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Critical thinking in the age of big data and AI

Authors
Elias Axsäter
Ruben Forsmark
Tala Badawi

Title: Critical thinking in the age of big data and AI

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Authors: Ruben Forsmark, Elias Axsäter, Tala Badawi

Supervisor: Niklas Lars Hallberg

External Supervisor: Stephanie Barnes

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Research questions: How does the perception and use of Big Data Analytics influence the critical thinking of white-collar workers?

Purpose: Disclose potential risks with too much weight put on data in organizational decision-making

Methodology: The thesis adopts a deductive and quantitative approach with the aim of addressing three hypotheses based on previous research in decision-making and critical thinking. Data collection was conducted through a survey and a cognitive test, which were distributed to white collar workers. The respondents were asked to describe how they use and perceive big data analysis in their work.

Theoretical perspectives: The study is grounded in the fields of critical thinking and decision-making.

Results: Based on the results of the study, no clear connections were found between critical thinking, the use of big data analysis, decision type, and experience.

Conclusions: It was not possible to identify a connection between the loss of critical thinking and the use of big data analysis. Furthermore, no connection was found between decision type and experience in relation to critical thinking

Examensarbetets titel: Critical thinking in the age of big data and AI

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Författare: Elias Axsäter, Ruben Forsmark, Tala Badawi

Handledare: Niklas Lars Hallberg

Extern handledare: Stephanie Barnes

Fem nyckelord: Critical thinking, Big data analytics, Decision-making, Cognitive demand, Skill decay

Forskningsfråga: Hur påverkar användningen och uppfattningen av stordata tjänstemäns förmåga att tänka kritiskt?

Syfte: Undersöka om det finns något samband mellan förmågan att tänka kritiskt och användande av stordatanalys

Metod: Uppsatsen antar en deduktiv och kvantitativ ansats med syftet att besvara tre hypoteser som baseras på tidigare forsking inom beslutsfatande och kritiskt tänkande. Insamling av data gjordes med hjälp av en enkätundersökning och ett kognitivt test som skickades ut till tjänstemän. Respondenterna fick svara på hur de använder och upplever stordataanalys

Teoretiska perspektiv: Studien grundar sig inom områdena kritiskt tänkande och beslutsfattande.

Resultat: Baserat på resultaten som framkommit av studien fanns det inga tydliga kopplingar mellan kritiskt tänkande,stordata analys användande,beslutstyp och erfarenhet

Slutsats: Det går inte att påvisa ett samband för förlust av kritiskt tänkande drivet av stordatanalys. Det fanns inte heller någon koppling mellan beslutstyp och erfarenhet med kritiskt tänkande.

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Abstract

This study examines the relationship between critical thinking and the use of Big Data Analytics (BDA) in decision-making among white-collar professionals. It focuses on three key areas: the influence of BDA reliance on critical thinking, the connection between professional experience and cognitive reasoning, and the demands of strategic decision-making compared to tactical and operational roles. A quantitative approach was used, combining a structured survey and the Watson-Glaser Critical Thinking Appraisal to gather data from a targeted sample of professionals. The survey assessed the perception and use of BDA of these professional demographics, while the Watson-Glaser test measured participants' critical thinking abilities.

The analysis employed regression and ANOVA to test hypotheses and identify significant trends. Results reveal that while BDA reliance can enhance decision-making processes, over-dependence on data tools may limit cognitive reasoning. Professional experience was shown to play a critical role in developing critical thinking, with experienced professionals demonstrating stronger cognitive abilities. Strategic decision-making was found to place higher demands on critical thinking compared to tactical and operational decisions. This research highlights the importance of balancing data-driven tools with critical thinking skills in organizational decision-making. It offers valuable insights for professionals and organizations looking to integrate BDA effectively while fostering cognitive reasoning. The findings contribute to ongoing discussions about the interaction between human cognition and technology in professional environments, offering a foundation for future research in decision-making and organizational behavior.

Keywords: Big Data Analytics (BDA), Critical Thinking, Professional Experience, Quantitative Research, Decision-Making, Watson-Glaser Critical Thinking Appraisal

List of Concepts

Data Analytics (BDA) - The use of BDA tools in decision-making processes, focusing on their impact on cognitive reasoning and professional judgment.

Critical Thinking - Cognitive abilities like inference, deduction, and argument evaluation, measured through the Watson-Glaser Critical Thinking Appraisal.

Bounded Rationality - A theoretical framework that explains decision-making under constraints, such as limited information, time, or cognitive capacity, affecting critical thinking and reliance on technology.

Decision-Making Types - Classification of decisions as operational, tactical, or strategic, with varying demands on critical thinking.

Professional Experience - The influence of career tenure on decision-making quality and critical thinking abilities.

White-Collar Workers - Professionals in roles that primarily involve intellectual, administrative, or analytical tasks rather than manual labor.

Causal Relationships - Examining how BDA reliance, professional experience, and decision-making types affect critical thinking.

Quantitative Methodology - Use of structured surveys, Likert scales, and statistical methods such as regression and ANOVA to test hypotheses.

List of tables

Table of contents

1. Introduction

Effective decision-making is a cornerstone of organizational success in today's complex business environment (Matt Gavin, 2020). The ability to make informed and sound decisions often determines an organization's capacity to survive and maintain a competitive edge in dynamic markets (Aljumah et al., 2022). The decision-making process is shaped by several factors, including the theoretical frameworks individuals use, whether naturalistic or rationalistic and the specific context in which decisions occur (Rehak et al., 2010; Snowden & Boone, 2007). Understanding these influences is vital for improving decision quality and fostering organizational resilience (Aljumah et al., 2022).

Decision-making situations emerge from internal and external organizational factors (Intezari & Pauleen, 2019). These situations differ in impact, complexity, and the decision-maker's familiarity with the context in which the decision will be made (Harrison, 1995). Ackoff (1990) categorizes decision types into *operational*, *tactical*, and *strategic*, each requiring a different approach. Recognizing the nature of a decision not only aids in selecting the appropriate strategy, such as intuitive (system 1) or deliberate (system 2) thinking, but also ensures that time and resources are allocated effectively to align with what the decision needs (Ackoff, 1990).

Big Data Analytics (BDA) has become integral to organizational decision-making, offering advanced tools for descriptive, predictive, and prescriptive analyses of complex datasets. According to Gressel et al. (2020, p. 270), BDA is "a huge volume of data collected from different sources and in different formats that can be analyzed in real-time." This capability allows organizations to generate insights that surpass the limits of human cognitive capacity for unaided data processing (Gandomi & Haider, 2015). By systematically applying advanced statistical, computational, and machine learning techniques to large and complex datasets, BDA enables the extraction of meaningful patterns and insights. These insights are essential, providing decision-makers with tools and information to enhance organizational performance. According to (Chen et al., 2012), BDA enables increased operational efficiency, identification of new opportunities, and optimization of strategies.

According to Pauleen and Wang's (2017) Big Data/Analytics-Knowledge Management (BDA-KM) model, contextual knowledge is essential for designing systems, selecting appropriate analytical tools, and converting raw data into actionable information that aligns with organizational objectives. Decision-makers play a critical role in this process, as their contextual knowledge ensures that data insights can effectively guide decision-making (Pauleen & Wang, 2017).

As organizations increasingly integrate BDA into their processes, decision-makers must develop the technical skills required to interpret data and critically evaluate the outputs (McAfee et al., 2012). This aligns with Persaud and Zare's (2023) definition of *Big Data Analytics Capabilities* (BDAC), which encompasses the ability to assemble and deploy resources specific to BDA, including human, technological, and organizational elements. These capabilities go beyond technical expertise and data analysis to *critical thinking* (CT), problem-solving, and collaboration.

Critical thinking (CT) is the ability to actively and skillfully interpret, evaluate, and synthesize information or arguments to make reasoned decisions based on evidence (Fisher & Scriven, 1997; Hatcher, 2000). It involves objectively assessing alternatives and carefully weighing available information before reaching a judgment or conclusion. It is a uniquely valuable skill that fosters problem-solving and adaptability, with research showing its strong correlation to positive outcomes in organizational and personal contexts (Butler et al., 2012). Furthermore (Butler et al., 2012) states that CT has a stronger correlation with favorable life outcomes than IQ and can be developed through targeted education and practice (Lai, 2011).

However, *skill decay* may pose a significant challenge to critical thinking, particularly in workplaces where reliance on BDA reduces opportunities for active cognitive engagement (Arthur Jr., 1998). Over Reliance on BDA may exacerbate this issue, as individuals increasingly avoid cognitively demanding tasks and instead rely on technology for decision-making (Kool et al., 2010).As BDA provides measurable and actionable insights, it often presents a simplified view of reality by focusing on quantitative factors and neglecting qualitative or contextual elements (Marcy Farrell, 2023). When decision-makers fail to critically engage with their data's underlying assumptions or contextual factors, they risk implementing strategies that lack alignment with broader organizational goals or market realities (Adhikari, N.P. 2023).

This detachment can lead to suboptimal outcomes, such as inefficient resource allocation or failure to adapt to changing environments (Williams, 2006; Gressel et al., 2020). Pauleen et al. (2016) highlight the dangers of unquestioningly trusting BDA in decision-making, particularly the erosion of judgment and CT within the finance industry. Referring to the *Financial Crisis Inquiry Report* (2011), Pauleen et al. (2016) emphasize how financial institutions and credit rating agencies placed undue trust in mathematical models as risk predictors, often at the expense of human oversight and discernment. This reliance led to the approval of tens of thousands of loans based solely on predictive analytics, which must be designed to be credibly objective. As a result, risk management devolved into risk judgment, contributing significantly to the financial crisis by obscuring underlying vulnerabilities and amplifying systemic risks.

Data analytics has transformed decision-making by providing decision-makers access to vast datasets, enriching the depth and precision of available information (McAfee, Andrew, et al., 2012). Studies have extensively demonstrated the advantages of data-driven approaches, focusing on the correlation between BDA usage and improved organizational performance. For instance, Ajah and Nweke (2019) highlight how companies like Walmart and American Express achieved significant gains, such as enhanced search functionalities leading to increased sales and revenues, showcasing the critical role of BDA in driving success and staying competitive.

Previous research highlights CT and problem-solving as essential skills in business decision-making processes. White-collar professionals routinely face diverse decision-making scenarios that vary in scope, ranging from operational to tactical and strategic levels, depending on their roles and responsibilities. Prominent organizations such as IBM and McKinsey have integrated critical thinking assessments into their recruitment processes to identify candidates with these competencies (IBM; McKinsey, 2024).

However, despite the acknowledged importance of CT in professional contexts, the interplay between white-collar workers' decision-making levels (operational, tactical, or strategic), their propensity to adopt BDA, and their CT remains an area yet to be investigated.

The lack of research in this area is fascinating, given the increasing reliance on BDA across industries. Although BDA offers decision-makers capabilities and insights that enhance decision-making efficiency and accuracy, there is limited understanding of whether this BDA adoption complements or undermines critical thinking. It remains unclear if integrating BDA supports CT or inadvertently fosters overdependence on data-driven systems, potentially diminishing independent critical reasoning. The present study aims to fill this gap by exploring the relationship between white-collar workers' use and perception of BDA and their CT, focusing on the potential correlational links between these factors.

The central focus of this research is to determine whether reliance on BDA in organizational decision-making is associated with reduced CT. As organizations increasingly adopt data-driven approaches, assessing how dependency on BDA affects critical reasoning skills and, by extension, organizational effectiveness and success is crucial. The study seeks to answer the central research question: *How does the perception and use of Big Data Analytics influence the critical thinking of white-collar workers?*

This study will adopt a quantitative research approach. A structured survey will be developed to collect data on two primary variables: the participants' perceptions and usage of BDA and their critical thinking (CT) abilities. The survey will incorporate a combination of items, including Likert-scale questions to gauge perceptions and practices related to BDA and a validated critical thinking assessment tool to measure CT capabilities.

The survey will specifically target white-collar workers across various industries, ensuring a diverse representation of individuals who engage in decision-making tasks within business organizations. After data collection, statistical analyses will be conducted to explore relationships between the use and perception of BDA and levels of CT. Correlation analysis and regression modeling will uncover potential patterns or connections in the data.

This approach is expected to provide empirical insights into whether and how BDA influences critical thinking, enabling the study to contribute valuable knowledge to academic literature and organizational practices.

2. Theoretical Framework

The decision-making process is traditionally defined as the ability to make informed choices by efficiently utilizing one's lifetime of knowledge, experience, reasoning, intuition, common sense, and confidence (Clayton C, 2007). This definition is based on the “Rational Choice Theory,” which states that when a decision-maker is supplied with all information about options, the rational individual will always choose the option that maximizes utility and gives the best possible outcome (Peng, 2013).

How well this defines the decision-making process is up for discussion, as it can be seen as a utopia with all possible outcomes presented. Steve W. Williams (2002) states, " Rational decision-making is a time-consuming, systematic process, which decision-makers rarely have means and cognitive abilities to apply. “The reality of business life is that we don't have time, energy or resources to use the rational process for most of the hundreds of decisions we face daily” (Steve W. Williams, 2002).

Herbert Simon introduced the concept of "Bounded Rationality," which posits that decision-makers are inherently constrained in their ability to make optimal decisions due to limitations in cognitive capacity and available resources (March and Simon, 1958). While decision-makers aim to adopt fully rational approaches, they face practical barriers such as incomplete or inaccurate information, limited time for analysis, and the human inability to process vast amounts of data or foresee all potential outcomes (Gressel, Pauleen & Taskin, 2020).

Ackoff (1990) further highlights that the extent to which rational decision-making can be employed depends on the specific nature of the decision. In a business context, decisions are typically classified into three types: operational, which focuses on routine efficiency and daily tasks; tactical, which aligns medium-term plans with broader strategic objectives; and strategic, which addresses long-term goals and involves significant complexity and impact. Each category requires a tailored decision-making approach, emphasizing the importance of understanding the decision's nature to select the most effective methodology (Ackoff, 1990).

Operational decisions are often straightforward, and due to their repetitive and structured nature, they can leverage rational, automated processes supported by big data and analytics (Ackoff, 1990).

However, as decisions involving human or environmental uncertainties become more complex, the application of pure rationality diminishes. In scenarios involving tactical or strategic decisions, factors like intuition, experience, and adaptability often play a crucial role, as the unpredictability of external variables limits the efficacy of purely rational approaches (Ackoff, 1990).

In more complex and dynamic decision situations, decision-makers may adopt a naturalistic approach, reflecting their personal preferences, including heuristics, experience, emotions, and gut feeling (Sadler-Smith, Eugene, 2023). As finding an optimal solution to business-based decision situations is often impossible and impractical, decision-makers may be more successful in applying their abilities and preferences (Simon, 1957; Kool et al., 2010).

Technological advancements have significantly transformed Business decision-making processes over time (McAfee, Andrew, et al., 2012). Decision-makers make tactical and strategic decisions traditionally based on human abilities, such as intuition, heuristics, and experience (Ackoff, 1990). The rapid advancements in big data, analytics, and artificial intelligence have fundamentally reshaped the conditions that form the foundation of decision-making processes (Elgendy, N., Elragal, A., 2014).

