

**American University Kyiv**

A Capstone Project

AI ADOPTION AND THE AUTONOMY-AUTHORITY GAP:  
EVIDENCE FROM A UKRAINIAN MARKETING FIRM

ШТУЧНИЙ ІНТЕЛЕКТ І АСИМЕТРІЯ АВТОНОМІЇ ТА ФОРМАЛЬНОЇ ВЛАДИ:  
ДОСВІД УКРАЇНСЬКОЇ МАРКЕТИНГОВОЇ КОМПАНІЇ

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## **Dedication**

*Dedicated to those who serve, and to Ukraine's future they protect.*

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## ABSTRACT

This study aims to examine the implications of artificial intelligence (AI) adoption in marketing for decision rights and corporate governance within organizations. The research focuses on how AI affects employee decision-making autonomy, perceived influence, and formal authority, as well as the role of organizational governance in shaping these relationships.

**The object of the study** is a large Ukrainian marketing organization.

**The subject of the study** is the impact of artificial intelligence adoption in marketing on organizational decision-making, decision rights, and governance in a management context, particularly within knowledge-intensive organizations.

The study employs a mixed-methods research design, combining a survey of 182 employees with ten semi-structured interviews conducted within the same organization. Quantitative data were analyzed using descriptive statistics and index construction, while qualitative data were examined through thematic analysis.

The findings show that AI adoption significantly increases employee autonomy in decision preparation, while formal decision authority remains largely centralized. Concurrently, AI enables the emergence of informal influence, where employees with higher AI-related competencies exert greater impact on decisions regardless of their formal roles. Governance mechanisms tend to lag behind practice, acting as a contextual safeguard rather than an active moderator of structural change. As a result, organizations rely more on infrastructure-based controls, such as secure AI tools, than on formal policies, enabling stable AI adoption without fundamentally altering the allocation of decision rights.

The study contributes to management research by explaining the persistence of formal authority structures under conditions of increased informational capacity and by introducing the concept of the Adoption–Authority Gap. It also provides practical implications for designing adaptive governance frameworks that balance flexibility and control in AI-enabled environments.

**Keywords:** artificial intelligence, decision rights, corporate governance, decision-making, organizational autonomy, management, marketing, Ukraine

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## CHAPTER 1. INTRODUCTION

In recent years, AI has become an integral part of organizational decision-making, particularly in knowledge-intensive functions such as marketing. What initially emerged as a set of experimental tools has rapidly evolved into a widely adopted infrastructure supporting everyday work processes. By 2026, generative AI is no longer limited to content generation but increasingly functions as a mechanism for information processing, analysis, and decision support.

This transformation is especially visible in high-paced environments, where employees actively rely on AI to structure information, generate insights, and accelerate workflows. As a result, AI expands the analytical capacity of individuals while simultaneously reshaping how decisions are prepared and executed within organizations.

Recent industry evidence further supports this shift, indicating that organizations are actively integrating AI into core business processes and restructuring workflows to capture value from these technologies. In the Ukrainian context, this global trend is reflected in the rapid transition of domestic technology and professional services firms toward systematic AI adoption (DOU, 2026). On the other hand, many firms continue to face challenges in aligning governance mechanisms with the pace of AI adoption, suggesting a gap between technological integration and organizational adaptation (McKinsey & Company, 2025; Deloitte, 2026).

Moreover, the growing integration of AI into routine work processes introduces new organizational challenges. As decision-making becomes increasingly supported by AI-generated outputs, traditional assumptions about authority, accountability, and control are called into question. This creates a need to better understand how AI adoption affects decision-making dynamics and the role of governance structures in this process.

### **1.1 Background: AI in Marketing and Governance Complexity**

The rapid adoption of AI technologies has significantly transformed how organizations process information and support decision-making. AI systems are increasingly used not only for routine operational tasks, but also as tools that assist employees in analysis, communication, and the preparation of strategic and tactical decisions.

However, the impact of technology on organizations should not be understood in a purely deterministic way. Rather than directly shaping organizational structures, technologies interact with existing practices and social dynamics within organizations. Prior research suggests that technologies act

as triggers of organizational change, influencing how structures evolve through patterns of use and interaction (Barley, 1986).

Building on this perspective, technology can be understood as both shaped by human action and simultaneously shaping it. This dual role highlights that organizational outcomes depend not only on technological capabilities but also on how these technologies are interpreted and used in practice (Orlikowski, 1992). In the context of AI, this dynamic is particularly visible, as employees actively configure AI tools while these tools influence how decisions are prepared, validated, and communicated.

One of the key mechanisms through which AI affects organizations is the transformation of information flows and access to knowledge. Because decision-making authority is closely linked to information, changes in how it is generated and circulated can reshape internal power dynamics. Prior research demonstrates that authority within organizations is strongly associated with the structure and allocation of information (Aghion & Tirole, 1997). In AI-enabled environments, individuals who can effectively use, interpret, and validate AI-generated outputs may therefore gain greater influence over decisions, even if formal authority structures remain unchanged.

Simultaneously, increased reliance on AI introduces governance challenges and associated risks. As socio-technical systems, AI outcomes depend on how these tools are implemented, monitored, and managed within organizational contexts (NIST, 2023).

Overall, these developments point to a growing gap between formal organizational structures and actual decision-making practices. While formal governance mechanisms continue to define authority and responsibility, the practical influence on decisions increasingly depends on access to AI tools, the ability to interpret their outputs, and the presence of effective governance frameworks.

## **1.2 Research Problem**

Despite the rapid integration of AI into organizational processes, its implications for decision-making and governance remain insufficiently understood. Existing research has primarily focused on the technological capabilities and efficiency gains associated with AI, while providing more limited empirical evidence on how these technologies reshape decision rights, authority structures, and organizational control mechanisms in practice.

From a theoretical perspective, prior research suggests that technological complexity influences organizational structures and coordination mechanisms. Organizations adapt their decision-making processes to the availability and distribution of information, which plays a central role in shaping internal structures (Galbraith, 1973). Moreover, agency theory emphasizes that the allocation of decision rights depends on information asymmetry and control systems within organizations (Jensen & Meckling, 1976).

As AI technologies transform how information is generated, accessed, and processed, they may affect how authority and control are distributed across organizational levels.

Recent research on AI in organizations further highlights that AI adoption does not necessarily replace human decision-making, but often augments it, creating new forms of interaction between humans and technology (Raisch & Krakowski, 2021). In this context, AI expands individuals' access to analytical capabilities while preserving formal hierarchical structures, potentially leading to a divergence between decision preparation and final decision authority.

