Vol. 2, No. 1, 2015), p. 21.

[37] Christopher W Karvetski et al., 'Structuring and Analyzing Competing Hypotheses with Bayesian Networks for Intelligence Analysis', *EURO Journal on Decision Processes* (Vol. 1, No. 3–4, 2013), pp. 205–31.

Theme	Technique	Typical Analytical Insight
Regression	Linear Regression[38]	After controlling for other variables, increases in X are consistently associated with proportional increases in Y, suggesting X is a meaningful driver rather than background noise.
Regression	Logistic Regression[39]	The probability of event A rises sharply once factors X and Y are present, indicating a threshold effect that distinguishes high-risk cases from the baseline.
Classification	K-Nearest Neighbours[40]	This actor's recent behaviour most closely resembles that of a small subset of previously observed cases, which historically went on to exhibit outcome B.
Classification	K-Means Clustering[41]	Observed entities naturally separate into four distinct behavioural groupings, each with internally consistent patterns and materially different risk profiles.
Causal Inference	Analysis of Covariance[42]	Once baseline capability and environment are accounted for, the apparent gap between actors narrows significantly, indicating that much of the observed difference reflects starting conditions rather than divergent behaviour.
Time Series	Trend Plotting[43]	The underlying trajectory shows a sustained upward movement over multiple periods, with short-term volatility masking a longer-term structural change.
Time Series	ARIMA[44]	Assuming current dynamics persist, activity levels are likely to remain within a bounded range over the next three periods, with a non-trivial risk of a sharp deviation thereafter.
Probabilistic Modelling	Bayesian Analysis[45]	Given the new reporting, confidence in hypothesis A has increased substantially, while alternative explanations now carry materially lower probability.
Probabilistic Modelling	Monte Carlo Simulation[46]	Over thousands of simulations, four plausible scenarios emerged, including a sharp deterioration scenario which occurs when both X and Y occur at a similar time.
Validation	Cross-Validation[47]	The model's predictive performance remains stable across unseen data, indicating that the identified patterns are likely to generalise rather than reflect overfitting.
Validation	Bootstrapping[48]	Across thousands of resampled datasets, the key estimate remains tightly clustered, suggesting the conclusion is robust and not driven by a small number of observations.

Table 1 - Core Statistical Analytical Techniques and Typical Insights They Can Provide

Several skills associated with general data literacy must be kept separate from statistical analytical techniques. The most fundamental is data ingest and cleaning, which sits firmly in the 'processing' stage of the intelligence cycle. Although this is likely to be a key skill for many intelligence professionals, it is

[38] Michael H Kutner et al., *Applied Linear Statistical Models*, 5th edition (Boston, MA: McGraw-Hill Irwin, 2005), pp. 2–38; see 'Linear Regression' in Christian Heumann, Michael Schomaker and Shalabh, *Introduction to Statistics and Data Analysis: With Exercises, Solutions and Applications in R* (Cham: Springer, 2022), pp. 267–314.
[39] Kutner (ed.), *Applied Linear Statistical Models*, pp. 555–640.
[40] See 'Prototype Methods and Nearest-Neighbors' in Trevor Hastie, Robert Tibshirani and Jerome Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction* (New York, NY: Springer, 2009), pp. 459–83.
[41] Hastie, Tibshirani and Friedman, *The Elements of Statistical Learning*, pp. 459–83.
[42] Andy Field, 'Analysis of Covariance (ANCOVA)', 2016, https://discoveringstatistics.com/repository/ancova.pdf, accessed 6 Sep 25.
[43] George E P Box et al., *Time Series Analysis: Forecasting and Control*, 5th edition (Hoboken, NJ: John Wiley & Sons, 2015), pp. 21–45.
[44] Box et al., *Time Series Analysis*, pp. 88–125.
[45] Andrew Gelman et al., *Bayesian Data Analysis*, 3rd edition (London: Chapman and Hall/CRC, 1995).
[46] See 'Simulation of Discrete-Event Systems' in Reuven Y Rubinstein and Dirk P Kroese, *Simulation and the Monte Carlo Method* (Hoboken, NJ: John Wiley & Sons, Ltd, 2016), pp. 91–106.
[47] See 'Model Assessment and Selection' in Hastie, Tibshirani and Friedman, *The Elements of Statistical Learning*, pp. 219–59.
[48] See 'Model Inference and Averaging' in Hastie, Tibshirani and Friedman, *The Elements of Statistical Learning*, pp. 261–94.

categorically not an analytical technique.[49] Other basic data analysis skills, such as exploratory data analysis and basic manipulation to identify distributions and correlations as well as data visualisations and tests for statistical significance, are also omitted given their foundational nature, akin to the crafting of intelligence assessments or writing of reports. It would not be surprising to see all of these on the syllabi of future intelligence training courses. However, these concepts and skills are necessarily separate from Statistical analytical techniques. Likewise, advanced techniques and theory such as machine learning, probability theory and complex analytical methods are not appropriate for core tradecraft given the heightened risk of intelligence failure from misapplication, relative inaccessibility of the concepts and availability of expert-level practitioners for cases where more specialist statistical analysis is required for intelligence purposes.