In today's organizations, decision-makers must use qualitative abilities and make decisions based on vast data and analytics (Andrew McAfee & Erik Brynjolfsson, 2012). According to (Andrew McAfee & Erik Brynjolfsson, 2012), it is clear that BDA improves decision-making on a general basis. In *Big Data: The Management Revolution, they* quote, “Data-driven decisions are better decisions - it's as simple as that” and refer to the fact that data enables decision-makers to decide based on evidence rather than intuition. Donthireddy, T.K (2024) exhibits the most prominent enhancing factors of business decision-making due to BDA, including AI, real-time insights, streamlined operations, cost reduction, and improved efficiency through automation and predictive analytics. Moreover, Andrew McAfee & Erik Brynjolfsson (2012) state that there are also challenges to the benefits of BDA in decision-making. In particular, they point out the decision maker's technical understanding of BDA and how to use it.

“Big data’s power does not erase the need for vision or human insight” Is also quoted by (Andrew McAfee & Erik Brynjolfsson, 2012), who means that if data is scarce, expensive to get your hands on,or only exists in paper form, it makes sense to let well-placed people make decisions, which by their experience can make decisions based on intuition.

However, as BDA becomes more prevalent, decision-makers can no longer rely solely on intuition in the organizational context; they must adopt techniques to handle data efficiently so as not to get bypassed by competitors. Andrew McAfee & Erik Brynjolfsson (2012) point out an essential capability of a successful decision-maker in the modern world. They summarize it with critical thinking and the ability to put out the necessary questions; “What do the data say?”, “Where did the data come from?” “What kinds of analyses were conducted?” and “How confident are we in the results?”. Simultaneously, they emphasize the importance of maintaining an openness to be overruled by data and putting information generated by BDA before personal intuition, even though there might be a disagreement.

2.1 Critical thinking

Fisher and Scriven define critical thinking as the ‘skilled, active interpretation and evaluation of observations, communications, information, and argumentation’(1997), and there are some who may define CT as "Thinking that attempts to arrive at a decision or judgment only after honestly evaluating alternatives concerning available evidence and arguments" (Hatcher, 2000). Both definitions share sentiments, such as decision-making and looking at all the available information before concluding. This means that it will be a part of everyday life, whether navigating information found on social media or taking advice from peers (Liedke and Wang, 2023).In an era of rapid innovation and technological advancement, CT's importance continues to grow. Kivunja (2014) highlights its essential role in achieving personal success and addressing modern society's complex global challenges.

CT can be applied in many areas of professional life where all the decisions that need to be made hang on the ability to discern what information is helpful to the current situation and whether or not it's an opportune moment to act (Archer & Davison, 2008). CT is not only beneficial for making decisions in a controlled environment, but it is also essential when negotiating a situation where you have to discern the other party's real intentions and evaluate their arguments in real time where you may not have access to information that can confirm what is being said (Deane & Borg, 2011).

Halpern (1998) states that critical thinking (CT) encompasses four key components: disposition, skills, structure training, and metacognition. Disposition in this context means the willingness to engage in type 2 thinking, not giving up on complex tasks, and not stopping being open-minded. The skills required for CT include verbal reasoning, argument analysis, hypothesis testing, probability assessment, and decision-making. Structure training involves recognizing patterns and applying appropriate thinking skills across different contexts, while metacognition focuses on reflecting on and adjusting one's thinking to minimize bias and improve accuracy. Similarly, Pearson (2020) identifies three core aspects of CT: recognizing assumptions (identifying implicit premises), evaluating arguments (assessing their quality and relevance), and drawing conclusions (making logical inferences based on evidence).

CT is a skill that can be applied across fields (Dwyer et al., 2015), but knowledge specific to a domain can dramatically enhance effectiveness. This allows individuals to apply CT more effectively within particular contexts, as familiarity with a domain provides the tools to assess complex arguments and draw informed conclusions. Jones (2007) underscores this connection, finding that immersion in business-related methods and strategies fosters the development of business-specific CT skills. Similarly, Alexander and Judy (1988) highlight that using strategic knowledge effectively depends on domain-specific expertise, which provides the framework for critical analysis and decision-making.

Domain knowledge enhances CT, particularly in high-impact decisions. Decision-makers in roles requiring greater strategic focus and complexity rely on their expertise to navigate uncertainty and synthesize information effectively. Thus, it is especially relevant to investigate whether those handling high-impact organizational decisions demonstrate stronger critical thinking skills than those in less impactful roles.

Hypothesis 1: Decision-makers handling high-impact organizational decisions demonstrate stronger critical thinking skills than those in less impactful roles.

The interplay between general and domain-specific CT abilities is further evidenced by research from Pascarella and Terenzini (1991), which revealed that CT develops progressively over an academic career, particularly during college. Dwyer et al. (2015) corroborate this, finding that individuals with college education outperform those without general and domain-specific CT tasks. Additionally, those with business-specific education demonstrate further advantages in business-related CT scenarios. This aligns with Nielsen et al. (2022) assertion that the most significant gains in CT development occur when general CT skills are cultivated alongside their application in a specific area of interest. Collectively, the research underscores that the most effective way to develop CT is by building foundational CT abilities and actively applying them within a specialized field of study or practice.

For a long time, researchers have debated whether critical thinking (CT) is an innate ability or a learned skill. While nativists argue that cognitive skills like CT are predisposed and vary in success among individuals, anti-nativists maintain that these abilities can be developed through training (Spelke et al., 2010). Recent research supports the anti-nativist view, showing that cognitive abilities, including CT, can be improved with experience and learning (Mameli & Bateson, 2011). Supporting this, King et al. (1990) found that individuals with more advanced education tend to score higher on critical thinking scales than undergraduates. Building on this, it is reasonable to hypothesize:

Hypothesis 2: Individuals with more work experience are better at critical thinking.

According to (Kool et al., 2010), cognitive demands significantly shape decision-making behavior. Their research suggests that individuals often seek to minimize cognitive effort, weighing it as a cost in their cost-benefit evaluations (Bröder & Schiffer, 2003; Payne et al., 1988). This tendency to reduce cognitive load can result in suboptimal decision-making behaviors, such as adopting non-compensatory strategies, where decision-makers aggregate evidence selectively or exclude alternatives without thorough evaluation (Hauser & Wernerfelt, 1990).Effort-minimization in cognitive processes compounds the risks associated with an over-reliance on data and analytics within organizational decision-making. As Kool et al. (2010) outlined, decision-makers frequently evaluate cognitive effort as a cost, favoring strategies that minimize mental exertion. This inclination aligns with dual-process theories of cognition (Kahneman, 2011), where System 1's intuitive and heuristic-based approach often precedes System 2's deliberate and analytical reasoning, especially under high cognitive demand.

Decision-maker’s tendency to prioritize easily interpretable metrics over nuanced or complex factors, bypassing critical evaluation of underlying assumptions or broader contextual elements can detach decisions from strategic alignment, leading to suboptimal outcomes (Bröder & Schiffer, 2003; Payne et al., 1988).

According to Butler et al. (2012), CT is both a skill and a disposition. While some individuals are naturally more adept at it, it is also a capability that can be developed through practice. However, CT requires regular application as a skill, as cognitive abilities like problem-solving and CT tend to decay more rapidly than physical skills when left unused (Arthur Jr., 1998). Adopting Big Data Analytics (BDA) in decision-making offers significant advantages but also presents risks. Barnes (2024) notes that over-reliance on analytics can obscure the rationale behind decisions, diminish experiential insights, and lead to suboptimal outcomes. CT must address these challenges, enabling decision-makers to identify problems, gather relevant information, and interpret data effectively. With the growing dependence on BDA, Given the increasing reliance on Big Data Analytics (BDA), it becomes intriguing to explore how this reliance might affect CT, which remains a cornerstone of sound decision-making.

Hypothesis 3: Decision-makers with more trust in BDA negatively correlate with critical thinking.

3. Method

3.1 Research Design

Bryman and Bell (2017) noted that research can broadly be classified as quantitative or qualitative, each offering distinct methodologies for investigating relationships and patterns. A quantitative approach was chosen for this study due to its ability to measure and analyze relationships between variables systematically. The reliance on numerical data allows for structured hypothesis testing and provides statistically robust insights. This method aligns with the deductive nature of the study, where theoretical frameworks are directly tested against empirical data. The quantitative approach also provides a framework for understanding decision types grounded by Ackoff (1990), see Chapter 2, each reflecting varying degrees of reliance on data analytics and personal judgment. This classification complements the study's aim to evaluate how decision-making interacts with critical thinking and data reliance.

This study adopts a quantitative research design to investigate the correlation between decision types defined by Ackoff (1990) and the critical thinking of these professional individuals—a deductive approach aligns data collection and analysis with theoretical frameworks. According to Bryman & Bell (2017), quantitative research methods enable examining relationships between variables, offer a structured approach to testing hypotheses, and derive statistically robust insights for further analysis. The data for this study was collected through a structured questionnaire, forming the basis for a quantitative analysis to explore the interplay between critical thinking, decision-making styles, and the use of BDA. This research employs a deductive approach, where empirical findings are evaluated within established theoretical constructs to assess predefined hypotheses (Bryman & Bell, 2017). Specifically, three hypotheses were formulated from the theoretical discussion in Chapter 2, focusing on the relationships between decision types, critical thinking, and individuals' usage and perception of AI & BDA professionally within organizations. These hypotheses were tested using the collected data, resulting in their validation or rejection.

As Merton (1967) highlighted, a deductive framework is particularly effective for sociological investigations involving group dynamics or institutional behavior. The design of this study was developed with a foundation in Bryman & Bell (2017) framework for conducting quantitative-oriented research. The approach emphasizes a systematic process for formulating, collecting, analyzing, and interpreting data to answer complex research questions. A deductive approach was adopted, particularly suited for research that seeks to test established theories and evaluate their applicability in new contexts (Bryman & Bell, 2017). The research began with a theoretical framework and predefined hypotheses that enabled and guided the study design and data collection development. The hypotheses were derived from existing theories on decision types and critical thinking. This deductive approach allows the research to use empirical data to support or contradict the proposed hypotheses. It ensures that research remains focused and aligned with established theoretical constructs, providing a clear pathway from theory to data analysis.

The research design adopts a structured data collection in which a structured and standardized questionnaire is constructed to ensure consistency in data collection across a diverse participant pool. This approach allows for comparability of the responses. When data is collected uniformly, meaningful comparison between participants is achieved. This approach also provides for reliability and efficiency. A well-designed questionnaire minimizes variability in responses caused by unclear or ambiguous phrasing. The structured format allows for efficient data processing and analysis, crucial for deriving robust conclusions from a large dataset. The questionnaire integrates established scales like the Watson Glaser critical thinking appraisal to ensure content validity and relevance to the research objectives.

This study employs a quantitative research design appropriate for systematically testing hypotheses and generalizing findings to a broader population. The deductive approach was chosen as it allows hypotheses derived from established theoretical frameworks to guide the study. By focusing on numerical data, this approach enables robust statistical analyses to determine causal relationships between variables. Quantitative research was preferred due to its ability to identify patterns and relationships among measurable constructs, such as the willingness to use data analytics and critical thinking.

Additionally, this design ensures replicability and facilitates the use of inferential statistics to test the significance of relationships outlined in the conceptual model.

The study primarily focuses on the use and perception of big data and analytics by examining the participants' reliance on big data and AI tools, highlighting how these technologies influence decision-making. This study also focuses on critical thinking by evaluating key cognitive abilities such as inference, deduction, and evaluation to understand how data reliance correlates with or impacts these skills. A core objective is to explore whether a balance between intuitive decision-making and data reliance fosters higher levels of critical thinking than exclusive reliance on either approach. This focus ensures the research remains aligned with its central aim: understanding the connection and interplay between technology and human cognition in decision-making contexts. By combining structured data collection with a focus on the identified variables, the research design ensures a systematic and comprehensive investigation of the hypotheses mentioned earlier.

3.2 Causal Model and Key Variable

The study's causal model investigates three primary direct relationships. The first examines how reliance on BDA directly impacts critical thinking, hypothesizing that BDA use may either complement or inhibit cognitive reasoning. The second relationship explores whether professional experience correlates positively with critical thinking, suggesting that greater experience provides individuals with more opportunities to develop advanced reasoning skills. The third relationship focuses on decision-making type, hypothesizing that strategic decision-making requires more critical thinking than tactical or operational decisions. The relationships are examined within a quantitative framework integrating survey and critical thinking test data, ensuring alignment between the theoretical model and the collected data. This study's operationalization of variables ensures that all constructs are rigorously defined and quantitatively measured. The perception and use of BDA is measured through a Likert scale, professional experience is categorized into years of experience, decision-making type is self-reported through structured classifications, and critical thinking is scored using theta-based analysis of WGCTA responses. This structured approach ensures that the research question and hypotheses are addressed within a robust causal framework, allowing for meaningful statistical analysis and contributing valuable insights to the intersection of BDA reliance, professional experience, decision-making, and cognitive reasoning.

3.2.1 Perception and Use of Big Data Analytics (BDApu)

The perception and use of BDA is the primary independent variable, representing the extent to which participants rely on data-driven tools in their decision-making processes. This variable is operationalized through self-reported responses on a Likert scale ranging from 1 (minimal reliance) to 7 (extensive reliance). The survey measures the frequency and intensity of BDA use, capturing participants' behaviors and attitudes toward incorporating analytics into their professional roles. The study hypothesizes that reliance on BDA may enhance critical thinking by supporting cognitive processes with data-driven insights or suppress it by fostering over-dependence on automated tools. These self-reported measures allow a nuanced understanding of how BDA use and perception relates to critical thinking.

3.2.2 Professional experience

Professional experience is another independent variable and reflects participants' cumulative exposure to decision-making scenarios throughout their careers. This variable is categorized into 0–5 years, 6–10 years, and 10+ years. The categorization is designed to capture distinct levels of career progression, from early career professionals to seasoned experts. Participants provide information about their professional experience through demographic questions included in the survey. The study hypothesizes a positive relationship between professional experience and critical thinking, as individuals with more experience are more likely to have encountered a broad range of complex and challenging scenarios, enhancing their cognitive reasoning skills.

3.2.3 Decision type

The decision-making type, derived from Ackoff's framework, constitutes a third independent variable. This variable categorizes participants' professional decision-making processes into operational, tactical, and strategic.

Operational decisions involve routine, structured tasks requiring minimal cognitive engagement. Tactical choices are medium-term and focus on aligning operational activities with broader organizational goals. Strategic decisions, in contrast, are long-term and involve significant complexity, uncertainty, and judgment.

Participants self-report their dominant decision-making type through survey items, enabling the study to explore whether different decisions demand varying levels of critical thinking. Compared to tactical and operational decision-making, strategic decision-making is hypothesized to require the highest levels of critical thinking.

3.2.4 Critical thinking

Critical thinking, the dependent variable, represents participants' ability to evaluate arguments, draw logical conclusions, and assess evidence. It is measured using an adapted version of the Watson-Glaser Critical Thinking Appraisal (WGCTA), a widely recognized tool for evaluating cognitive reasoning. The assessment focuses on three core dimensions of critical thinking: inference, deduction, and evaluation of arguments. Inference involves the ability to draw logical conclusions from evidence, deduction assesses whether conclusions logically follow from premises, and assessment of arguments consists in judging the strength and validity of claims. The critical thinking assessment is fully integrated into the survey, allowing the study to connect test results directly to participants' reported behaviors and characteristics.