At the individual level, AI systems can also influence how decisions are made. Studies on AI-assisted decision-making suggest that users may increasingly rely on AI-generated recommendations and shift from active reasoning toward evaluation of AI outputs (Zhang & Reicherts, 2025). This creates potential risks related to overreliance and reduced engagement in decision processes, particularly in complex or high-stakes contexts.

Despite these developments, several important gaps remain. First, empirical research examining the relationship between AI adoption, decision-making autonomy, and influence is still limited, particularly in applied organizational settings. Second, existing studies rarely integrate governance, risk allocation, and decision-right restructuring into a single analytical framework, often treating these dimensions separately. Third, there is a lack of evidence from knowledge-intensive service industries such as marketing, where AI is deeply embedded in everyday workflows. Finally, research in this area remains largely concentrated in Western contexts, with limited insights from emerging or post-transitional economies such as Ukraine.

As a result, there is a need for empirical research that examines how AI adoption affects different dimensions of decision-making within organizations, including autonomy in decision preparation, influence over final decisions, and the role of governance structures in shaping these relationships.

### **1.3 Research Aim and Research Questions**

The aim of this study is to examine how the adoption of AI affects decision-making processes within organizations, with a particular focus on autonomy, influence, and governance. The study seeks to provide an empirical analysis of how AI integration reshapes the preparation of decisions, the distribution of influence over outcomes, and the role of formal governance structures in this process.

To achieve this aim, the study addresses the following research question:

**How does AI adoption influence employee decision-making autonomy and perceived influence, and what role does organizational governance play in this relationship?**

## 1.4 Hypotheses

Based on the research question and the theoretical arguments outlined above, the study tests the following hypotheses:

H1: Higher levels of AI adoption are positively associated with employee decision-making autonomy.

H2: Higher levels of AI adoption are positively associated with employees' perceived influence on decision-making outcomes.

H3: Organizational governance moderates the relationship between AI adoption and decision-making autonomy and influence.

These hypotheses reflect the expectation that AI adoption enhances individual capabilities in decision preparation, while the role of governance structures in shaping these effects remains subject to empirical testing.

## 1.5 Contributions

This study contributes to the existing literature by introducing the concept of the autonomy–authority gap, defined as the divergence between employees' increasing autonomy in decision preparation enabled by AI and the persistence of formal decision authority within hierarchical structures. This concept provides a framework for understanding how AI reshapes decision-making dynamics without fundamentally redistributing formal authority.

The study also offers an integrated empirical analysis of how AI adoption influences organizational decision-making. It advances current understanding by examining multiple dimensions of decision-making, including autonomy in decision preparation and perceived influence over outcomes. While prior studies often focus on technological capabilities or performance outcomes, this research provides a more granular perspective on how AI transforms decision-making processes at the individual level.

Furthermore, the study contributes to the literature on organizational governance by analyzing the role of governance structures in shaping AI-related decision dynamics. In particular, it explores whether formal governance mechanisms influence the relationship between AI adoption and decision-making, addressing the gap between formal organizational frameworks and actual practices.

The research additionally provides empirical evidence from a knowledge-intensive service context, specifically the marketing and communications industry. This sector represents a relevant setting due to its intensive use of data, fast-paced workflows, and growing reliance on AI tools in everyday operations.

Finally, the study contributes to the limited body of evidence on AI adoption in emerging and post-transitional economies by examining the case of Ukraine. This context offers additional insights into how organizations adopt and govern AI under conditions of uncertainty and rapid technological change.

Overall, the study integrates perspectives from strategic management, organizational theory, and AI research to provide a comprehensive understanding of how AI adoption shapes decision-making within organizations.

## **1.6. Structure of the Thesis**

This thesis is structured into eight chapters.

Chapter 1 introduces the research background and motivates the study by outlining the research problem, research question, hypotheses, and contributions.

Chapter 2 reviews the relevant literature on artificial intelligence in organizations, decision-making autonomy and influence, and organizational governance. It synthesizes existing theoretical and empirical research to establish the foundation for the study.

Chapter 3 develops the conceptual framework and formulates the research hypotheses. It presents the conceptual model linking AI adoption, decision-making autonomy, perceived influence, and governance structures, defines the key constructs, conceptualizes governance as a contextual layer, and outlines the theoretical rationale underlying the hypotheses.

Chapter 4 describes the research design and methodology, including the case context, data collection procedures, sample characteristics, and measurement of key variables. It also explains the analytical methods used to test the proposed hypotheses.

Chapter 5 presents the empirical results of the study. It reports descriptive statistics, evaluates the reliability and validity of the measurement instruments, and presents the findings of the hypothesis testing.

Chapter 6 discusses empirical findings in relation to the research question, hypotheses, and prior literature. It interprets the results, highlights theoretical implications, and reflects on how AI adoption and governance structures shape organizational decision-making.

Chapter 7 focuses on the practical implications of the study. It converts the empirical findings into governance-oriented frameworks and tools, including a governance risk map, AI oversight architecture, models of legal involvement, mechanisms for balancing learning and control, decision boundary design, recognition of informal AI expertise, and the embedding of governance into organizational workflows.

Finally, Chapter 8 concludes the thesis by summarizing the main findings, revisiting the study's contributions, discussing its limitations, and outlining directions for future research.

## CHAPTER 2. LITERATURE REVIEW

This chapter reviews the theoretical foundations relevant to understanding how AI influences organizational decision-making. Building on insights from management, information systems, and organizational theory, the chapter integrates perspectives on AI adoption, decision rights, information processing, and technology use to develop a comprehensive analytical framework tailored to knowledge-intensive environments.

The review proceeds by examining how AI reshapes decision-making processes, alters the distribution of authority and knowledge, and interacts with patterns of technology use within organizations. Particular attention is given to the role of governance and institutional pressures in shaping these dynamics, exploring the potential tension between formal rules and emergent practices. Rather than treating these elements in isolation, the chapter adopts an integrative approach to explain how AI-enabled decision-making emerges from the interaction between structural, informational, and behavioral factors.

The chapter concludes by identifying key gaps in the existing literature, which form the basis for the research question and hypotheses of this study.

### **2.1 AI and Decision-Making in Organizations**

The increasing adoption of AI in organizations has fundamentally reshaped how decisions are prepared, structured, and executed. Rather than merely automating existing tasks, AI technologies introduce new forms of interaction between humans and data-driven systems, thereby altering both the process and the locus of decision-making. As a result, organizational decision-making is no longer solely a human-centered activity but increasingly emerges from the interplay between human judgment and algorithmic prediction.