Some contextualisation of statistical analytical techniques will be required. Most importantly, they must be understood through an uncommon analytical taxonomy for intelligence analysts that is more familiar to the finance industry and to statisticians. The separation of descriptive, inferential and predictive analysis is intuitive to intelligence practitioners, but is not generally applied in the context of structured techniques.[50] Nonetheless, it offers a useful means of communicating the value of the various statistical techniques that are available. Additionally, analytical standards must be reiterated and perhaps clarified in the context of statistical analytical techniques. Of particular importance are the requirement to maintain auditability of data, methods (such as code) that are repeatable especially as data is updated, the need to limit the scope of analysis, and the requirement to provide clear insight and foresight from statistical analysis which can be communicated independently of the (often very sensitive) source data. Supplementary guidance and new standards for statistical techniques are the keystone of this new tradecraft, and will be the final prerequisite for their effective implementation.

Implementing Statistical Analytical Techniques

The formal adoption of statistical analytical techniques in tradecraft and policy is only the first step in ensuring their effective use and mitigating the risks of intelligence failure from total information overload. Without proper implementation, the risk of intelligence failure may, in fact, increase. Some analysts may fail to overcome their own cognitive biases and skill shortfalls due to the Dunning–Kruger effect and misapply their skills, while others are underconfident and may not apply these techniques at all.[51]

Robust training will be essential to the implementation of statistical analytical techniques. Intelligence professionals must be prepared by their organisations to handle vast quantities of data and gain effective insight from them. Crisis mapping in the aftermath of the 2010 Haiti earthquake shows why this is crucial.

[49] Ministry of Defence, 'Intelligence, Counter-intelligence and Security Support to Joint Operations', p. 56.
[50] See 'Motivation' in Ivo D Dinov, *Data Science and Predictive Analytics: Biomedical and Health Applications Using R* (Cham: Springer, 2018), pp. 1–12.
[51] Gordon Pennycook et al., 'Dunning–Kruger Effects in Reasoning: Theoretical Implications of the Failure to Recognize Incompetence', *Psychonomic Bulletin & Review* (Vol. 24, No. 6, 2017), pp. 1774–84, 1774.

Then, professionals were suddenly given access to dramatically more information but without appropriate training. The wide variety of sources and sheer quantity of data ended up overwhelming personnel, hindering the overall task.[52] Training is already firmly embedded into Western intelligence culture. Organisations such as the Sherman Kent School for Intelligence Analysis in the US and the Defence Intelligence Academy in the UK are now well-established for delivering through-career training to intelligence professionals.[53] Training will need to take many forms: incorporation into initial training for new recruits; parallel training packages for established professionals to learn the required new skills; top-up mathematical training to foster deeper understanding of statistical methods; requalification intervals to ensure that appropriate standards are maintained; and expert-level training in advanced techniques and the instruction of others.[54]

Providing intelligence professionals with in-demand skills prompts discussions among practitioners of the risk of inadvertently making compensation packages for intelligence organisations uncompetitive. This is not borne out by available evidence. In the UK, government sources list a salary range for data analysts between £23,000 and £62,000.[55] MI5 offers a salary of £37,281 for data analysts and GCHQ offers a salary of £36,408, well within expected salaries for early career analysts.[56] Meanwhile, mid-level military intelligence analysts at OR-6 and OF-2 have a core salary of £47,763 and £52,815 respectively, along with other compensation such as subsidised accommodation.[57] Similarly, in the US, the CIA offers a starting salary of $69,923 for roles with data analyst responsibilities compared with a national average of $58,000–96,000.[58] Although generally not at the top end of salary ranges, compensation packages for Western intelligence organisations are far from uncompetitive compared with the industry at large. This pattern changes when high-end skills such as data science and data engineering are introduced. In the UK, for example, these attract a significantly higher salary range of £32,000 to £82,500, with top salaries comfortably exceeding £100,000.[59] Against these industry norms, Western intelligence organisations must either rely on unique opportunities and other qualitative benefits, or adjust their compensation to remain competitive for the smaller number of data science and engineering positions required. The remedy for intelligence organisations is therefore not to avoid skilling personnel in statistical methods altogether, but

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[52] Huiji Gao; Geoffrey Barbier and Rebecca Goolsby, 'Harnessing the Crowdsourcing Power of Social Media for Disaster Relief', *IEEE Intelligent Systems* (Vol. 26, No. 3, 2011), pp. 10–14.

[53] Jack Davis, 'Sherman Kent and the Profession of Intelligence Analysis', *Sherman Kent Center for Intelligence Analysis Occasional Papers* (Vol. 1, No. 5, 2002), p. 7; Gov.uk, 'Defence Intelligence Academy Photographer', 2025, https://www.civilservicejobs.service.gov.uk/csr/index.cgi?SID=cGFnZWNsYXNzPUpvYnMmc2VhcmNocGFnZT02JmpvYmxpc3Rfdmlld192YWM9MTk2ODkzNCZ1c2Vyc2VhcmNoY29udGV4dD0xNDk1NDA3NTImc2VhcmNoc29ydD1jbG9zaW5nJm93bmVyPTUwNzAwMDAmb3duZXJ0eXBlPWZhaXImcGFnZWFjdGlvbj12aWV3dmFjYnlqb2JsaXN0, accessed 9 Sep 25.