The critical thinking test results are calculated using theta scoring, a psychometric approach based on Item Response Theory (IRT). Unlike traditional methods that simply count the number of correct answers, theta scoring considers the difficulty of each question and the participant's performance. Theta scores range from approximately -3, representing low ability, to +3, representing high ability. Participants who answer more challenging questions correctly receive higher theta scores, providing a nuanced and precise measure of critical thinking ability. This method ensures that variations in test difficulty are accounted for, making the scores more reliable and meaningful. Furthermore, the theta scores are norm-referenced, allowing for comparisons between participants' scores and those of a broader reference population. For instance, a percentile ranking may indicate that a participant performed better than 75% of the norm group, contextualizing their critical thinking ability within a larger sample.

The causal relationship between big data exploration and critical thinking was explored to answer the research question and confirm or reject the hypotheses. This study adopts a quantitative causal framework represented by a box and arrow model to delineate the causal pathway and relationships between variables. The independent variable in the box and arrows model is the perception and use of big data and analytics measured through self-reported Likert scale questions. The dependent variable is critical thinking, measured through the thinking appraisal test based on Watson Glaser.

The model also studies other variables, such as professional experience and decision-making type. The arrows in the model represent hypothesized causal pathways that are meant to be explored within the scope of this study. The first arrow represents the extent to which reliance on data analytics influences critical thinking. The second arrow reflects how professional experience is hypothesized to correlate with critical thinking. The third is the decision-making type, which shows how differences in decision-making can require different critical thinking.

To align with the causal model, specific variables are defined and operationalized. The independent variable of perception and use of BDA is measured on a 1-7 Likert scale where 1 indicates minimal reliance on big data and 7 indicates extensive reliance. These questions capture the participant's self-reported frequency and intensity of big data usage. Critical thinking as a dependent variable is assessed using questions adapted from Watson Glaser Critical Thinking Appraisal that focuses on skills like inference, deduction, and evaluation of arguments. Another relationship explored using this model is the decision type adopted from Ackoff's framework, which is determined through questionnaire items designed to classify participants' decisions into one of the three decision types. Control variables professional experience is categorized as 0-5 years, 6-10 years, and 10+ years. Decision type is classified as the decisions the participants take and as strategic, tactical, or operational. Industry context is categorized by broad industry sectors, e.g., consulting, manufacturing, finance, etc. These variables are clearly defined and measured quantitatively, aligning with the research's causal focus. This approach is designed to clearly define and maintain the unit of analysis as the individual professional, establish a causal framework that aligns with the research question and hypotheses, and ensure that all variables and measures are operationalized for quantitative analysis, supporting statistical precision and hypotheses testing.

3.2 Sample Selection

3.2.1 Target Population:

Bryman & Bell (2017) also highlight the importance of identifying a target population closely aligned with the studied phenomenon. This alignment strengthens the collected data's relevance and the subsequent analysis's validity. The target population consists of white-collar workers within business organizations. These individuals were chosen based on their familiarity with data analytics and the cognitive demands of decision-making roles. The population includes professionals across levels who have different industrial backgrounds. By researching this group of individuals, the study ensures that variation in decision-making approaches is captured, explores how varying contexts affect the interplay between BDA exploration and critical thinking without limiting it to a specific industry or sector, and ensures relevance to the research objectives. The chosen population ensures responses from participants with the necessary experience to provide valuable insights into the correlation between data reliance and critical thinking.

The target population for this study comprises white-collar workers. This term refers to individuals who perform professional, managerial, or administrative work, typically in an office or other administrative setting. These roles often involve tasks that require mental effort rather than physical labor. Professional individuals actively engaged in decision-making processes within their respective organizations use big data & analytics in their business processes and to navigate diverse business scenarios. These professionals are positioned at the intersection of different decisions, requiring them to balance data-driven insights with critical thinking to navigate complex decision-making scenarios. This population was chosen due to their active engagement in decisions that influence organizational outcomes, making them an ideal group for examining the relationship between BDA exploration, decision-making types, and critical thinking.

Furthermore, focusing on professionals with various positions ensures the study captures diverse decision-making approaches influenced by organizational culture, experience, and resource constraints. These individuals span diverse industries and represent various decision-making roles, such as strategic, tactical, and operational. The focus on this group ensures the study captures individuals with firsthand experience in applying critical thinking and using data analytics tools.

3.2.2 Sampling Frame

The sampling frame is a curated list of professionals identified through LinkedIn, alum networks, and industry-specific associations. These sources provide access to individuals with relevant roles and experience. The individual professional is the unit of analysis for this study, as their responses to the questionnaire represent distinct data points that align with the research objectives. The study aims to achieve a response rate of 20-30%, which is sufficient to ensure statistical power and generalizability. Three hundred individuals were invited to participate, with a target of 80-100 completed responses. The sampling was employed to select participants from a list chosen from the predefined population identified through professional platforms like LinkedIn, Alumni networks, and industry-specific associations and personal networks. In the screening process, individuals were screened to ensure they fall into the requested criteria of white-collar workers with active involvement in decision-making processes. The questionnaire was distributed through professional networking platforms such as LinkedIn, and emails were sent to personal networks. This approach ensures access to a diverse and geographically dispersed sample of professionals while maintaining alignment with the demographic characteristics outlined in Section 3.2. Additionally, the distribution strategy may involve leveraging alum networks and industry-specific associations, as Bryman and Bell (2017) recommended, to maximize participation from the desired respondent pool.

The study aims to achieve a minimum sample size of 30 participants which is sufficient for a solid statistical analysis while maintaining practical feasibility (David R. et al. 2024). The central limit theorem (CLT) states that, under appropriate conditions, the distribution of a normalized version of the sample mean converges to a standard normal distribution if the population size is large, approximately above 30 (David R. et al 2024). This sample size balances the need for adequate data to support the analysis with the logistical constraints of respondents and participant recruitment. By including diverse participants across various organization types and industries, the study's insights enrich the understanding of how decision-making styles and critical thinking manifest across contexts. While this mixed approach in sampling enhances representation, certain limitations remain. Bias and the participants' reliance on big data are self-reported, which may not fully align with the actual usage pattern.

The unit of analysis for this study is the individual professional. Based on their responses to the questionnaire and the critical thinking appraisal test. Each individual represents a single data point for analysis with a focus that ensures consistency and alignment with the research goals. This is achieved through the structured questionnaire to study the relationship between decision-making types, experience, critical thinking, and data usage at the individual level in a professional setting. All questionnaire items and variables are constructed to measure attributes and behaviors linked explicitly to the particular professional. The focus on the individual professional as the unit of analysis ensures clarity and precision in the methodological design.

3.2.3 Sampling Method

The sampling frame is a curated list of professionals identified through LinkedIn, alumni networks, and industry-specific associations. These sources provide access to individuals with relevant roles and experience. The unit of analysis for this study is the individual professional, as their responses to the questionnaire represent distinct data points that align with the research objectives. The purposeful sampling method ensures that participants are selected based on their relevance to the research objectives. It allows the inclusion of individuals actively involved in operational, tactical, or strategic decision-making and familiar with using BDA in their roles. Purposeful sampling aligns with the study's aim to capture meaningful insights from individuals with relevant expertise, enhancing the validity of the findings (Bryman & Bell, 2017). However, this method may introduce selection bias, as the researcher's judgment could inadvertently exclude potentially valuable perspectives.

On the other hand, convenience sampling ensures practical accessibility to participants by leveraging professional networks like LinkedIn and alumni associations. Given resource constraints, convenience sampling facilitates timely data collection and provides a sufficient sample size. However, the method may limit generalizability, as participants may not fully represent the broader population of white-collar workers. Combining these methods, the study balances practicality with a targeted approach, ensuring relevance and efficiency in data collection.

This mixed approach in the sampling method is particularly effective in studies aiming to test hypotheses on variables and explore relationships in a particular population where the goal is to understand a context in a population subset. An example is examining behaviors, attitudes, or skills tied to specific roles or responsibilities to ensure who possesses the desired attributes, making it suitable for this research. This is especially true when the study focuses on variables or characteristics that are not evenly distributed across the general population but are concentrated in specific groups (professionals involved in decision-making processes). The sampling method is designed to select participants who meet inclusion criteria such as the professional role, decision-making involvement, and familiarity with data utilization. This technique was employed by forming a curated list of eligible professionals through the questionnaire and thinking appraisal. This approach ensures that the sample is suitable for the population in the research focus and captures individuals whose positions and experiences align with the study's theoretical framework. It also allows the inclusion of participants with diverse industrial backgrounds and organizational contexts, which enhances the generalizability of the findings within the scope of the research.

3.3 Data Collection Method

The data collection for this study is conducted through a structured questionnaire designed to capture the relationship between white-collar workers' perception and use of BDA in decision-making and critical thinking, as assessed using a framework adapted from the Watson Glaser Critical Thinking Appraisal derived by Pearson TalentLens. The questionnaire integrates selected items from these two assessment tools to ensure relevance to the study's research questions and objectives. The selection process for these items is guided by pragmatic and strategic considerations to balance respondent engagement, ease of completion, and the high-quality data collection necessary for robust analysis.

The questionnaire comprises three main sections. The first is the demographic of the participants. This section gathers contextual information, ensuring respondents align with the target population identified in section 3.2 above. It includes questions mainly regarding the respondent's industry of operation, types of decisions regularly made (operational, tactical, strategic), and experience level. The second section aims to grasp the workers' use and perception of big data and analytics. The selected questions are tailored to provide insights into the respondents' reliance on and integration of data analytics and personal judgment in their decision-making processes. The last component of the questionnaire is a critical thinking test based on the Watson Glaser Critical Thinking Appraisal, which focuses on evaluating respondents' reasoning, analysis, and decision-making abilities. Questions were chosen strategically to align with the scope of this study while maintaining brevity to ensure respondent engagement. The questionnaire design prioritizes clarity and conciseness, with a focus on achieving the dual goals of respondent accessibility and the collection of data relevant to the study's hypotheses.

3.3.1 Questionnaire

The BDA survey is intended to understand the use and attitude toward BDA in organizational decision-making. The survey utilizes a combination of multiple-choice and Likert scale questions to ensure clarity and ease of completion for respondents while minimizing the potential for subjective interpretations. This structured approach avoids open-ended text questions, which are more suited for qualitative analysis and could introduce variability in interpretation that is outside the scope of this study's quantitative focus. Multiple-choice and scale-based questions provide standardized responses, facilitating efficient data analysis and enabling the application of robust statistical methods (Mazikana, 2023). These question formats also enhance respondent engagement by streamlining the survey process, thereby increasing the likelihood of obtaining complete, high-quality data for the subsequent analytical stages.

The survey is structured to align with the study's objectives and consists of two sections. Firstly, demographic Information that aims to collect essential background data about respondents, including their industry, role, years of experience, and decision-making levels (e.g., strategic, tactical, or operational). The second section aims to capture BDA use and perception with Likert scale questions (on a scale of 1 to 7) to assess the frequency and intensity of reliance on BDA tools.

These questions capture the extent to which respondents use and value data-driven decision-making within their professional contexts. The questionnaire was distributed digitally via LinkedIn and targeted email networks to ensure accessibility and reach a wide range of professionals. The mobile-friendly design further facilitated ease of participation across devices. Measures were taken to encourage completion, such as streamlining the survey's length and focusing on straightforward, clearly phrased questions. The full questionnaire, including all survey items and their corresponding formats, is provided in the Appendix for transparency and replicability. This ensures that the design process is well-documented and the methodology is accessible for future studies.

The Likert scale is a widely used instrument in quantitative research for assessing attitudes, opinions, and perceptions. Introduced by Rensis Likert in 1932, it gives respondents a symmetric range of options to express the intensity of their agreement or disagreement, typically on a 5- or 7-point scale. The scale is valued for its simplicity, making it easy for respondents and researchers to use. Its straightforward design minimizes cognitive load, allowing respondents to understand and respond to questions quickly. This feature is handy for efficiently collecting large volumes of data (Malapane & Ndlovu, 2024).

Furthermore, the scale's quantifiability enhances its utility for statistical analysis, enabling applying robust techniques such as descriptive statistics, correlation, and regression analysis. These characteristics make it versatile for various contexts, from evaluating employee satisfaction to understanding consumer behavior. The flexibility of the Likert scale allows it to capture nuanced opinions, providing insights into the intensity of respondents' attitudes and tendencies. It is also cost-effective to administer, particularly in digital formats, further increasing its appeal for large-scale studies.

The limitations of the Likert scale are also to be addressed for the method of this study. Likert scale has a central tendency bias where respondents usually gravitate towards choosing the middle choice and being neutral in their answers and opinions. This reduces the variability and richness of the questionnaire's selected data (Malapane & Ndlovu, 2024). Additionally, biases in response style, such as a predisposition to agree with statements regardless of the content. This leads to compromised validity of results. The ordinal nature of Likert-scale questions results in data that also presents challenges, as it is often misused as interval data in statistical analyses, which can lead to inaccurate conclusions. While the scale effectively captures general attitudes, its closed-ended format restricts respondents from explaining their opinions and choices, potentially ignoring underlying reasons for their views. This limitation can make the Likert scale less suitable for exploratory studies that seek in-depth insights. Likert scale also doesn't manage for the differences in interpretation across cultural or linguistic groups, which may affect the reliability of results, and lengthy surveys using multiple Likert items can lead to respondent fatigue, diminishing the quality of data collected.

3.3.2 Watson Glaser Critical Thinking Appraisal

A tool used for assessing an individual's critical thinking capacity is the Watson-Glaser Critical Thinking Appraisal (WGCTA), developed by Watson and Glaser in 1964. The WGCTA measures critical thinking as interrelated cognitive abilities essential for logical reasoning, problem-solving, and informed decision-making (Watson & Glaser, 1964). The WGCTA by Pearson employs the use of theta scores ranging from -3 to 2.7, factor in the number of correct answers and the difficulty of the items answered correctly. This scoring method has been validated for its ability to better reflect individual abilities by acknowledging variations in item difficulty (Baker, 2001; Embretson & Reise, 2013). Two candidates answering 20 questions correctly may achieve different theta scores if one answers more challenging questions correctly. The theta scoring system adjusts for item difficulty, rewarding proficiency in more challenging items and enabling a more accurate measurement of an individual's critical thinking.

To interpret theta scores, they are compared to a norm group, where you're given a percentile rank after completion of the assessment. Candidates receive a version of the test with 40 questions balanced across these difficulty levels, ensuring a consistent testing experience. (Pearson, 2020)

3.4 Data Analysis

To ensure the quality of the collected data, descriptive statistics were conducted. For parametric tests to be valid, assumptions of normality, equal variance (homoscedasticity), independent observations, and linear relationships between variables must be satisfied. To assess these assumptions, QQ-plots and boxplots were used to graphically examine the linear relationships between variables and to identify potential outliers or deviations from normality.