A growing body of research suggests that AI does not uniformly replace human decision-makers but instead reconfigures decision-making processes. A central distinction in this literature is between automation and augmentation. While automation refers to the substitution of human input with algorithmic decision-making, augmentation emphasizes the complementary relationship between humans and AI systems. However, recent work demonstrates that these two modes are not mutually exclusive but coexist in tension, forming a dynamic relationship over time (Raisch & Krakowski, 2021).

This perspective is further supported by research on human–AI collaboration, which emphasizes that AI is most effectively used as a complement to human judgment rather than a substitute for it. In such contexts, decision-making emerges as a joint cognitive process, where humans contribute contextual understanding and critical evaluation, while AI systems provide data-driven insights and predictions

(Jarrahi, 2018; Brynjolfsson et al., 2023). Empirical evidence also suggests that individuals may either appropriately rely on or over-rely on algorithmic recommendations, highlighting the importance of human judgment in moderating AI influence (Logg et al., 2019).

At the organizational level, this transformation is reflected in the emergence of new decision-making structures. Rather than a binary shift from human to machine control, decision processes increasingly take hybrid forms, where AI contributes to information filtering, prediction, or optimization, while humans retain final judgment and accountability (Shrestha et al., 2019). This results in a redistribution of participation in decision-making, where more actors become involved in the preparation and shaping of decisions, even if formal authority remains unchanged.

At a more granular level, research on algorithmic decision-making highlights the role of human-AI interaction in shaping outcomes. Decision processes are mediated through technological interfaces that both enable and constrain human involvement, creating a simultaneous sense of detachment from and attachment to decisions (Bader & Kaiser, 2019). Similarly, the concept of hybrid intelligence frames decision-making as an integrated system in which humans and AI jointly contribute to problem-solving, learning, and execution (Dellermann et al., 2019).

Importantly, AI systems also transform the informational foundations of decision-making. With the increasing digitalization of work, organizations generate large volumes of “digital exhaust” that can be aggregated into behavioral profiles and used for predictive analytics (Leonardi, 2021). This shift enables organizations to move from retrospective evaluation toward anticipatory decision-making, where actions are informed by predicted outcomes rather than past performance.

In addition, AI introduces new forms of organizational control. Algorithms can guide behavior, evaluate performance, and discipline outcomes through embedded mechanisms such as recommendations, monitoring, and automated evaluation (Kellogg et al., 2020). These mechanisms often operate implicitly, blurring the boundary between technological support and managerial control.

Finally, AI reshapes the nature of work itself. Learning algorithms redistribute expertise, redefine task boundaries, and alter coordination patterns within organizations (Faraj et al., 2018). Decision-making becomes increasingly data-driven and distributed, with humans acting as interpreters, supervisors, and validators of algorithmic outputs rather than sole decision-makers.

Taken together, this literature suggests that AI affects decision-making primarily by restructuring how decisions are produced, rather than by directly transferring decision authority to machines. First, AI expands individual autonomy in the preparation of decisions by providing access to analytical tools, predictive models, and generated insights. Second, it increases the potential for influence by enabling broader participation in the generation and evaluation of decision alternatives. However, these changes

do not necessarily lead to shifts in formal authority, as ultimate responsibility and accountability remain anchored in human actors (Shrestha et al., 2019).

Moreover, decision-making becomes increasingly dependent on the interaction between humans and AI systems. The quality and nature of decisions depend not only on the capabilities of algorithms but also on how individuals interpret, trust, and integrate algorithmic outputs into their work (Bader & Kaiser, 2019; Dellermann et al., 2019). As a result, decision-making outcomes are shaped by both technological capabilities and behavioral dynamics. In this context, trust in AI systems becomes a critical mediating factor. Research shows that both over-trust and under-trust can distort decision-making outcomes, leading either to uncritical acceptance of algorithmic outputs or to their unwarranted rejection (Glikson & Woolley, 2020). Furthermore, the perceived reliability and transparency of AI systems significantly influence how individuals incorporate algorithmic recommendations into their decision processes (Burton et al., 2020).

Despite significant advances, the literature reveals several unresolved tensions. First, the coexistence of automation and augmentation creates ambiguity in the role of human decision-makers, leading to potential over-reliance on or resistance to AI systems (Raisch & Krakowski, 2021). Second, while AI can enhance efficiency and coordination, it may simultaneously reduce transparency and increase dependency on opaque systems (Leonardi, 2021; Kellogg et al., 2020). Third, although AI introduces new mechanisms of control, these mechanisms are often embedded within technological systems rather than formal governance structures, raising questions about how control is exercised and understood in practice (Faraj et al., 2018). Recent research also highlights that human–AI collaboration does not consistently outperform either human-only or AI-only decision-making. Instead, performance depends on factors such as task complexity, user expertise, and the design of interaction between humans and AI systems (Steyvers & Kumar, 2024). This suggests that the benefits of AI-enabled decision-making are contingent rather than universal.

These tensions highlight a critical gap in understanding how AI-driven changes in decision-making interact with organizational governance and authority structures. In particular, it remains unclear whether and how formal governance mechanisms shape the relationship between AI adoption and individual decision-making outcomes.

To address these questions, it is necessary to examine decision-making not only as a process but also as a function of authority and control within organizations. The following section therefore draws on agency theory and the concept of decision rights to analyze how authority is allocated and how it may be affected by the integration of AI systems.

## 2.2 Agency Theory and Decision Rights

Organizational decision-making is fundamentally shaped by how authority and control are distributed within firms. While formal structures define who has the right to make decisions, actual decision-making often depends on access to information, expertise, and the ability to influence outcomes. As organizations become more complex and information-intensive, the separation between formal authority and practical influence becomes increasingly pronounced.

Agency theory provides a foundational framework for understanding how decision rights are allocated and exercised within organizations. At its core, the theory distinguishes between principals, who delegate authority, and agents, who execute decisions under conditions of incomplete information (Jensen & Meckling, 1976). Because agents typically possess superior task-specific knowledge, organizations face persistent information asymmetry, which complicates the effective control of delegated decision-making.

Building on this logic, the allocation of decision rights becomes a central organizational problem. Decision rights refer not only to the formal authority to make choices but also to the practical ability to shape decisions through information, expertise, and problem framing. In this context, authority is often distributed across hierarchical levels, but the effective exercise of decision-making depends on where relevant knowledge resides (Aghion & Tirole, 1997).

A key distinction in this literature is between formal authority and real authority. Formal authority reflects officially assigned decision rights, whereas real authority emerges from the ability to act on information and influence outcomes in practice. When agents possess critical information that principals cannot fully observe or verify, they may exercise real authority even without formal control over decisions (Aghion & Tirole, 1997). This creates a structural tension between centralized control and decentralized discretion.