[54] Duffield, 'Analytic Standards in the Context of Military Intelligence', pp. 48–49.

[55] National Careers Service, 'Data Analyst-statistician', 2025, https://nationalcareers.service.gov.uk/job-profiles/data-analyst-statistician, accessed 4 Sep 25.

[56] MI5, 'Intelligence and Data Analyst Development Programme'; GCHQ, 'Intelligence Data Analyst Ref. 3544'.

[57] Armed Forces' Pay Review Body, *Armed Forces' Pay Review Body: Fifty-Fourth Report 2025*, CP 1330 (London: The Stationery Office, 2025).

[58] CIA, 'Technical Careers', 2025, https://www.usajobs.gov:443/job/839081400, accessed 4 Sep 25.

[59] National Careers Service, 'Data Scientist', 2025, https://nationalcareers.service.gov.uk/job-profiles/data-scientist, accessed 4 Sep 25.

simply to avoid over-skilling all practitioners with unnecessarily high-end skills.[60] Any resulting shortfalls in the most advanced skills are better remedied by personnel in generalist statistical roles such as in the UK's Government Statistical Service, Defence Science and Technology Laboratory and small operational analysis community.

Intelligence organisations also require digital capabilities that are fit for repeatable and secure analysis of enormous datasets, as well as auditable sharing of the insights contained within. As discussed above, given the pace at which many industries have adapted to information overload, commercial capabilities are already available to Western governments for precisely this purpose, but full adoption of industry-leading data platforms is essential to make best use of statistical methods. This draws parallels with the historic adoption of office productivity software such as Microsoft Office and even the adoption of personal computers – full implementation often took place over many years in parallel with traditional methods until the transition was complete.[61] Most importantly for data analytics capabilities, they must be integrated with the wide range of source data collected by intelligence organisations, and with the intelligence outputs that inform decision-making. Doing so creates unbroken audit chains and allows analysis to be repeated as available information changes.

Some cultural realignment will be required to achieve effective implementation. Quantitative techniques yield insight into the data, but further inference is required to truly understand the environment, which remains a qualitative intelligence skill. A careful balance is necessary, as analysts and customers must not become wedded to reassuringly specific numbers produced by statistical analytical techniques, a risk raised repeatedly by scholars.[62] Data rarely provides a complete picture, and as increasingly complex methods are used to gain insight, recognition of the limitations of this insight, potential gaps and key assumptions become more important than ever to avoid intelligence failure. It will be vital to ensure that quantitative methods do not create false certainty at the expense of rigorous intelligence work. There is still much value in generalising highly specific numerical values into the general yardstick measures of uncertainty such as 'likely' and 'highly unlikely' that are in common use by Western intelligence organisations.[63] Conversely, Statistical analytical techniques may be ignored altogether due to relative complexity and limited interest from customers. Overcoming this requires a strong and consistent top-down impetus from policymakers, who should demand data-driven insight as part of the analytical mix supporting intelligence assessments.

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[60] Monica Collins-Hines, 'Strategies to Retain Science, Technology, Engineering, and Mathematics Civilian Employees in U.S. Army Cyberfocused Organizations', PhD thesis, Walden University, 2024, p. 91.

[61] *BBC News*, 'How the Computer Changed the Office Forever', 2013, https://www.bbc.com/news/magazine-23509153, accessed 9 Sep 25.

[62] Van Puyvelde, Coulthart and Hossain, 'Beyond the Buzzword', p. 1415.

[63] PHIA, 'PHIA Professional Development Framework', 2019, p. 207, https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1146217/2019-01_PHIA_PDF_First_Edition_Electronic_Distribution_v1.1__1_.pdf, accessed 30 Aug 23; Office of the Director of National Intelligence, 'Analytic Standards', p. 3.

Conclusion

The quantitative methods proposed here to counter total information overload are not themselves novel, but their absence from formal intelligence standards and tradecraft is increasingly conspicuous. Failure to implement them alongside existing qualitative methods presents a growing risk of intelligence failure. Such failure may stem from a variety of sources, including the unassured use of statistical techniques, the inability to reliably gain insight from vast data sets, and the misunderstanding of how to properly apply the insight that analysis of data can offer. The need to incorporate statistical analytical techniques into core intelligence tradecraft is now critical, and the demand for auditable and repeatable statistically driven analytical insight from intelligence customers must grow as a counterpart to the increasing use of AI to meet the challenges of total information overload elsewhere in the intelligence cycle.

By formally adopting a basic toolkit of widely applicable statistical analytical techniques with a relatively low mathematical baseline, and fully implementing them as core tradecraft, Western intelligence communities can dramatically grow the scope of insight that they can provide in an operating environment that is more data-rich than ever.

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