With a sample size of 42 observations, ensuring a normal distribution poses challenges due to the relatively small number of participants. This limitation is particularly evident in the ANOVA tests for variance, where the sample is divided into two groups based on work experience (<10 years and >10 years) and into three groups for decision-maker types (operational, tactical, and strategic). The small sample size complicates the assumption of normality, a critical requirement for parametric tests like ANOVA. To maintain statistical power and adhere to the guideline of 10-15 observations per predictor, the number of predictors was limited. Additionally, the work experience categories were adjusted by merging the 1-5 years and 5-10 years groups to ensure an adequate number of respondents in each category.

QQ-plots are employed for both Theta-score and BDApu to assess the normality of these variables' distributions. Regarding Theta-score, the QQ-plot helps in determining if the distribution of decision-making effectiveness across different decision types or levels of work experience aligns with a normal distribution, which is crucial for validating the assumptions necessary for parametric statistical tests. Similarly, the QQ-plot for BDApu is used to examine the distribution of business data analytics usage, providing insight into whether this usage follows a normal pattern. By plotting the quantiles of the observed data against the quantiles of a theoretical normal distribution, any deviations from the straight line indicate departures from normality, such as skewness or the presence of outliers. This analysis is vital for ensuring that the data meet the prerequisites for subsequent statistical analyses, thereby enhancing the reliability and validity of the findings related to decision-making quality and the application of business data analytics within the study's context.

Boxplots are utilized with CT on the y-axis. One boxplot features decision type (operational, tactical, strategic) on the x-axis to visualize the distribution of Theta-scores across different decision types, facilitating a comparison of these distributions to gain insights into decision-making quality, identify variability, and check for assumptions like normality and equal variance. Another boxplot employs work experience (above and under 10 years of experience) on the x-axis to explore variations in Theta-scores based on experience level, offering further insights into the relationship between experience and decision-making effectiveness. Additionally, by examining these boxplots, the skewness of the data distributions can be assessed, indicating any asymmetry in the Theta-score distributions within each category, and outliers can be identified, which are extreme values that might influence the analysis or highlight unique decision-making scenarios, ensuring a thorough understanding of the data's characteristics.

Pearson's correlation test is applied to analyze the relationship between BDApu (big data analytics usage and perception) and critical thinking measured by Theta-score. This test measures the strength and direction of the linear relationship between these two variables, with a correlation coefficient ranging from -1 to 1. A value closer to 1 indicates a strong positive relationship, while a value closer to -1 suggests a strong negative relationship. Given our interest in determining if there exists a negative association between BDApu and Theta-score, a one-tailed (one-sided) test was conducted. This approach focuses solely on detecting a negative correlation, enhancing the test's power to identify such a relationship if it exists. Our hypothesis that increased usage of business data analytics might inversely affect decision-making effectiveness, as measured by Theta-score, justified this choice. Given our sample size, correlations exceeding 0.312 were considered statistically significant at the p=0.05 level (two-tailed), guiding the selection of variables for subsequent regression analyses.

3.4.2 Inferential Statistics

Following the correlation analysis, a linear regression analysis is employed to examine hypothesis 3, the potential causal relationship between BDApu and critical thinking. Regression is an appropriate statistical tool when examining the relationship between a continuous dependent variable, such as critical thinking (measured using Theta scores), and an independent variable, in this case, BDApu (David R. et al 2024). This method allows for the exploration of the strength and direction of the relationship between variables, as well as the ability to control for potential confounding factors. By using regression, it becomes possible to determine whether changes in BDApu have a measurable influence on critical thinking scores. Additionally, this approach enables us to estimate the proportion of variation in critical thinking that may be attributed to BDApu.

While Hypothesis 3 directly addresses the research question, *How does the perception and use of Big Data Analytics influence the critical thinking of white-collar workers?* Hypothesis 1 and 2 do not directly explore the role of Big Data Analytics in critical thinking. To test hypothesis 1 and 2, that the decision-makers handling high-impact organizational decisions demonstrate stronger critical thinking skills than those in less impactful roles, and that more experienced workers demonstrate higher critical thinking than less experienced, one-way ANOVA was utilized as an analytical method. ANOVA is suitable when comparing the means of two or more groups to determine whether there are statistically significant differences between them (David R. et al 2024). The ANOVA is conducted to investigate whether significant differences in critical thinking exist between groups based on decision types (operational, tactical, and strategic) and work experience (above and below 10 years). These tests are not designed to examine the potential moderating role of BDApu (perception and use of Big Data Analytics) in the relationship between the independent variables and critical thinking.

Given the theoretical basis suggesting BDApu as a potential moderator, the study instead aims to conduct a regression analysis to test for such an effect. However, if the ANOVA tests, testing for hypothesis 1 and 2 do not show statistically significant differences, a regression analysis to examine moderation will not be conducted, as its results would likely lack reliability. Instead, as part of the exploratory nature of this study, additional ANOVA tests are conducted to assess whether BDApu shows significant differences across groups based on decision types and work experience, providing preliminary insights into its *potential* as a moderating variable.

3.4.4 Statistical Software

All analyses were conducted using SPSS. The significance level was set at $\alpha = 0.05$ for all statistical tests, and confidence intervals were calculated at the 95% level to provide precision measures for the estimated effects.

3.5 Validity and Reliability

According to Bryman and Bell (2017), replicability, the ability to replicate results using the same methodology, is a critical criterion in business and organizational research. As such, all details regarding the method and the questionnaire have been meticulously provided in the appendices to ensure transparency and potential replication. However, it is important to note that while the study could be fully replicated, variations in results may still occur due to the presence of noise and bias introduced by human factors. These factors could include individual differences, variations in the branches sampled, or other uncontrolled variables.

Assessing validity is essential to ensure the robustness and credibility of the findings. Yin (2018) sees different validation criteria as crucial for determining the validity of research. Construct validity, being one of the criteria, refers to how well the operational measures align with the theoretical concepts they are intended to capture, which in our study means how well the Likert-scale survey measuring attitudes toward BDA, as well as how well the Watson-Glaser Critical Thinking Appraisal (WGCTA) measures critical thinking. By employing the WGCTA, a widely recognized tool for assessing critical thinking, and carefully designing the BDA survey questions based on established frameworks, the aim was to ensure that the constructs measured truly reflect the intended variables. The BDA survey questions were intentionally phrased in varied ways while maintaining consistent meaning to reduce the risk of comprehension bias and calculating the mean of similarly structured Likert-scale responses to capture participants' overall perception and use of BDA.

On the other hand, internal validity concerns the degree to which the observed relationships between BDA use and critical thinking can be attributed to the variables measured rather than external factors or confounding variables. While the study's exploratory design minimizes some risks by focusing on these specific constructs, the absence of experimental controls limits the extent to which causal relationships can be inferred.

External validity refers to the applicability of the study's results beyond the sampled population Yin (2018). Given the combination of convenience and purposive sampling, the findings are limited in generalizability to broader populations or other professional contexts. Convenience sampling was chosen due to its practical approach and ease of access to respondents, while purposive sampling allows us to target specific individuals with relevant characteristics for our research. However, this limitation is consistent with the study's exploratory nature, which seeks to identify trends and patterns that can guide future research. To strengthen external validity, subsequent studies could utilize randomized sampling methods and target more specific populations or industries, ensuring the findings apply to broader or more defined contexts.The sample size determines the study's ability to detect significant relationships between variables.

While this study aimed to capture meaningful insights, the exploratory nature and potential limitations in sample size may have reduced statistical power, increasing the likelihood of Type II errors (failing to detect an existing effect). Future studies could address this limitation by increasing the sample size and applying more rigorous sampling methods to ensure sufficient statistical power and representativeness. WGCTA is reliable and valid. Studies done to test validity show high internal validity (0.70-0.90) and test-retest stability (0.73-0.89). It also has minimal demographic bias, which makes it viable for testing a wide range of demographic variables. It also correlates highly with academic performance in business and law students (Pearson, 2020). There are also numerous studies showing the validity of this test such as "Validating the Watson Glaser Critical Thinking Appraisal" by Hassan et al and 'Test Review: Watson, G., & Glaser, E. M" by Sternod et al.

3.6 Ethical Considerations

This study adheres to ethical standards to ensure the integrity of the research process and the protection of participants' rights. In compliance with the General Data Protection Regulation (GDPR), the study implemented comprehensive measures to safeguard the privacy and confidentiality of respondents while respecting their autonomy and ensuring their participation was fully informed. Participation in the survey was entirely voluntary, and informed consent was obtained from all participants before their involvement. Each respondent was provided with a clear explanation of the study's purpose, the types of data being collected, and the specific ways their information would be used. Furthermore, participants were informed of their rights under GDPR, including the ability to withdraw their participation at any time, access their responses, or request the deletion of their data without any negative repercussions. The survey platform used for data collection complied with GDPR standards, ensuring secure data processing and storage throughout the study.In the interest of transparency and fostering trust, participants were given the option to receive a copy of the final research findings upon the study's completion. This measure reflects the researchers' commitment to ethical practices while allowing participants to evaluate the study's conclusions independently. This approach further highlights how participant contributions informed the research findings, reinforcing the validity and reliability of the results.

These measures ensured that the study maintained the highest ethical standards, protecting participant privacy and confidentiality while promoting professionalism. By maintaining an open and honest exchange of information, the study enhanced its credibility and assured participants that their data was used meaningfully. The survey design prioritized ethical considerations by limiting data collection to only what was necessary to address the research objectives, thereby avoiding intrusive or unnecessary data collection. Anonymity was offered to all participants and maintained throughout the study, ensuring that responses could not be linked to individual identities. This commitment to anonymity safeguarded participants' privacy and upheld data confidentiality during analysis and reporting. These ethical practices guided the research process, ensuring that the results and subsequent discussions were conducted with integrity and aligned with the study's academic and professional obligations. The data was erased no less than 2 weeks after the completion of the paper.

3.7 The Use of AI

Some AI tools have been used during the writing of this research paper. More specifically has ChatGPT and Claude been used. These two were used to brainstorm ideas and answer questions about what research is relevant in the area of study as well as summarizing articles to see whether they contain information relevant to the purpose of the study. Another AI tool that was used is Grammarly which is a grammatical and structure correcting AI, this was used to make sure the quality and language of the paper holds the academic standard. No AI generated text has been used in the paper.

4. Results

4.1 Data Collection

The quantitative data collection amounted to a total of 42 respondents who completed both the survey and assessment. A total of 63 individuals answered the questionnaire, but only 42 of these respondents completed the assessment. In total, 300 white-collar workers were asked to participate in the study, which means that the answer rate for the survey was 21%, and the completion rate was 14% for the assessment. Since the study aims to find out if there is a connection between critical thinking and the use and perception of big data analytics, only those who completed both the survey and the questionnaire will be included in the analysis, which means the answer rate is 14%.

4.1.1 Descriptive Statistics, independent variables

The first questionnaire was made to measure independent variables. By asking many similar questions about different levels of agreement with BDApu on a Likert scale of 1-7, a mean was calculated to measure the respondent's average perception/usage of BDA. The second independent variable was *work experience,* in which respondents were supposed to answer whether they worked 0-5, 5-10, and above 10 years of work experience. As the group of respondents with only 6-10 years of experience was very few, the 1-5- and 6-10-group were merged, creating two groups, above and below 10 years of work experience. The third and last independent variable was the *type of decision* the respondent most commonly makes, whether operational, tactical or strategic. The comparing groups in this variable are, therefore, three.

The dependent variable, critical thinking, was measured in the WGCTA-test. The respondents answered 40 questions, after which the theta score was calculated. The theta scores vary from -3 to +2.7.

Descriptives

Variables	n	Minimum	Maximum	Average	Std. Deviation
BDApu	42	1.9	5.7	4.145	
Work Experience	42	.00	1.001	.71431	
Decision-Type	42	1.00	3.00	2.2381	
Critical thinking	42	-1.88	1.51	-.2191	.72871

Table 1: Descriptive statistics for the study variables, the values were computed in SPSS

Table 1 provides a representation of our study's variables, offering insight into the capabilities of our sample. The average score for Big Data Analytics usage (BDApu) is 4.145, which falls near the middle of our Likert scale, indicating a moderate level of BDA involvement among our participants, from a low of 1.9 to a high of 5.7. For Decision Type, coded from 1 (operational) to 3 (strategic), the mean is 2.2381, which shows that there are more respondents in the category of strategic decisions, with an even spread across all three categories, suggesting our sample includes decision-makers at various levels of organizational strategy. Boxplot 3 (*appendix D)* provides more details about the distribution and spread over the levels. Lastly, Work Experience is quantified on a scale from 0 to 1, averaging at .7143, which implies that most of our respondents responded with work experience above 10 years. Boxplot 4 (*appendix D)* provides more details about the distribution and spread over the levels. Turning to the dependent variable, critical thinking (CT), measured by the Theta score from the Watson-Glaser Critical Thinking Appraisal, we find an average of -.2191. This negative value suggests that, on average, our sample's critical thinking does not surpass the baseline set by the test. The scores span from -1.88 at the 6th percentile to 1.51 at the 98th percentile, showcasing a considerable disparity in critical thinking skills among our respondents.

In order to do parametric tests the data had to be normally distributed. The theta score measuring critical thinking and BDApu was both examined for its distribution. QQ-plots (appendix D) were made to give a graphic view of the distributions. Both variables showcased a normal distribution. To investigate the hypothesis that "Decision-makers with more trust in BDA negatively correlate with critical thinking," a correlation test was first performed to investigate a potential negative correlation between the variables. The respondents' BDApu was compared to theta score for critical thinking. A regression test was thereafter also performed to test for a potential causality.

Correlation

		CT	BDApu
Pearson Correlation	CT	1.000	-.043
	BDApu	-.043	1.000
Sig. (1-tailed)	CT	.	.393
	BDApu	.393	.
N	CT	42	42
	BDApu	42	42

Table 2: Negative correlation between CT and BDApu

Table 2 presents the Pearson correlation coefficients and significance levels for the relationship between Critical Thinking (CT) and Big Data Analytics usage (BDApu). The correlation between CT and BDApu is very weak and negative, at -.043, suggesting virtually no linear relationship between these variables in our sample. The significance level (0.05) of .393 for a one-tailed test indicates that this correlation is not statistically significant, meaning we cannot conclude there's a meaningful association between the use of Big Data Analytics and critical thinking skills within our sample of 42 participants.