Closely related to this is the trade-off between monitoring and discretion. Organizations can attempt to reduce information asymmetry through monitoring mechanisms, thereby strengthening control over agents. However, increased monitoring may limit the ability of individuals to act autonomously and respond effectively to local information. Conversely, granting discretion enhances flexibility and responsiveness but reduces the capacity for centralized oversight. As a result, firms must continuously balance the need for control with the need to leverage distributed knowledge.

The introduction of AI technologies has significant implications for the allocation and exercise of decision rights. By expanding access to information and analytical capabilities, AI can reduce certain forms of information asymmetry, enabling individuals at lower hierarchical levels to participate more

actively in decision-making processes. This can lead to an increase in decision-making autonomy, as employees gain greater capacity to prepare, structure, and evaluate decisions independently.

In parallel, AI does not necessarily alter formal authority structures. Even when individuals contribute more substantially to the development of decisions, ultimate accountability and decision rights often remain concentrated at higher levels of the organization. As a result, AI may increase autonomy without a corresponding shift in formal authority.

Furthermore, AI enables new forms of influence that are not directly tied to hierarchical position. Individuals who are able to effectively use AI tools to generate insights, frame problems, and propose solutions may exert greater influence over decision outcomes, even in the absence of formal decision rights. This suggests that influence becomes increasingly linked to informational capabilities rather than positional authority.

Taken together, these dynamics reveal a central tension in AI-enabled organizations: increases in autonomy and participation in decision-making do not necessarily result in changes in formal authority. Consequently, autonomy and influence become increasingly disconnected from hierarchical power.

This tension underscores the critical role of information in shaping decision-making authority and influence. To further understand how AI affects the distribution of autonomy and influence within organizations, it is necessary to examine how information is processed, distributed, and utilized across organizational actors. The following section therefore draws on information processing theory and knowledge-based perspectives to analyze the relationship between information, expertise, and decision-making in AI-enabled environments.

### **2.3 Information Processing and Knowledge Integration**

Organizational decision-making is fundamentally constrained by the capacity of firms to process information. As organizations grow in complexity, uncertainty, and scale, the volume and diversity of information required for effective decision-making exceed the cognitive limits of individual actors. Consequently, organizations develop structures and processes designed to distribute information, reduce uncertainty, and enable coordinated decision-making across multiple levels.

Information processing theory conceptualizes organizations as systems that exist to manage uncertainty through the acquisition, interpretation, and integration of information. The greater the uncertainty in the environment, the higher the information-processing requirements imposed on the organization (Tushman & Nadler, 1978). To cope with these demands, firms rely on mechanisms such as task decomposition, lateral communication, and information systems that enable the efficient flow of information across organizational units.

Complementing this perspective, the knowledge-based view of the firm emphasizes that knowledge is not uniformly distributed but dispersed across individuals and units within the organization. Decision-making, therefore, depends on the ability to integrate specialized knowledge held by different actors (Grant, 1996). Under this view, the allocation of decision-making authority should align with the location of relevant knowledge, as individuals possessing task-specific expertise are better positioned to evaluate alternatives and make informed decisions.

The introduction of AI technologies significantly alters the information-processing capacity of organizations. By enabling the rapid analysis of large datasets, pattern recognition, and predictive modeling, AI reduces the costs of acquiring and processing information. As a result, information that was previously inaccessible or too costly to analyze becomes available to a broader set of organizational actors. This expansion of informational access can lower barriers to participation in decision-making processes, allowing individuals at different hierarchical levels to contribute more actively to the preparation and evaluation of decisions. At the same time, increased participation in decision-making does not necessarily imply greater control over outcomes. While AI may enhance individuals' ability to process information and prepare decisions, concerns remain regarding the preservation of human autonomy in AI-supported environments, particularly when decision processes are increasingly shaped by algorithmic outputs (Buijsman et al., 2024).

Additionally, AI reshapes the way knowledge is generated and utilized. Rather than relying solely on human expertise, organizations increasingly depend on algorithmically generated insights, which may be derived from complex models that are not fully interpretable by users (Leonardi, 2021). This creates a shift from experience-based judgment toward data-driven inference, where decision-making is informed by probabilistic predictions rather than deterministic reasoning.

Importantly, while AI enhances the availability of information, it does not eliminate the need for knowledge integration. Human actors remain responsible for interpreting outputs, contextualizing insights, and making final decisions. Moreover, the distribution of knowledge becomes more dynamic, as individuals who are able to effectively leverage AI tools gain access to insights that were previously concentrated at higher levels of the organization. This can lead to a redistribution of influence, where decision-making is shaped not only by formal authority but also by the ability to mobilize and apply information.

However, increased information-processing capacity also introduces new challenges. The reliance on algorithmic outputs may create dependencies on opaque systems, limiting the ability of individuals to critically evaluate recommendations. In addition, the abundance of information does not necessarily improve decision quality, as cognitive overload and misinterpretation remain potential risks.

These dynamics highlight that improvements in information processing do not automatically resolve underlying tensions related to authority, control, and decision-making responsibility.

Overall, the integration of AI into organizational processes suggests that decision-making is increasingly shaped by the interaction between information availability and knowledge distribution. While AI expands access to information and supports more distributed participation in decision-making, it simultaneously reinforces the need for coordination, interpretation, and judgment. As a result, decision-making outcomes depend not only on technological capabilities but also on how information is structured, shared, and utilized within the organization.

These considerations point to the importance of examining the broader organizational context within which AI-enabled decision-making unfolds. In particular, the relationship between increased informational capacity and formal control mechanisms remains unclear. The following section therefore explores the role of corporate governance and institutional pressures in shaping how organizations manage AI adoption and its implications for decision-making.

#### **2.4 Technology Use, Interaction, and Structuring**

The impact of technology on organizational outcomes cannot be understood solely through its formal capabilities or intended functions. Instead, research suggests that the effects of technology emerge through patterns of use and interaction within specific organizational contexts. As a result, the relationship between technology and organizational structures is not deterministic but is continuously shaped and reshaped through human action.

The concept of the duality of technology emphasizes that technologies are both shaped by and shape organizational practices (Orlikowski, 1992). Rather than imposing fixed structures, technologies provide a set of possibilities that are enacted differently depending on how individuals engage with them in practice. Consequently, the same technological system can lead to different organizational outcomes across contexts, depending on patterns of use, interpretation, and adaptation.

Empirical research further demonstrates that technologies influence organizations through changes in interaction patterns rather than through direct structural transformation. New technologies alter communication flows, coordination mechanisms, and work routines, which over time can lead to shifts in organizational structures (Barley, 1986). This perspective highlights that structural change is mediated by everyday practices, rather than driven solely by top-down design or formal implementation.