4.1.2 Parametric Statistics - Regression & ANOVA

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.063	2	.531	1.001	.377
Within Groups	20.709	39	.531		
Total	21.772	41			

Table 3: ANOVA table. Comparing means of Critical Thinking (theta score) by group Decision Type (operational, tactical, and strategic)

In Table 3, The results of the one-way ANOVA is presented, showing the comparison of critical thinking measured by theta score across three groups based on decision type (operational, tactical, and strategic). It reveals that the difference between these groups is not statistically significant, with an F-value of 1.001 and a p-value of 0.377, greater than the accepted significance level of 0.05. This indicates that decision type does not significantly affect critical thinking, as measured by the Theta Score. The total variance in critical thinking scores is 21.772, with most of the variance occurring within groups (20.709) rather than between groups (1.063), showing that the CT score is very equally spread between the three groups. As there is no significant difference between the decision-type groups no post-hoc test is needed to see between which two group the significant difference occur

Anova	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.091	1	1.091	2.110	.154
Within Groups	20.680	40	.517		
Total	21.772	41			

Table 4: ANOVA: Comparing means of Critical Thinking (theta score) by group Work Experience (<10 years and 10+ years)

The results of the one-way ANOVA, as presented in Table 4, show the comparison of critical thinking (measured by Theta score) across two groups based on work experience (under 10 years vs. 10+ years). The analysis reveals that the difference between the groups is not statistically significant, with an F-value of 2.110 and a p-value of 0.1 is greater than the commonly accepted significance level of 0.05. This indicates that work experience does not significantly affect critical thinking as measured by the CT score. The total variance in critical thinking scores is 21.772, with the majority of the variance occurring within groups (20.680) rather than between groups (1.091)

Regression

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.041	1	.041	.075	.786[b]
	Residual	21.731	40	.543		
	Total	21.772	41			

Table 5: Dependent Variable: ThetaMean. Predictor: AvarageBDA

Table 5 presents a regression analysis that examines the relationship between BDApu (Big Data Analytics usage) and CT (critical thinking score). The model explains very little of the variance in CT ,with an F-value of 0.075 and a non-significant p-value of 0.786. The residual variance (21.731) is much larger than the explained variance (0.041), indicating no significant predictive relationship between BDApu and CT.

ANOVA

BDApu

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	3,321	2	1,660	2,006	,148
Within Groups	32,283	39	,828		
Total	35,604	41			

Table 6: ANOVA table. Comparing means of BDApu by group Decision Type (operational, tactical, and strategic)

Table 6 displays the results of a one-way ANOVA conducted to examine differences in BDA usage (BDApu) across three decision-making types: operational, tactical, and strategic. The analysis revealed no statistically significant differences between the groups, as indicated by an F-value of 2.006 and a p-value of 0.148. The total variance in BDApu is 35.604, with the majority attributed to within-group variance (32.283) rather than between-group variance (3.321), showcasing that the distribution of BDApu was equally spread between decision-types. Boxplot 1 *(appendix D)* provides more details about the distribution and spread over the levels. To conclude, this suggests that decision type does not significantly influence BDApu within the sample.

ANOVA

BDApu	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	,104	1	,104	,117	,734
Within Groups	35,500	40	,888		
Total	35,604	41			

Table 7: ANOVA. Comparing means of BDApu by group Work experience. (<10 years and 10+ years)

Table 7 presents the results of a one-way ANOVA examining differences in BDApu (BDApu) between the two groups of work experience (<10 years and ≥10 years). The analysis indicates no statistically significant difference between the groups, as evidenced by an F-value of 0.117 and a p-value of 0.734. The total variance in BDApu is 35.604, with nearly all of it attributed to within-group variance (35.500) rather than between-group variance (0.104), showcasing that the distribution of BDApu was equally spread between decision-types. Boxplot 2 *(appendix D)* provides more details about the distribution and spread over the levels. To conclude, this table suggests that work experience does not significantly impact BDApu within the sample.

4.2 Analysis of Results

This section analyzes and interprets the study's empirical findings, focusing on critical thinking, measured by the CT score, as the dependent variable. The independent variables examined include Big Data Analytics usage (BDApu), decision-maker type (strategic, tactical, operational), and work experience (<10 years vs. >10 years).

Table 2 and table 5, testing the correlation and regression for BDApu and critical thinking, relates to hypothesis 3. Table 3 and 4 testing ANOVAs for work experience and decision type towards critical thinking respectively, relates to hypothesis 1 and 2. Hypothesis 3; relates directly to the research question; How does the perception and use of Big Data Analytics influence the critical thinking of white-collar workers? Hypothesis 1 and 2 does not. Based on theory hypothesis 1 and 2 testing for significant differences in critical thinking based on groups above and under 10 years of work experience as well as the decision types (operational, tactical and strategic). These tests do not count for the potential moderating effect of BDApu between the two independent variables and critical thinking. Therefore, the aim was to conduct a regression analysis to discover the potential moderating effect of BDAup, but as the ANOVA test for hypothesis 1 and 2 did not show statistical significant results, the potential interaction effect was not worth investigating as the result would not be dependable.

However, due to the exploratory aim of this study, instead of conducting regressions measuring the moderating effect, two new ANOVA's were conducted to test if BDApu could be a potential moderator in the relation between decision type and critical thinking as well as between work experience and critical thinking. Furthermore, BDApu in table 6 and 7 will be analyzed as a potential moderator between both decision type and critical thinking, as well as work experience and critical thinking.

4.2.1 Descriptive Analysis of Critical Thinking and Independent Variables

The Quantile-Quantile (Q-Q) plots presented the normality of the two variables, CT and BDApu. Given that the sampling method carried the risk of non-normal data distribution, combined with the relatively small sample size, Q-Q plots were necessary to determine the feasibility of applying parametric tests. The alignment of the data points with the reference line indicated that, despite the use of convenience sampling, neither variable displayed significant skewness or kurtosis. This validation supported the decision to proceed with parametric tests. As no substantial deviations were observed, we confidently applied inferential statistics that assume normally distributed data.

The average Theta score for critical thinking (CT), as shown in Table 1, is negative (-0,43), indicating that the sample as a whole has below-average critical thinking relative to the benchmark distribution. This finding is surprising as decision-making roles, especially at strategic and tactical levels that according to (Andrew McAfee & Erik Brynjolfsson, 2012) require robust critical thinking skills to evaluate complex data, identify patterns, and make informed decisions. The negative below-average score also attracts attention as a greater part of the sample was doing tactical and strategic decisions, that according to (Ackoff, 1990) require factors like intuition, experience, and adaptability, which in turn require more critical thinking to be efficient compared to the operational more automatically made decisions.

The descriptive statistics for BDApu reveal an average score of 4.145, aligning closely with the midpoint of the 7-point Likert scale. This indicates that participants generally have a moderate perception of and engagement with big data analytics in their decision-making processes. However, the range of BDApu scores, spanning from 1.9 to 5.7, reflects a noticeable variability among respondents, which could be influenced by factors, such as differing levels of familiarity with analytics tools, the extent to which such tools are integrated into their organizational processes, or individual attitudes toward data-driven decision-making. As the scores between 1.9 and 5.7 is the respondents means of several questions on BDApu, the aim and hope is that it is an explanatory predictor to the level of BDA amongst the sample.

Regarding the descriptive statistics for work experience, it is evident that the sample predominantly consists of individuals with extensive work experience, over 10 years. This might be due to the fact that many roles in the white-collar sector require substantial experience, leading the sample to be biased towards individuals with more than a decade of experience. Additionally, as illustrated in the boxplot 2 (appendix D), the variability in CT-score is greater for respondents with less than 10 years of work experience, whereas those with more than 10 years of experience exhibit both a higher average score and less variability. This disparity suggests that individuals with longer professional experience might have a more established understanding of, and approach to BDA. On the contrary, those with less experience may be in earlier stages of adoption, reflecting a mix of enthusiasm and unfamiliarity with these tools.

The descriptive statistics regarding CT-scores across three decision-maker categories; operational, tactical, and strategic indicates that strategic decision-makers do not exhibit higher

CT scores despite the complexity and abstract nature of their roles. The data reveals substantial variability both within and across categories. Boxplot 1 (Appendix D) illustrates a wider range of CT scores for strategic decision-makers compared to tactical and operational roles, suggesting that not all individuals in these positions uniformly exhibit advanced critical thinking skills.

One interpretation of this variability is that while strategic roles require more abstract reasoning, the skill sets and experiences of individuals in these roles might differ significantly. For instance, individuals with formal education in critical thinking or more experience in handling complex decisions may naturally perform better, which would align with Halpern (1998). In contrast, tactical and operational decision-makers, who often focus on structured, routine, or short- to medium-term decisions, show narrower ranges of CT scores. This could be explained by the fact that their roles require more operational decisions, that might rely more on procedural knowledge and less on the synthesis and evaluation of abstract information (Ackoff, 1990).

4.2.2 Correlation, Regression and ANOVAs: Independent Variables impact on Critical Thinking

The Pearson correlation between BDA perception and usage (BDApu) and critical thinking (CT) is -0.043, as shown in Table 2. This weak negative correlation is not statistically significant ($p = 0.393$), indicating no meaningful linear relationship between these variables. The low correlation suggests that reliance on Big Data Analytics tools neither enhances nor diminishes critical thinking ability across the sample. Our study highlights the nuanced relationship between Big Data Analytics (BDA) and Critical Thinking (CT) in decision-making processes. While previous research, such as McAfee and Brynjolfsson (2012), emphasizes the transformative potential of BDA in improving organizational decisions, our findings reveal limited direct influence of BDApu on CT. This is evident from the weak correlation and non-significant regression results ($p=0.786$). These results suggest that while BDA facilitates access to extensive information, its ability to enhance the cognitive aspects of decision-making remains limited. This aligns with Simon's (1958) concept of Bounded Rationality, which underscores the cognitive and informational constraints within decision-making. The findings also underscore a potential conflict between intuitive judgment and analytical reasoning. Although dual-process theories, such as those by Kahneman (2011), advocate the importance of deliberate thought (System 2) in complex decisions, our results suggest that decision-makers may not consistently leverage CT alongside BDA. Instead, they may rely on System 1 (intuition), especially when faced with high complexity or uncertainty. This prompts further questions about whether organizational training and development programs adequately integrate BDA with CT to address such challenges.

Regression analysis further examines the predictive relationship between BDApu and CT. Applying the regression analysis on CT and BDApu accounts for a small portion of the variance in CT, with a Sum of Squares for Regression of .041 compared to a Residual Sum of Squares of 21.731. The F-statistic of .075 with a p-value of .786 indicates that the model does not significantly predict CT based on BDApu. Since the p-value is higher than 0.05, it suggests no statistically significant linear relationship between BDA use and an individual's ability to think critically. This means there is a significant likelihood that you cannot predict CT with the help of BDApu within our sample. This result contradicts the study by McAfee & Brynjolfsson (2012), who found that exposure to processes with big data might improve the user's cognitive ability. This could either mean that the relationship between BDA and cognitive skills may be more complicated than what was assumed in this study

The analysis of decision-maker type also reveals inconclusive trends when examining critical thinking (CT) across operational, tactical, and strategic roles. Contrary to the hypothesis that strategic decision-makers would demonstrate stronger CT abilities due to the higher complexity and potential impact of their decisions, the ANOVA results (Table 3) indicate no significant differences in CT scores between the three groups ($F(2, 39) = 1.001$, $p = .377$). This lack of statistical significance suggests that the relationship between decision type and critical thinking may not be as straightforward as hypothesized. One potential explanation is the overlap in decision-making responsibilities across roles, as individuals in operational or tactical positions may also engage in tasks requiring high cognitive demand and critical thinking. Additionally, inconsistencies in how these roles utilize data or engage with cognitive challenges may further obscure the expected distinctions. For instance, while strategic decision-makers might theoretically benefit more from advanced analytical tools and broader organizational perspectives, practical constraints or limited exposure to training in critical thinking could mitigate these advantages. The within-group variability (Mean Square = .531) also highlights that factors other than decision type may play a more influential role in shaping CT capabilities, which could include individual differences, access to education or training, or organizational culture.

Comparing work experience groups using one-way ANOVA (Table 3) indicates no statistically significant difference in CT scores between respondents with less than 10 years and those with 10 or more years of experience ($p = 0.154$). The absence of a significant effect highlights that experience alone is not a reliable determinant of critical thinking. Instead, contextual factors such as the complexity of decisions faced, exposure to training programs, or decision-maker type may mediate this relationship. ANOVA analysis showed no significant difference in CT scores between individuals with less than 10 years of work experience and those with more. This challenges the idea that simply having more work experience automatically leads to better critical thinking skills. Instead, it suggests that other factors, such as education, specialized training, or the specific responsibilities of a person's job, might be more important in developing critical thinking. These findings connect to (Spelke et al., 2010; Mameli & Bateson, 2011) debate about whether critical thinking is a skill that can be learned and improved or an ability people are born with.

4.3 ANOVA, test for potential moderating variables

The analysis of potential moderators between decision type and work experience on the relationship between BDApu and CT indicate no statistically significant results as shown in Tables 6 and 7. However, they contribute to the discussion of whether contextual factors, such as decision-making roles and experience, influence the integration of BDA into decision-making processes. Table 6 shows the results of the one-way ANOVA comparing BDApu across decision-maker roles (operational, tactical, and strategic). The between-groups sum of squares (3.321) accounts for only a small portion of the total variance (35.604), with an F-value of 2.006 and a non-significant p-value of 0.148, indicating that BDApudoes not differ significantly based on decision type. While strategic decision-makers hypothetically relies more heavily on analytical tools like BDA due to the complexity and high stakes of their decisions, the data does not support this assumption. There are many possible explanations for this result. One is that decision-making responsibilities are often fluid and overlap between these roles. Organizational factors such as training, access to data, and a unified decision-making culture could also equalize BDApu across groups.

This lack of differentiation does not align with the hypothesis that strategic decision-makers demonstrate superior critical thinking skills due to greater reliance on BDA. The absence of significant differences may point to the need for further stratification of roles or a deeper examination of how specific decision-making contexts influence the relationship between BDA and CT. Similarly, Table 7 examines the relationship between BDApu and work experience (<10 years versus 10+ years). The results reveal an F-value of 0.117 and a p-value of 0.734, indicating no significant difference in BDApu between the two groups. The between-groups sum of squares (0.104) is negligible compared to the total variance (35.604), suggesting that work experience does not significantly influence how individuals perceive or use BDA tools. This does not support that BDApu has a potential moderating effect between work experience and critical thinking, due to their accumulated knowledge and familiarity with organizational decision-making processes. The lack of significant differences in BDApu suggests that factors beyond mere work experience play a more influential role on critical thinking, aligning with Kahneman's (2011) theory of dual-process decision-making, where the balance between intuitive (System 1) and more analytical (System 2) thinking may vary based on context rather than tenure alone.

The findings of this study highlight the intricate and multifaceted relationship between Big Data Analytics (BDA) usage and critical thinking (CT), emphasizing the challenges in enhancing cognitive decision-making processes through data-driven tools. As critical thinking served as the dependent variable throughout this research, the results suggest that neither decision type nor work experience significantly moderates the relationship between BDApuand CT. However, this does not diminish the importance of understanding how contextual factors influence the integration of BDA tools into decision-making processes.

To better understand how BDApu influences critical thinking, future studies should explore additional moderating and mediating variables. While decision type and work experience showed no significant effects, organizational culture, cognitive training programs, or individual differences such as openness to new technologies or cognitive ability could play a critical role in shaping this relationship. For instance, understanding whether decision-makers in strategic roles utilize different cognitive strategies, such as relying on intuition or experience alongside BDA, could provide valuable insights into how to foster stronger critical thinking skills.

A mixed-methods approach, incorporating both quantitative and qualitative research, could also enhance the understanding of how BDA tools impact critical thinking in practice. In-depth interviews or case studies might reveal the specific challenges and opportunities decision-makers face when integrating data analytics into their cognitive processes. Such an approach could uncover how factors like organizational priorities, access to training, or the perceived usefulness of BDA tools influence the relationship between BDApu and CT.

Additionally, future research should aim to address the limitations of this study, particularly its small sample size and reliance on convenience sampling. Larger, more diverse samples could improve statistical power and generalizability, allowing for a more nuanced analysis of the relationship between BDApu and critical thinking across different industries and organizational levels. Stratifying decision-making roles more granularly, such as by including more specific categories or examining cross-functional teams, may also provide deeper insights.

From a practical perspective, these findings suggest that organizations seeking to improve decision-making outcomes should focus on more than just increasing access to BDA tools. Instead, efforts should prioritize training programs that explicitly connect the use of data analytics with the development of critical thinking skills. For example, structured training could teach decision-makers how to critically evaluate data outputs, question assumptions, and integrate analytical insights into their broader cognitive processes.

In addition, organizations might consider fostering a culture that values both analytical rigor and cognitive reflection. By encouraging decision-makers to balance data-driven approaches with critical thinking and intuition, companies can better address the complexities of modern decision-making environments. This approach could bridge the gap between the technological capabilities of BDA tools and the human cognitive processes necessary for effective decision-making.

5. Conclusion and Discussion

5.1 Conclusion

The present study investigated the relationship between critical thinking (CT) and decision-making in high-impact organizational roles, the influence of work experience on CT, and the interplay between trust in Big Data Analytics (BDA) and CT. Drawing upon established theoretical frameworks and prior research, three hypotheses were developed. These were tested using data collected through surveys, followed by statistical analyses, including correlation, regression and ANOVA to evaluate their validity.

Hypothesis 1: Decision-makers handling high-impact organizational decisions demonstrate stronger critical thinking skills than those in less impactful roles.

The first hypothesis explored whether individuals in high-impact decision-making roles exhibit stronger CT than those with less organizational significance. Based on the statistical analyses, no significant difference in CT was observed between these groups. Consequently, the study provides no empirical support for this hypothesis, which must be rejected based on the current findings. This result suggests that CT may not be exclusively tied to the perceived importance of decisions within organizational hierarchies.

Furthermore, the ANOVA tests exploring whether BDApu might serve as a moderating variable in the relationship between decision-making type or work experience and critical thinking also failed to show statistically significant results. One potential explanation for this lack of significance could be the relatively moderate level of BDApu observed across the participant group. This suggests that while big data analytics is acknowledged as valuable, its integration into decision-making processes remains inconsistent and underutilized. As such, its moderating effect on the relationship between decision-making type, work experience, and critical thinking may be weak or non-existent in the current sample.

Hypothesis 2: Individuals with more work experience are better at critical thinking.

The second hypothesis posited a positive relationship between work experience and CT. However, the findings indicate that the correlation between these variables is not statistically significant. Thus, the hypothesis cannot be supported and is rejected. This result challenges the assumption that extended professional exposure directly enhances CT and suggests that other factors, such as education or targeted training, may play a more prominent role in developing CT capabilities.

Additionally, the ANOVA tests conducted to explore whether BDApu could act as a moderating variable in the relationship between work experience and critical thinking also yielded no statistically significant results. One potential explanation for this finding is that the integration of big data analytics into decision-making processes is not yet fully mature or widespread among the participant group. This may result in inconsistent usage patterns across individuals with varying levels of work experience, limiting the potential for BDApu to influence the relationship between experience and CT meaningfully.

Hypothesis 3: Decision-makers with more trust in Big Data Analytics negatively correlate with critical thinking.

The third hypothesis examined whether a higher level of trust in BDA correlates negatively with CT. The results indicated a weak and non-significant correlation, offering no evidence to support the hypothesis. Therefore, this hypothesis is rejected. The findings highlight the complexity of the relationship between perception and usage of BDA and critical thinking, suggesting that increased trust in BDA does not necessarily hinder CT.

Specifically, this approach enables the study to uncover whether work experience or decision type potentially moderates the relationship between BDApu and critical thinking. For instance, a finding that strategic decision-makers exhibit higher BDA use could indicate a potential interaction between decision-making type, big data reliance, and critical thinking. Similarly, differences in BDA use between respondents with more or less work experience may reflect varying degrees of perception and usage with data-driven decision-making. These insights establish a deeper understanding of how BDA perception and usage interacts with critical thinking, which could create incentives for future research.

In summary, the study provides limited evidence to support the hypotheses. While the results do not confirm the expected relationships, they raise important questions about these hypotheses assumptions. The findings suggest that broader factors beyond work experience, different decision types, or increased perception and usage of BDA influence CT. Additionally, this study emphasizes the need for further research to explore these relationships in greater depth, including longitudinal studies or qualitative approaches to better capture the nuances of CT development and its interaction with organizational decision-making. Through testing these hypotheses the research question "*How does the perception and use of Big Data Analytics influence the critical thinking of white-collar workers?"* has been explored and answered.

5.2 Discussion

Since all of the hypotheses were rejected it's easy to assume that either the chosen method or the logical reasoning was incorrect and in our case, it is a bit of both. The method used ended up giving us unreliable data which the analysis was based on, even though normally distributed. The combination of convenience and purposive sampling is not the most optimal when doing quantitative research, it would have been more optimal if a probability sampling method was used to be able to draw conclusions on the entire population. The small sample size is also a limiting factor for the results of the study which is mostly because of the low response rate. The observed response rate raises important considerations about the challenges of participant engagement, particularly with the Watson-Glaser Critical Thinking Appraisal test.

One significant factor contributing to this component's low response rate is the test's length and complexity. The Watson-Glaser test is designed to assess nuanced cognitive abilities, including inference, deduction, and evaluation of arguments. These features make the test inherently demanding, both in terms of the time required to complete it and the intellectual effort it demands from respondents. Compared to the Big Data Analytics survey, which focuses on professional behaviors and attitudes and is less cognitively taxing, the Watson-Glaser test likely posed a greater barrier to completion.

Participants may have found the test too challenging or time-consuming, discouraging them from finishing it. This is especially pertinent in professional contexts where respondents might lack the motivation to complete a test explicitly measuring critical thinking abilities. Additionally, such assessments can feel intimidating or overly evaluative, even though the results were anonymized and intended solely for research purposes.

This reluctance may also stem from a perceived fear of being judged or scrutinized based on cognitive performance, further decreasing engagement with the test. Another plausible explanation for the lower response rate is survey fatigue. Participants who were initially willing to engage with the Big Data Analytics survey may have been overwhelmed by the prospect of completing an additional, more complex instrument like the Watson-Glaser test. The cognitive and temporal disparity between the two instruments likely contributed to the drop-off rate. The Big Data Analytics survey, being less intensive, garnered greater completion rates, as evidenced by the 63 participants who finished only this portion. External constraints, such as time limitations due to work or personal responsibilities, may have also influenced participants' willingness to fully engage with the study. Professionals juggling demanding schedules might have prioritized shorter, less intensive components of the survey over the more rigorous Watson-Glaser test. Despite these challenges, the data collected from the participants who completed both instruments provide significant insights into the relationships between Big Data Analytics usage and critical thinking. These results, though obtained under challenging conditions, contribute meaningfully to the study's objectives and offer a foundation for further research on the interplay between professional decision-making and cognitive reasoning.

Another limitation is the reliance on self-reported data and cross-sectional design may restrict the generalizability of the findings. Future research should consider longitudinal studies and more diverse samples to better understand the long-term relationship between BDA, CT, and decision-making. Additionally, it would be valuable to explore specific interventions, such as training programs or decision support systems, that could strengthen the interplay between BDA and CT.

The validity and reliability of the study can be said to be pretty low because of the low number of observations combined with the sampling method which would be better suited for some types of qualitative research, even though this method was employed because of time restraints it would be better if a probability method were used. Another reason the validity and reliability of the research is low is that logical reasoning for one hypothesis was clunky. The third hypothesis may also be a bit flawed, the assumption that critical thinking is a skill that can decay without use is not far fetched but it is an incorrect assumption that the only time critical thinking would be employed in scenarios where the individual makes decisions with BDA. Since the skill is domain-general the use of it can be in another domain and that would prevent the decay from happening. You could also argue that there are too many steps in the logic for it to be valid where BDA use into cognitive demand into skill decay is too many steps to make sense. The BDA variable that was derived from the questionnaire was solid but the same can't be said about the work experience variable. To make it more clear whether or not it is the use or perception of BDA that would cause the decay of critical thinking the BDApu variable should have been divided into two different ones instead of them being combined.

The work experience variable is not faulty on its own but the scale that was used is, if another study was done it would be better if the respondents would answer with the number of years in the field instead of choosing between three different categories, this would make it easier to find relationships through analysis. There is also another blunder where the questionnaire did not include a question about the education level of the respondents, it was argued in the theoretical chapter that a longer education leads to a better ability to critically think. If this variable was collected a better understanding of how a good level of critical thinking is achieved and its relationship with different types of responsibility that the individuals inhabit and also the connection between BDApu. It would also be interesting if a study was made studying if there is a difference between critical thinking ability gained through education compared to what is gained through experience.

Since some big companies like IBM and McKinsey have integrated critical thinking assessments into their recruitment process it is important to test whether or not this is important for decision making or not, this study suggests that it may not be the case, even though the results has low reliability it is important to solidify the impact that CT has. Maybe a good decision maker not only has good cognitive skills but also social skills and other attributes.

Further research that would be interesting is to redo the study with the new variable and corrected scale for experience with a larger sample size and better sampling method, this way would yield stronger results and this area of research would become less empty. It would also be interesting to see a study that is more focused on the critical thinking ability of senior personnel compared with employees and some research where the focus would lay more towards newly educated and BDA use that would explore whether or not universities are preparing students for the modern future where the use of BDA will be vast.

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Appendix A: Research Questionnaire

Critical Thinking in the age of Big Data and AI

Introduction to the Survey

Thank you for participating in this survey! Your responses will help us explore how the use of Big Data Analytics (BDA) and Artificial Intelligence (AI) relates to critical thinking skills.

Big Data Analytics (BDA) is the process of examining large datasets to identify patterns and insights that guide decision-making. With the growing use of BDA and AI in organizations, it is important to understand how these tools influence critical thinking, which is essential for making rational and well-informed decisions. By fostering a balance between analytical tools and human reasoning, organizations can improve their decision-making processes.

In this survey, you will first answer a series of questions about your use of BDA, your attitude toward these tools, and your perspective on their role in decision-making. Most questions will be answered on a scale from 1 to 7. After completing this section, you will be directed to Pearson TalentLens' website to take the Watson-Glaser Critical Thinking Appraisal, a test designed to assess critical thinking skills.

The survey and test takes approximately 20-30 minutes.

Important:

- This survey is completely anonymous, and your responses will only be used for research purposes.
- If you do not frequently use data in your work, your input is still highly valuable to our research. We are just as interested in understanding how intuitive decision-making compares to data-driven approaches.
- Upon completing the Watson-Glaser test, your results will be sent to the email address you provided during registration.

Thank you for participating. Your valuable input is crucial to our research, and we greatly appreciate your time and contributions.

Please provide your name below. If you prefer to remain anonymous, you can use a pseudonym. *
Make sure the name or pseudonym you enter matches the one you use on the Watson-Glaser test, linked when finishing this form.

Do you wish to be sent the research paper when it's completed?
If yes, please **make sure** you provide an email below

How many years work experience do you have? *

- ◯ 0-5 years
- ◯ 6-10 years
- ◉ 10+ years

What types of decisions do you make? *

Choose the type of decision you most commonly make

- ○ Operationall (Short-term, day-to-day decisions focused on managing ongoing activities)
- ○ Tactical (Medium-term decisions aimed at implementing strategies and optimizing process)es
- ◉ Strategic(Long-term, high-level decisions that define the organization's overall goals and direction)
- ○ Other: ____________

In what industry does your workplace belong *

- ○ Tech
- ○ Healthcare
- ○ Finance
- ◉ Consulting
- ○ Manufacturing
- ○ Energy
- ○ Logistics
- ○ Other: ____________

When big data analytics (BDA) provides you with insights, do you still consult other information sources before making a decision? *

	1	2	3	4	5	6	7	
Never	○	○	○	○	◉	○	○	Always

How comfortable are you using tools like AI or machine learning in decision-making? *

	1	2	3	4	5	6	7	
Not at all	○	○	○	○	◉	○	○	Very comfortable

What is your opinion on BDA/AI, does it help your decision-making? *

	1	2	3	4	5	6	7	
Absolutely not	○	○	○	◉	○	○	○	Absolutely

To what degree do you balance big data analytics (BDA) and personal judgment in decision-making? *

If you DON'T use data pick completely intuition driven

	1	2	3	4	5	6	7	
Completely intuition-driven	○	○	○	○	○	◉	○	Completely data-driven

Do you believe Big Data and AI enhances the quality of decision-making. *

	1	2	3	4	5	6	7	
Strongly disagree	○	○	○	○	○	○	◉	Strongly agree

How much do you trust data-driven insights when making important decisions? *

	1	2	3	4	5	6	7	
Not at all	○	○	○	○	○	○	◉	Completely

How frequently do you rely BDA in your decision-making processes? *

	1	2	3	4	5	6	7	
Never	○	○	○	○	◉	○	○	Always

If you found yourself in a situation when the data conflicts with your intuition what would you trust more - data or your judgement? *

	1	2	3	4	5	6	7	
Always intution	○	○	○	○	○	◉	○	Always data

How often do you rely on your intuition when making decisions? *

	1	2	3	4	5	6	7	
I always rely on intuition	○	○	○	○	○	◉	○	I never rely on intuition

How likely are you to act on a decision without verifying data-driven recommendations? *

If you DON'T use BDA imagine if you had data that could be used in your decision-making

	1	2	3	4	5	6	7	
Not likely	○	○	○	○	○	◉	○	Very likely

To the next survey!

On the next page, after submitting, there will be a link to the **NEXT PART OF THE SURVEY**, a Watson Glaser Critical thinking Appraisal. **Make sure you use the same name/pseudonym.**

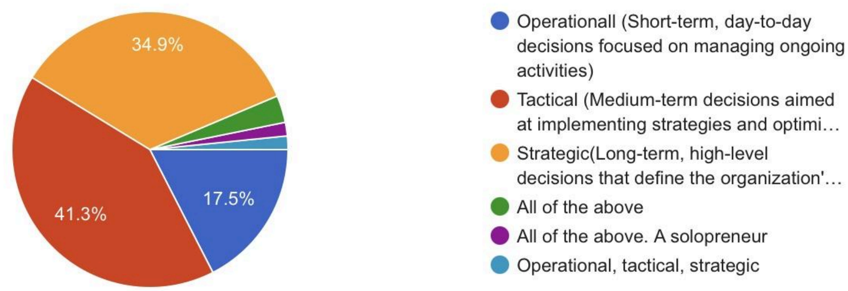
Thank you for your time and support!

Appendix B: Survey Answers

What types of decisions do you make?

Copy chart

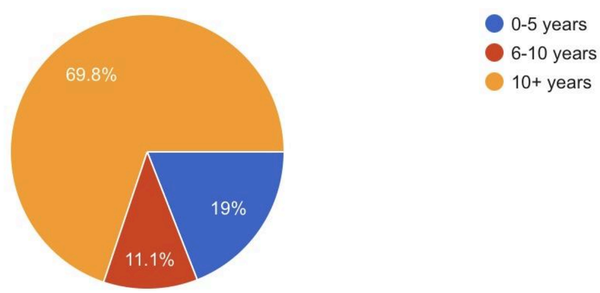
63 responses



How many years work experience do you have?