In the context of AI, these insights suggest that the effects of technology are closely tied to how AI tools are integrated into daily work processes. AI systems are typically embedded in routine activities such as information search, content generation, and data analysis, becoming part of the micro-level practices through which decisions are prepared and evaluated. Importantly, the influence of AI on

decision-making is not a one-step output but unfolds as an iterative dialogue between human intent and machine-generated responses, gradually reshaping the boundaries of individual expertise. As a result, the impact of AI on decision-making emerges through repeated engagement with systems, rather than through discrete organizational changes.

Moreover, AI-enabled work is characterized by continuous interaction between users and systems. Decision-making is shaped through iterative processes of querying, interpreting, and refining algorithmic outputs, rather than through one-time exchanges. This reinforces the idea that technology use is not passive but involves active engagement, where users adapt tools to their needs while simultaneously being influenced by system design and outputs (Bader & Kaiser, 2019).

Also, the increasing digitalization of work generates extensive data traces that further shape patterns of use. Digital exhaust produced through everyday activities is aggregated into behavioral representations that can be analyzed and used to guide future actions (Leonardi, 2021). This creates feedback loops in which user behavior informs algorithmic outputs, which in turn influence subsequent behavior. As a result, decision-making practices become co-produced by human actors and technological systems.

These dynamics also imply that control and governance are enacted through use rather than solely through formal structures. While organizations may introduce policies regulating AI usage, the actual influence of AI on decision-making depends on how individuals adopt, interpret, and integrate these tools into their workflows. In practice, governance is therefore partially embedded in technology use, as systems guide behavior through interfaces, recommendations, and constraints, often in ways that are not explicitly formalized.

Importantly, the situated and emergent nature of technology use helps explain variation in AI outcomes across organizations and contexts. Even when similar tools are deployed, differences in user practices, skill levels, and organizational cultures can lead to divergent effects on autonomy, influence, and control. This suggests that AI does not produce uniform changes in decision-making but instead operates in conjunction with existing structures and practices in complex and context-dependent ways.

Overall, the literature indicates that the effects of AI on organizational decision-making are mediated by patterns of use and interaction. Rather than directly determining outcomes, AI technologies are enacted through practice, leading to gradual and often unintended changes in how decisions are prepared, influenced, and controlled within organizations.

These insights highlight the importance of examining the broader governance context within which technology use occurs. While technology is enacted through practice, organizations still attempt to regulate its use through formal structures and external pressures. The following section therefore

explores how corporate governance and institutional forces shape, constrain, and respond to AI-enabled organizational practices.

## **2.5 Governance and Institutional Context**

Organizational decision-making is shaped not only by internal structures and practices but also by formal governance mechanisms and broader institutional environments. Corporate governance systems are designed to define accountability, regulate behavior, and ensure alignment between organizational actions and strategic objectives. In principle, these mechanisms establish formal rules and oversight structures that determine how decisions are made and who is responsible for their outcomes.

Traditionally, governance operates through formalized systems of control, including policies, reporting procedures, and monitoring mechanisms aimed at reducing information asymmetry and managing risks associated with delegated decision-making. In the context of AI, this logic has been extended through the development of responsible AI frameworks emphasizing transparency, accountability, and fairness (Papagiannidis et al., 2025). These frameworks conceptualize governance as a structured system of principles intended to guide the design and use of AI systems.

More recently, emerging perspectives highlight that AI governance involves not only formal rules but also trade-offs between utility and risk. In particular, organizations must balance the performance benefits of AI systems with concerns related to trust, reliability, and unintended consequences (Engin, 2025). This introduces a tension between maximizing the value of AI-enabled decision support and maintaining sufficient control over its outputs and implications.

However, the rapid and decentralized integration of AI tools into everyday work processes challenges the effectiveness of formal governance mechanisms. AI systems are often adopted at the level of individual users and teams, becoming embedded in routine practices such as information search, content generation, and analytical work. As a result, the development of formal governance structures frequently lags behind actual usage, leading to a misalignment between prescribed rules and enacted practices. This gap is further reinforced by the limited operationalization of governance principles, which are often articulated at a high level but remain difficult to embed in concrete organizational routines (Papagiannidis et al., 2025).

These challenges become even more pronounced in discussions of advanced AI systems, where the potential emergence of autonomous agents raises questions about accountability and control. Prior research suggests that traditional governance models may be insufficient in contexts where decision-making is partially delegated to algorithmic systems, requiring new approaches to responsibility allocation and oversight (Shrestha et al., 2019; Kellogg et al., 2020). However, in many organizational

settings, AI remains primarily a decision-support tool rather than an autonomous decision-maker, limiting the direct applicability of such models.

Beyond internal organizational dynamics, institutional theory highlights the role of external pressures in shaping governance arrangements. Organizations operate within environments characterized by regulatory requirements, professional norms, and industry expectations. Under conditions of uncertainty, firms often adopt governance structures to maintain legitimacy rather than to directly improve efficiency (DiMaggio & Powell, 1983). In the context of AI, regulatory developments such as the European Union's AI Act further intensify these pressures by requiring organizations to implement formal governance mechanisms related to transparency, risk management, and accountability. For organizations operating in or connected to European markets, such regulation represents a significant external driver of governance formalization.

Taken together, these perspectives suggest that governance in AI-enabled organizations operates across multiple layers, including formal rules, technological infrastructures, and institutional pressures. While governance frameworks define acceptable practices and provide oversight, their practical influence on decision-making may remain limited. This reflects a form of decoupling, where formal governance structures exist alongside, but remain partially disconnected from everyday organizational practices (DiMaggio & Powell, 1983).

As a result, governance is more accurately understood as a contextual boundary that shapes the conditions under which AI is used, rather than as a direct mechanism that determines decision-making outcomes. The effects of AI on autonomy, influence, and decision-making processes are therefore more strongly driven by information flows, knowledge distribution, and patterns of technology use than by formal governance structures.

This perspective highlights an important gap in the literature. While governance frameworks and institutional pressures are widely discussed, there is limited empirical evidence on how governance interacts with AI-enabled decision-making at the individual level. In particular, it remains unclear whether formal governance structures meaningfully influence the relationship between AI adoption and outcomes such as autonomy, influence, and authority within organizations.