Copy chart

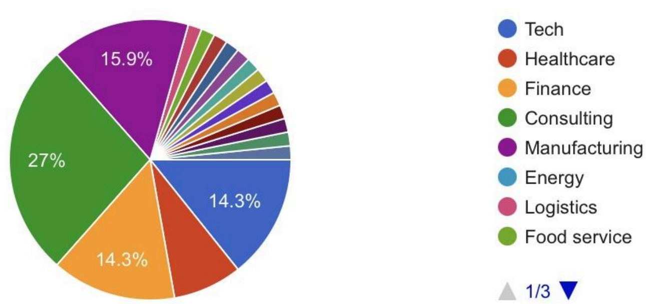
63 responses



In what industry does your workplace belong

Copy chart

63 responses



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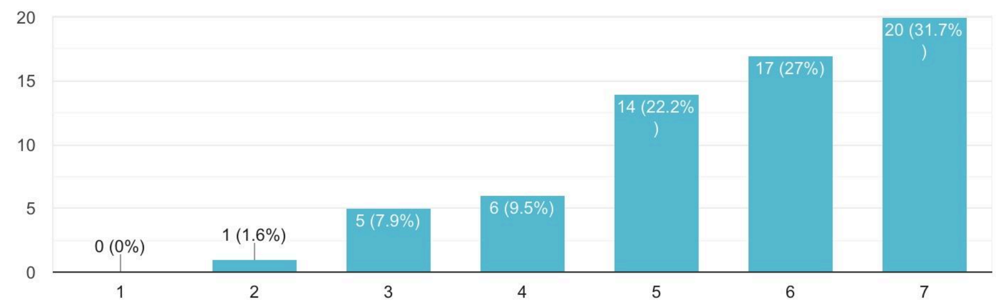
Do you believe Big Data and AI enhances the quality of decision-making.

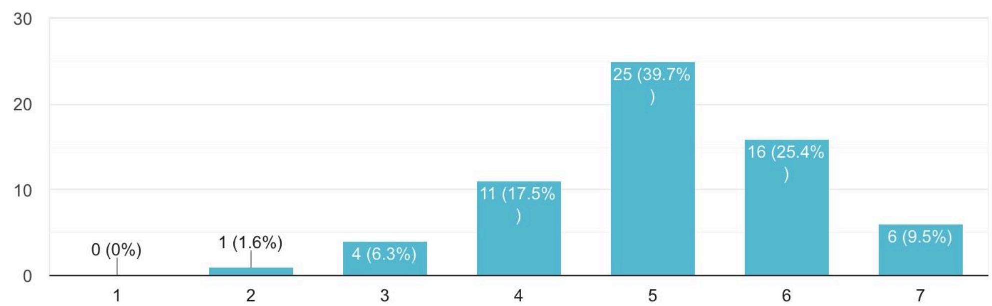
63 responses



How much do you trust data-driven insights when making important decisions?

Copy chart

63 responses



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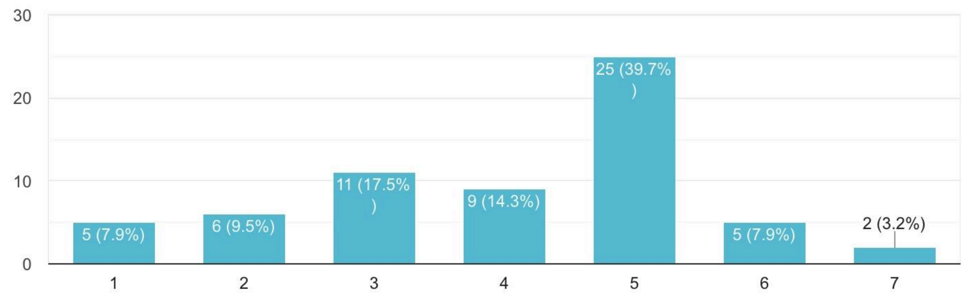
How frequently do you rely BDA in your decision-making processes?

63 responses



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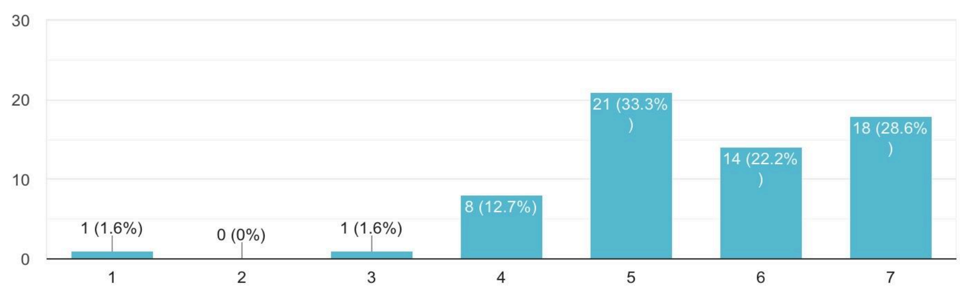
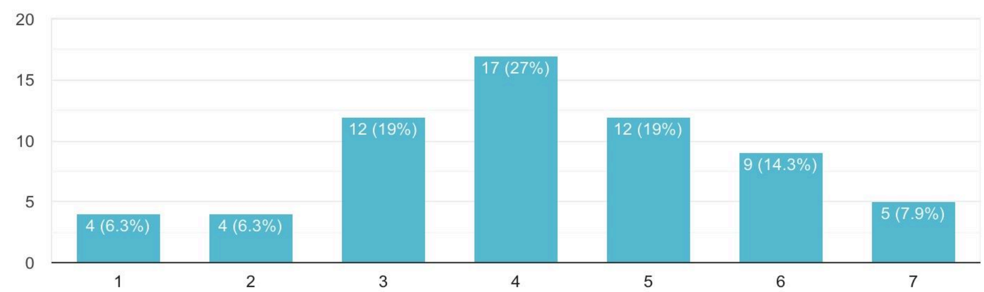
When big data analytics (BDA) provides you with insights, do you still consult other information sources before making a decision?

63 responses



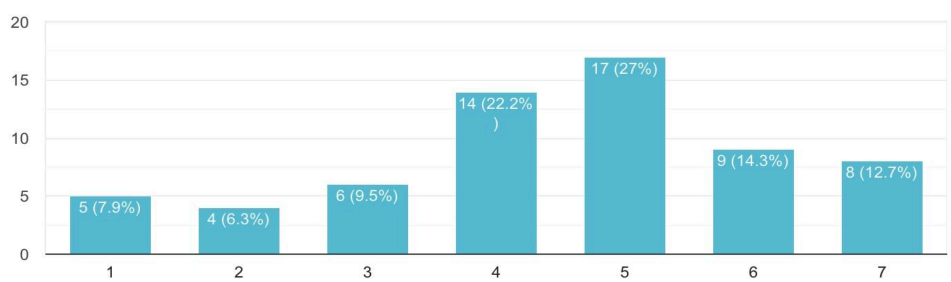
If you found yourself in a situation when the data conflicts with your intuition what would you trust more - data or your judgement?

63 responses



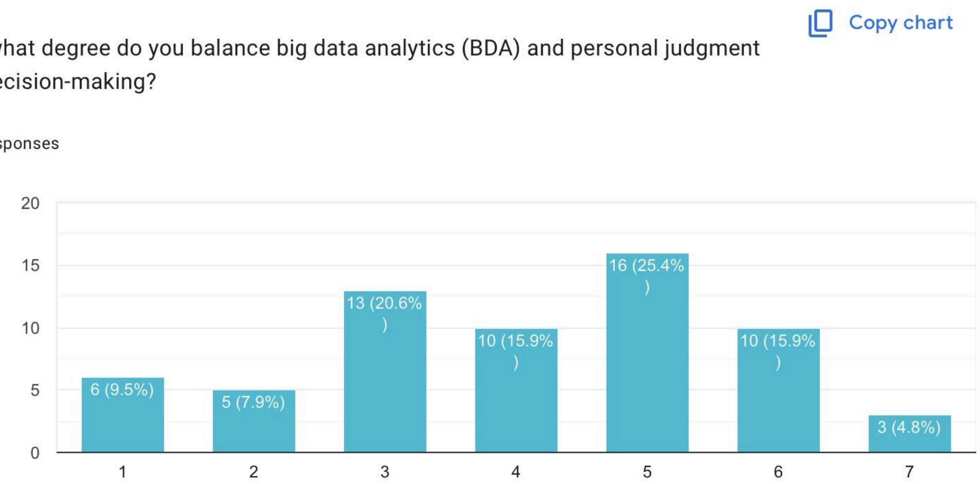
How comfortable are you using tools like AI or machine learning in decision-making?

63 responses



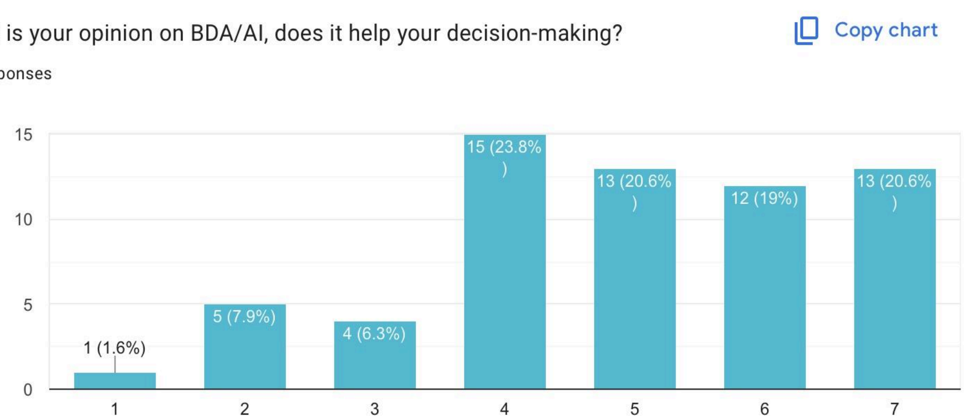
To what degree do you balance big data analytics (BDA) and personal judgment in decision-making?

63 responses



What is your opinion on BDA/AI, does it help your decision-making?

63 responses



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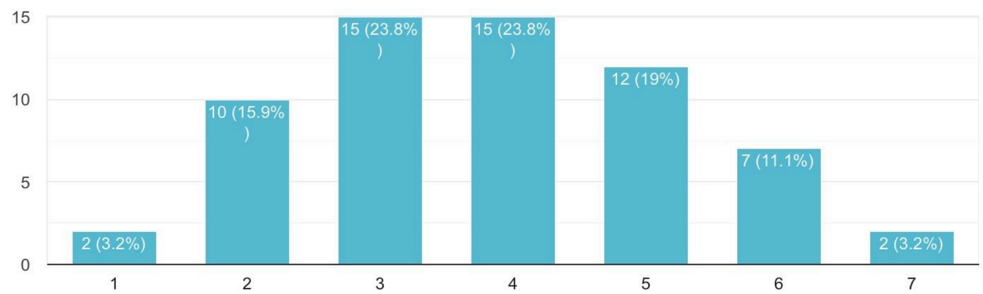
How often do you rely on your intuition when making decisions?

63 responses



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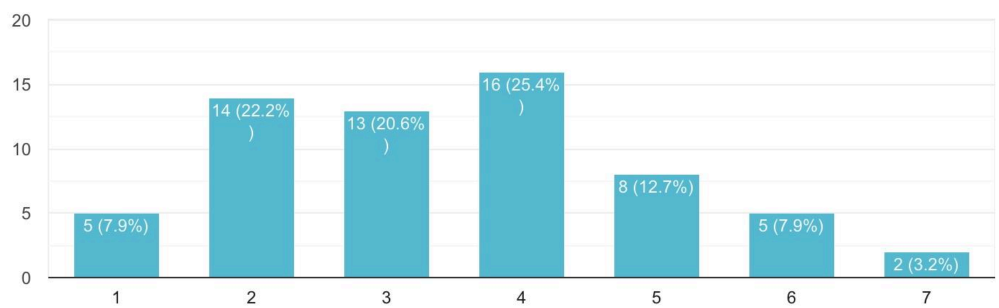
How likely are you to act on a decision without verifying data-driven recommendations?

63 responses



Appendix C: Watson-Glaser Thinking Appraisal Test Sample

Test 3: Deduce

Directions

In this test, each exercise consists of several statements (premises) followed by several suggested conclusions. *For the purposes of this test, consider the statements in each exercise as true without exception*. Read the first conclusion beneath the statements. If you think it *necessarily follows* from the statements given, click on the circle next to "**Conclusion follows**." If you think it is *not a necessary conclusion* from the statements given, click on the circle next to "**Conclusion does not follow**" even though you may believe it to be true from your general knowledge.

Likewise, read and judge each of the other conclusions. Try not to let your prejudices influence your judgement - just stick to the given statements (premises) and judge each conclusion as to whether it *necessarily* follows from the statement.

The word *some* in any of these statements means an indefinite part or quantity of a class of things. *Some* means *at least* a portion, and *perhaps* all of the class. Thus, "Some Sundays are rainy" means *at least* one, possibly more than one, and *perhaps* even all Sundays are rainy.

Study the example carefully before starting the test.

Please click **Next Page** to continue.

« Previous Page　　Next Page »

Test 3: Deduce

Example

Some Sundays are rainy. All rainy days are boring. Therefore, ...

No clear days are boring.

- ○ Conclusion follows
- ◉ Conclusion does not follow

(The conclusion does not follow. You cannot tell from the statements whether or not clear days are boring. Some may be.)

Next Page »

Test 3: Deduce

Example

Some Sundays are rainy. All rainy days are boring. Therefore, …

Some Sundays are boring.

- (●) Conclusion follows
- ( ) Conclusion does not follow

(The conclusion necessarily follows from the statements because, according to them, the rainy Sundays must be boring.)

Next Page »

Test 4: Interpret

Directions

Each of the following exercises consists of a short paragraph followed by several suggested conclusions.

For the purpose of this test, assume that everything in the short paragraph is true. The problem is to judge whether or not each of the proposed conclusions logically follows beyond a reasonable doubt *from the information given in the paragraph*.

If you think that the proposed conclusion follows beyond a reasonable doubt (even though it may not follow absolutely and necessarily), click on the circle next to "**Conclusion follows**." If you think that the conclusion does not follow beyond a reasonable doubt from the facts given, click on the circle next to "**Conclusion does not follow**." Remember to judge each conclusion independently.

Look at the next example.

Please click **Next Page** to continue.

« Previous Page   Next Page »

Test 4: Interpret

Example

A study of vocabulary growth in children from ages eight months to six years old shows that the size of spoken vocabulary increa
at age eight months to 2,562 words at age six years.

None of the children in this study had learned to talk by the age of six months.

- (•) Conclusion follows
- ( ) Conclusion does not follow

(The conclusion follows beyond a reasonable doubt because, according to the statement, the size of the spoken vocabulary at eight months was zero words.)

Next Page »

Test 4: Interpret

Example

A study of vocabulary growth in children from ages eight months to six years old shows that the size of spoken vocabulary inc
at age eight months to 2,562 words at age six years.

Vocabulary growth is slowest during the period when children are learning to walk.