## **2.6 Research Gap**

The existing literature provides substantial insights into how AI affects organizations, decision-making processes, and governance structures. Prior research has demonstrated that AI reshapes decision-making through automation and augmentation dynamics, alters the distribution of information and knowledge, and introduces new forms of interaction between humans and technology (Raisch & Krakowski, 2021; Shrestha et al., 2019; Faraj et al., 2018). Additionally, studies grounded in agency

theory and information processing perspectives highlight the importance of decision rights, information asymmetry, and knowledge distribution in shaping organizational decision-making outcomes (Aghion & Tirole, 1997; Grant, 1996; Tushman & Nadler, 1978).

Despite these advances, several important gaps remain.

First, while prior research has examined the impact of AI on decision-making structures, less attention has been paid to how AI affects individual-level decision-making outcomes, particularly in terms of autonomy and influence. Existing studies tend to focus either on macro-level organizational structures or on technological capabilities, leaving the micro-level dynamics of how employees experience and exercise decision-making under AI insufficiently explored.

Second, although governance mechanisms and institutional pressures are widely recognized as important factors in shaping organizational behavior, their role in AI-enabled decision-making remains insufficiently understood. Recent literature has emphasized the growing importance of responsible AI frameworks and governance principles; however, these are often formulated at a high level and lack clear operationalization in everyday organizational practices (Papagiannidis et al., 2025). As a result, it remains unclear whether formal governance structures meaningfully influence the relationship between AI adoption and decision-making outcomes, or whether their role is primarily indirect.

Third, while recent studies highlight the importance of human–AI interaction and the augmentation of human capabilities, there is limited integration between these perspectives and traditional theories of decision rights and organizational control. In particular, existing research does not fully explain how AI can simultaneously expand individual autonomy in decision preparation while leaving formal authority structures largely unchanged.

Taken together, these gaps point to a lack of integrated understanding of how AI adoption influences decision-making at the individual level, and how this relationship is shaped by organizational governance and patterns of technology use in practice.

To address these limitations, this study examines how AI adoption affects employee decision-making autonomy and influence and investigates the role of organizational governance in this relationship. By combining insights from agency theory, information processing, and technology use perspectives, the study aims to bridge the gap between structural, informational, and behavioral explanations of AI-enabled decision-making.

## CHAPTER 3. CONCEPTUAL FRAMEWORK AND HYPOTHESES

This chapter develops a conceptual framework explaining how AI adoption affects decision-making in organizations. While Chapter 2 reviewed the theoretical background, this chapter synthesizes those insights into a clear and testable model that separates operational capabilities from formal authority structures.

The core idea of the framework is that AI primarily acts as an operational accelerator. It improves access to information, speeds up analysis, and simplifies decision preparation. However, it does not fundamentally change formal decision rights (Aghion & Tirole, 1997). This is because accountability, risk, and responsibility remain tied to individuals who hold formal authority. As a result, the effects of AI are constrained by the need for human validation and organizational legitimacy.

This creates a dual dynamic. On one hand, AI increases individual autonomy and supports the emergence of informal, expertise-based influence. On the other hand, formal authority structures remain stable and continue to define who makes final decisions.

In this context, governance does not operate as a direct driver of behavior. Instead, it functions as a boundary that defines acceptable use of AI, especially in areas related to risk and accountability (NIST, 2023). Furthermore, the role of AI is best understood as augmenting human capabilities rather than replacing decision-makers (Raisch & Krakowski, 2021).

The following sections define the key constructs, present the logic of the model, and develop the hypotheses tested in the empirical analysis.

### 3.1 Conceptual Model: The Multi-Layered Approach

The study proposes a multi-layered model that explains how AI adoption affects decision-making across different levels of organizational activity. The core premise is that technological adoption and operational change occur faster than shifts in formal authority structures. To capture this dynamic, the model is structured into five interconnected layers (A through E).

#### **Layer A: Capability Effects (Operational Acceleration).**

At the primary level, AI enhances individual capabilities by reducing the cost of information search and analysis. This allows employees to perform complex preparatory tasks more independently. This layer represents the direct link between AI adoption and decision-making autonomy (H1).

#### **Layer B: Second-Order Effects (Emergence of Informal Influence).**

As individuals develop higher levels of AI proficiency, new behavioral patterns emerge. Strong users become informal reference points within teams, and their input gains more weight in discussions.

This layer explains how AI adoption shapes perceived influence (H2), primarily through expertise rather than formal authority.

**Layer C: The Constraint Layer (Central Bottleneck).**

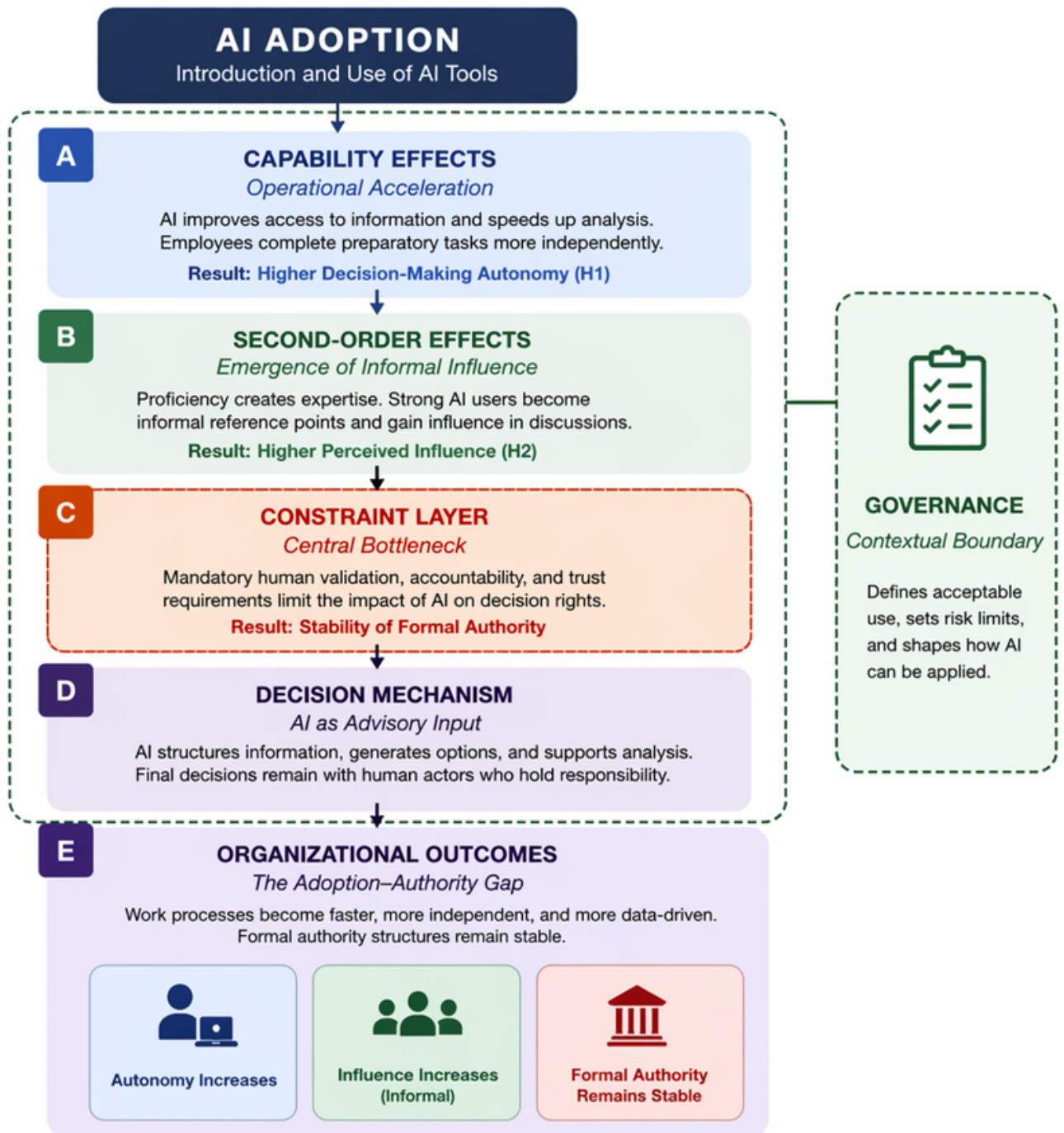
The model introduces a constraint layer that limits how far AI-driven capabilities can reshape decision-making structures. This layer includes mandatory human validation, accountability requirements, and trust in AI outputs. Even when AI provides strong analytical input, it is not accepted as an independent source of authority. This bottleneck explains why increased autonomy does not lead to a change in formal hierarchy.