- ( ) Conclusion follows
- (•) Conclusion does not follow

(The conclusion does not follow because there is no information given that relates growth of vocabulary to walking.)

Next Page »

Test 5: Evaluate Arguments

In making decisions about important questions, it is desirable to be able to distinguish between arguments that are strong and arguments that are weak, as far as the question at issue is concerned. *For an argument to be strong, it must be both important and directly related to the question.*

An argument is weak if it is not directly related to the question (even though it may be of great general importance), or if it is of minor importance, or if it is related only to trivial aspects of the question.

Next is a series of questions. Each question is followed by several arguments. *For the purpose of this test, you are to regard each argument as true.* The problem then is to decide whether it is a strong or a weak argument.

When the word *should* is used as the first word in any of the following questions, its meaning is, "Would the proposed action promote the general welfare of the people in your country?"

Click on the circle next to "**Argument strong**" if you think the argument is strong, or on the circle next to "**Argument weak**" if you think the argument is weak. Judge each argument separately on its own merit. *Try not to let your personal attitude toward the question influence your evaluation of the argument, because each argument is to be regarded as true.*

In the example, note that the argument is evaluated as to how well it supports the side of the question indicated.

Please click **Next Page** to continue.

« Previous Page   Next Page »

Test 5: Evaluate Arguments

Example

Should all young adults in this country go to university?

Yes; university provides an opportunity for them to wear university scarves.

- ○ Argument strong
- ◉ Argument weak

(This would be a silly reason for spending years in university.)

Next Page »

Test 5: Evaluate Arguments

Example

Should all young adults in this country go to university?

No; a large percent of young adults do not have enough ability or interest to derive any benefit from university training.

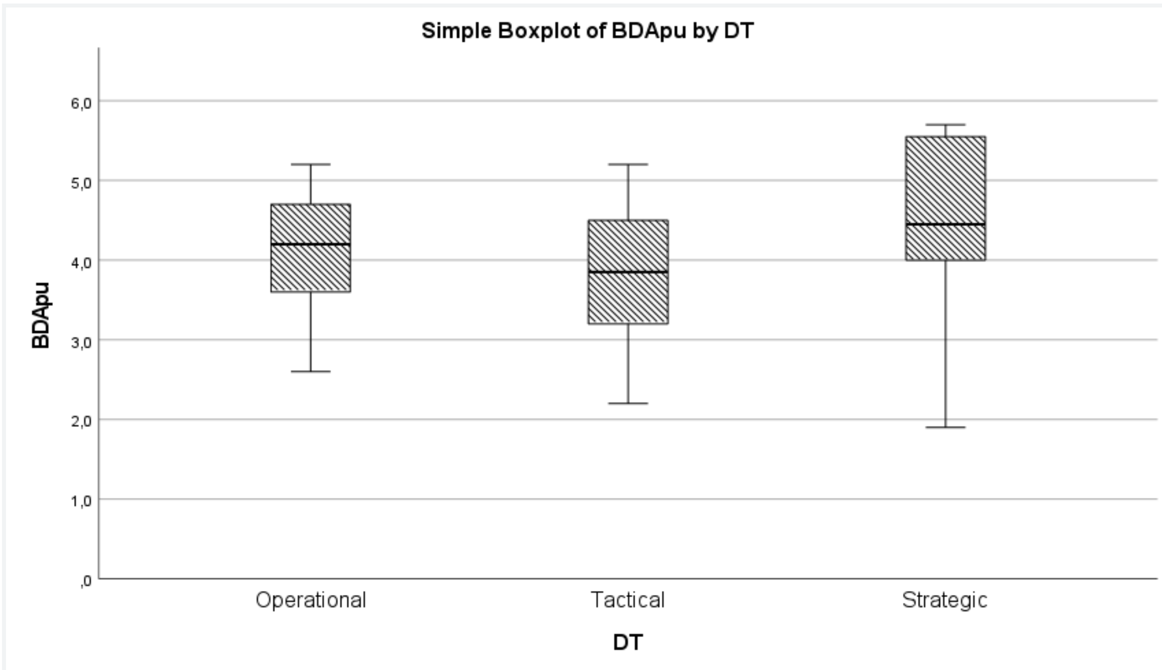
- ◉ Argument strong
- ○ Argument weak

(If this is true, as the directions require us to assume, it is a weighty argument against all young adults going to university.)

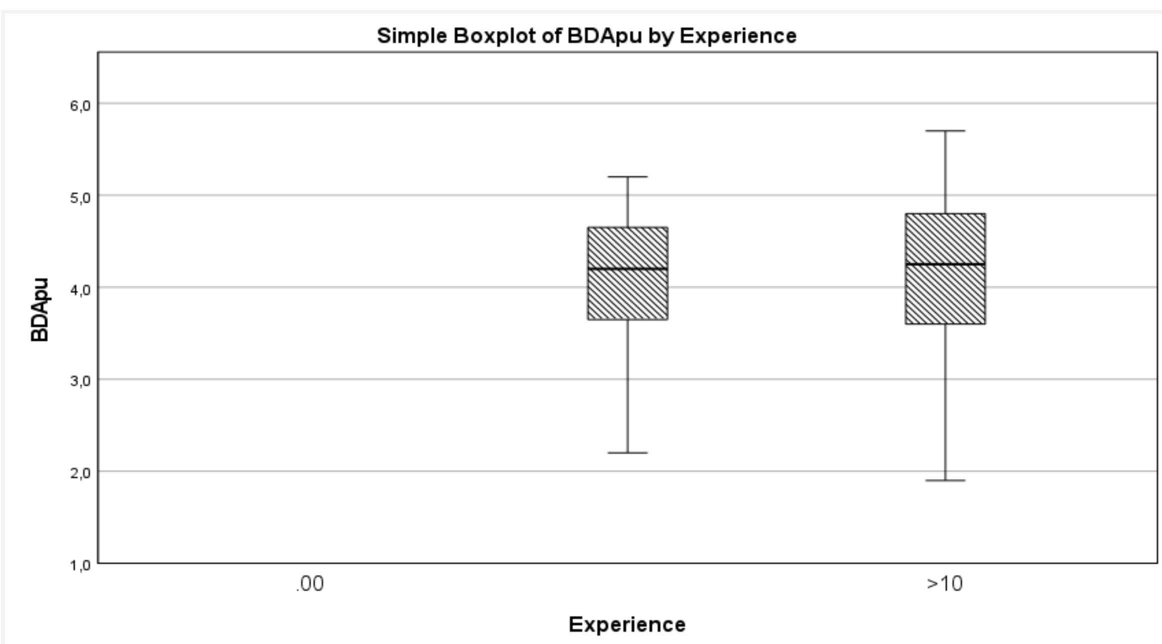
Next Page »

Appendix D Boxplots

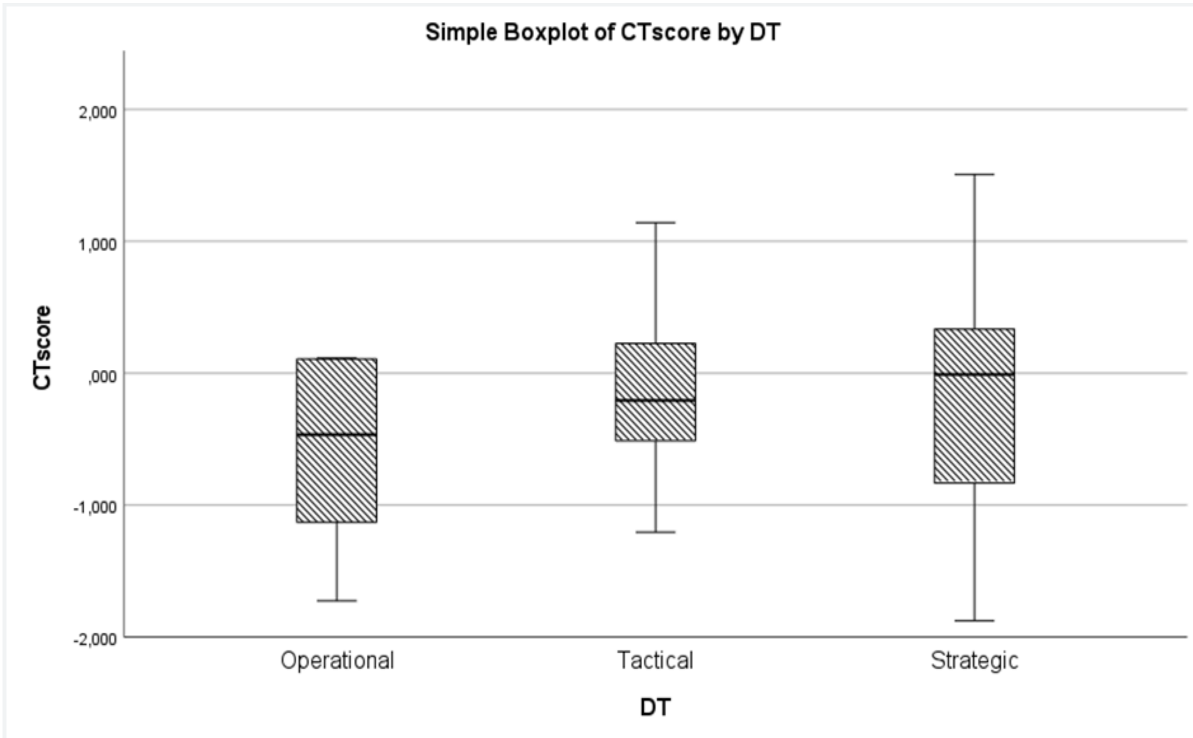
Boxplot 1: Relationship between BDApu and DT



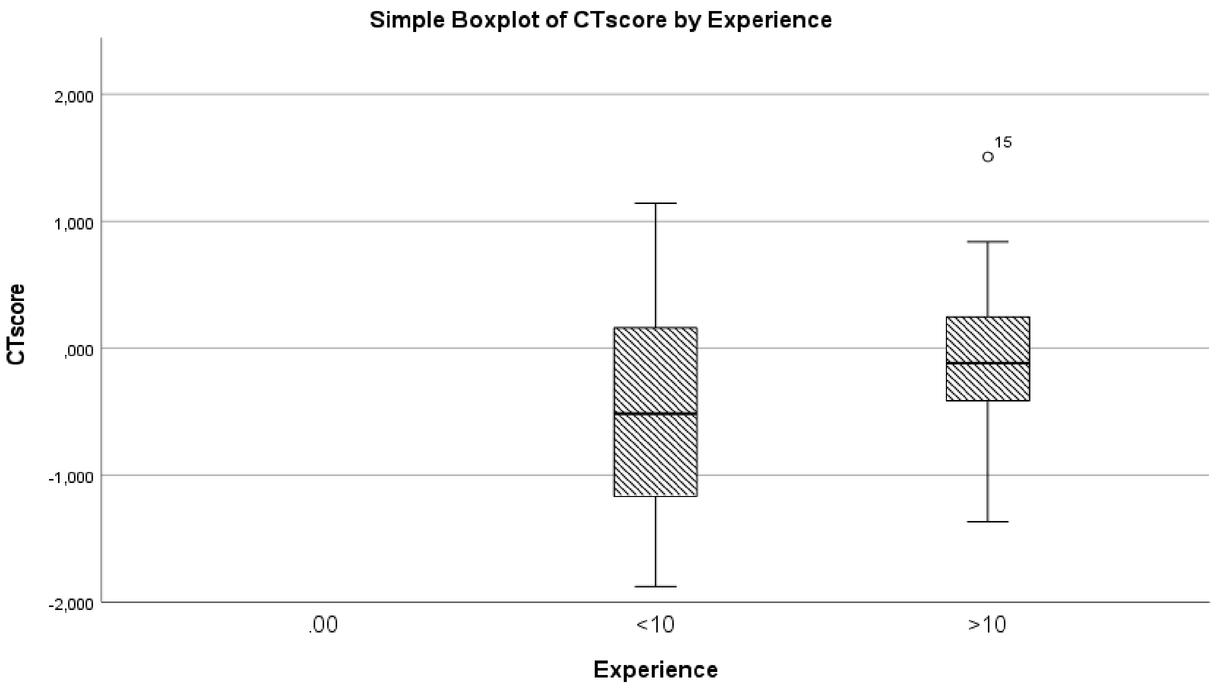
Boxplot 2:Relationship between BDApu and Experience



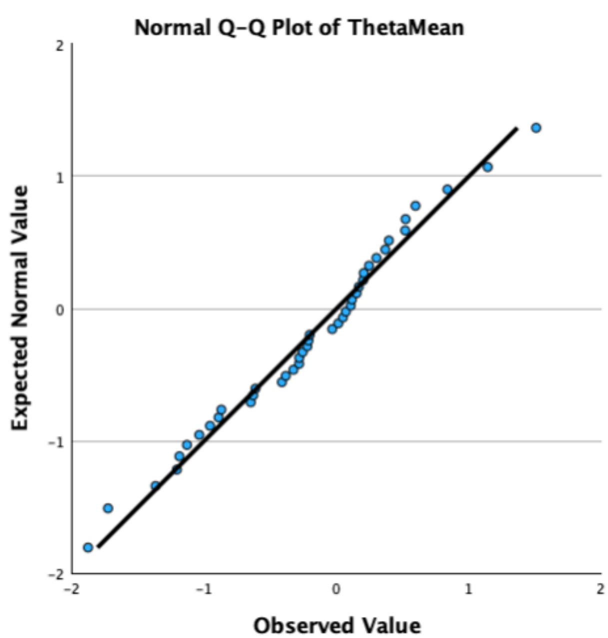
Boxplot 3:Relationship between CT and DT



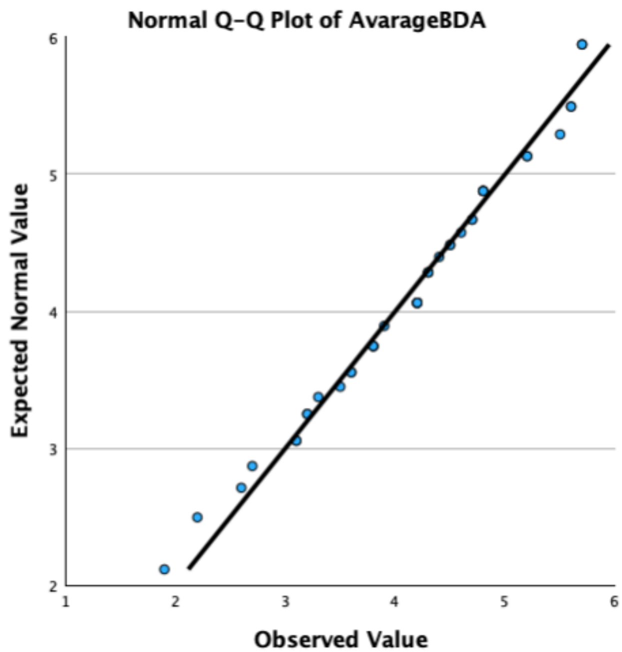
Boxplot 4:Relationship between CT and Experience



QQ-plot ThetaMean



QQ-plot Avarage BDApu



Appendix E: AI prompts

Can you summarize a document?

What is current research within x area.

These two prompts were used to sort through and validate if the study was of interest to the research, which saves a lot of time.