**Layer D: The Decision Mechanism (AI as Advisory Input).**

Decision-making is modeled as a hybrid process. AI structures information, generates options, and supports analysis, but final decisions remain with human actors who hold responsibility. In this sense, authority follows accountability, not just access to information.

**Layer E: Organizational Outcomes (The Structural Gap).**

The combined effect of these layers leads to an uneven transformation. Work processes become faster, more independent, and more data-driven, while formal authority structures remain stable. This creates an "Adoption-Authority Gap", where decision preparation evolves significantly, but decision rights do not. The relationships described above are summarized in Figure 1, which presents the multi-layered conceptual model of AI adoption and decision-making and illustrates how capability effects contribute to autonomy and influence, while being constrained by accountability, validation, and organizational structures.



**Figure 1 Multi-layered conceptual model of AI adoption and decision-making**

*Source: Developed by the author.*

### 3.2 Key Constructs and Variables

To empirically test the conceptual model, the study defines a set of key variables that capture AI adoption, decision-making outcomes, and organizational constraints. The selection of variables follows directly from the multi-layered logic presented in Section 3.1 and provides a clear link between the theoretical framework and the empirical analysis.

The independent variable is the AI Adoption Index. It reflects the extent to which employees integrate AI tools into their daily work. The index includes frequency of use, self-assessed proficiency, level of workflow integration, and the share of tasks supported by AI. Consistent with prior research, AI is treated as a tool that augments human capabilities rather than replaces them (Raisch & Krakowski, 2021).

Two dependent variables are used to capture decision-making outcomes.

The first is the Decision-Making Autonomy Index, defined as the degree to which individuals can independently prepare decisions, gather and process information, and develop alternatives without relying on hierarchical input. This variable reflects the capability effects described in Layer A of the model and captures changes in how work is performed rather than changes in formal authority.

The second is the Perceived Influence Index, defined as the extent to which individuals' AI-supported input affects discussions and final decision outcomes. This includes the ability to shape decision alternatives and contribute to decision processes. This variable reflects the second-order effects described in Layer B and captures the emergence of informal, expertise-based influence.

In addition to the main variables, the model includes the Governance Index as a boundary condition. This variable captures the extent to which formal policies, risk controls, and accountability requirements regulate the use of AI in the organization. It also reflects perceived constraints such as trust in AI outputs and the need for human validation. Rather than acting as a direct driver of behavior, governance defines the scope within which AI can be applied in decision-making processes.

Together, these variables reflect the core logic of the model. AI adoption increases individual capabilities and enables greater autonomy in decision preparation. It also supports the emergence of informal influence. On the other hand, governance and accountability constraints limit the extent to which these changes affect formal authority.

All variables are operationalized as composite indices based on survey measures, as described in Chapter 4.

### **3.3 The Logic of Constraints: Power vs. Information**

A central mechanism through which AI reshapes organizational decision-making lies in the relationship between formal authority and informational control. Organizational theory suggests that decision authority is determined not only by hierarchical position but also by access to and control over information.

A key distinction in this context is between formal authority and real authority. Formal authority refers to the officially assigned right to make decisions, while real authority reflects the ability to influence decisions through control over relevant information (Aghion & Tirole, 1997). In practice,

individuals who possess superior information can shape decision alternatives and influence outcomes even without formal decision rights.

AI directly affects this relationship by reducing the cost of information search and analysis and by expanding access to analytical capabilities. Employees can generate insights, evaluate options, and structure decisions more independently. This weakens traditional information asymmetries and allows influence to emerge at lower levels of the organization.

From an information-processing perspective, organizations are systems that manage uncertainty by matching their information-processing capacity with environmental demands (Tushman & Nadler, 1978). AI increases this capacity by accelerating data analysis and simplifying complex tasks. As a result, employees using AI tools may gain an informational advantage in specific situations, especially where speed and analytical depth matter.

However, this shift does not lead to a redistribution of formal authority. Instead, it creates structural tension. Information becomes more widely distributed, while formal decision rights remain concentrated. This reflects a trade-off between control and initiative. Greater access to information improves local problem solving and increases initiative, but it also reduces the ability of centralized actors to fully control outcomes (Aghion & Tirole, 1997). In this context, formal authority acts as an "accountability anchor"; even when information is decentralized, the ultimate right to decide is held by those who carry the legal and organizational risk.

AI strengthens this tension. It enables more actors to participate in decision preparation, accelerates decision cycles, and creates differences in capabilities based on AI proficiency. These factors increase the role of informal influence without changing formal roles.

Organizations typically respond to these changes by reinforcing governance mechanisms rather than redistributing authority. From an agency theory perspective, improved access to information does not remove coordination problems but changes how they are managed (Jensen & Meckling, 1976). Control becomes embedded in processes and tools, while accountability remains tied to formally designated decision-makers.

Institutional factors further explain why authority structures remain stable. Organizations tend to preserve existing arrangements due to pressures for legitimacy and consistency (DiMaggio & Powell, 1983). Even when AI enables alternative ways of organizing decisions, firms often integrate these tools into existing structures instead of redesigning them.

The relationship between power and information should therefore be seen as dynamic. Technology shapes organizational processes, but its effects depend on how it is used and interpreted in

practice. As argued by Orlikowski (1992), technology and organizational structures evolve together through ongoing interaction.

In summary, AI changes how information is created and distributed, but it does not automatically change who has the right to make decisions. This results in a situation where autonomy in decision preparation increases, while formal authority remains largely unchanged. This reinforces the core principle of the model: power follows accountability, not information. AI expands information access, but authority remains human because accountability remains non-delegable.

### **3.4 Hypotheses Development**

Building on the conceptual model, this section develops testable hypotheses on how AI adoption affects decision-making outcomes. The model distinguishes between direct capability effects, second-order behavioral effects, and the role of organizational constraints.

#### **3.4.1 AI Adoption and Decision-Making Autonomy (H1)**

The first level of impact reflects capability effects. AI improves access to information, accelerates analysis, and simplifies routine cognitive tasks. As a result, employees can prepare decisions more independently and rely less on hierarchical support.

From an information-processing perspective, autonomy increases when the cost of acquiring and analyzing information decreases (Tushman & Nadler, 1978). AI directly reduces these costs by enabling faster data processing and structured output generation. This allows individuals to perform tasks that previously required coordination, approval, or input from others.

Importantly, this effect operates at the level of decision preparation rather than final decision-making. AI does not replace human judgment but expands the ability of individuals to structure problems, evaluate alternatives, and develop recommendations.

Based on this logic, AI adoption is expected to increase perceived autonomy in decision-making.

**H1: Higher levels of AI adoption lead to increased perceived decision-making autonomy at the individual level.**

#### **3.4.2 AI Adoption and Perceived Influence (H2)**

Beyond direct capability effects, AI adoption generates second-order effects related to informal influence. As individuals develop higher levels of proficiency in AI tools, they gain an advantage in generating insights, structuring arguments, and supporting decisions with data.

This advantage functions as a signal of competence within teams. Employees who consistently produce higher-quality outputs are more likely to be consulted, trusted, and included in decision-related discussions. In this sense, AI enables the emergence of influence based on expertise rather than formal position.

This mechanism aligns with the distinction between formal and real authority, where influence can arise from control over information rather than hierarchical role (Aghion & Tirole, 1997). However, this form of impact remains constrained by formal authority structures and does not extend to direct decision rights.

As a result, the effect of AI on influence is expected to be positive but weaker than its effect on autonomy.

**H2: Higher levels of AI adoption lead to increased perceived influence over organizational decision-making outcomes.**

### **3.4.3 Governance as a Boundary Condition (H3)**

The model also considers the role of organizational governance and constraints. Formal policies, risk controls, and accountability requirements define the conditions under which AI can be used in decision-making.

Governance does not directly determine how individuals use AI in everyday tasks. Instead, it defines the boundaries of acceptable use, particularly in areas involving risk, data sensitivity, and responsibility. These constraints shape how far AI-enabled capabilities can manifest into actual influence within the organization.

Concurrently, governance mechanisms often lag behind technological adoption and are not fully embedded in daily workflows. As a result, their impact may be indirect and inconsistent across contexts.

Based on this reasoning, governance is expected to shape the conditions under which AI affects decision-making outcomes rather than directly strengthening or weakening these relationships.

**H3: Organizational governance mechanisms shape the boundary conditions under which AI adoption transforms into decision-making outcomes, rather than acting as a strong statistical moderator.**

## CHAPTER 4. RESEARCH DESIGN AND METHODOLOGY

This chapter outlines the research design and methodological approach employed in the study. To address the research questions, a sequential mixed-methods design is adopted, combining quantitative survey data (N = 182) with qualitative insights from 10 semi-structured interviews conducted within dentsu Ukraine.

The chapter begins by describing the overall research design and case context, followed by a detailed account of the qualitative and quantitative data collection and analysis procedures. It then discusses the measures taken to ensure validity and reliability, including the internal consistency of the constructed indices and the use of triangulation. Finally, the chapter outlines the ethical considerations guiding the research process, including issues of confidentiality, voluntary participation, and responsible data handling.

### 4.1 Research Design

The study follows an explanatory sequential mixed-methods design, in which quantitative data are collected and analyzed first to identify general patterns and relationships, followed by qualitative interviews aimed at contextualizing and explaining these findings. The quantitative component is based on a survey of 182 employees, enabling statistical testing of the relationships between AI adoption, decision-making autonomy, and perceived influence. The qualitative component consists of 10 semi-structured interviews with key organizational actors, aimed at uncovering underlying mechanisms, behavioral patterns, and contextual factors that may not be fully captured through quantitative measures.

The integration of these methods enables triangulation, where qualitative insights are used to interpret and contextualize the statistical relationships identified in the quantitative analysis. This approach allows for a more comprehensive understanding of the phenomenon by combining measurement with explanation.

The research is conducted within a single organizational context, dentsu Ukraine, selected as an information-rich case characterized by intensive AI adoption in a knowledge-intensive marketing environment. This setting provides a relevant context for examining how AI is integrated into everyday work practices and decision-making processes.

The unit of analysis in this study is the individual employee. This level of analysis is appropriate given the research focus on how AI adoption affects decision-making practices at the operational level, particularly in terms of autonomy and perceived influence within organizational processes.

Overall, this research design provides a structured and context-sensitive framework for examining the relationship between AI adoption and decision-making dynamics within organizations.

#### **4.2 Case Context: dentsu Ukraine**

This study is conducted within the organizational context of dentsu Ukraine, an advertising and media communications holding operating in the Ukrainian market and affiliated with Dentsu Group Inc., a global communications network. While integrated into the international structure, dentsu Ukraine retains a significant degree of operational autonomy at the local level, creating a hybrid organizational environment that combines global standards with local market dynamics.

The company provides a full range of advertising and media services, including strategic planning, media buying, digital marketing, analytics, creative services, and technology-driven solutions. Its client portfolio includes both international corporations served through the global network and locally acquired clients, contributing to a complex and dynamic operating environment.

From an organizational perspective, dentsu Ukraine operates as a group of legally independent entities connected through affiliation and licensing arrangements. Core support functions such as finance, legal, IT, and human resources are partially centralized, while operational units retain autonomy in project execution and client interaction. This structure enables flexibility in decision-making and creates conditions for variation in how work practices are implemented across teams.

The organization is characterized by a strong technological orientation and a history of early adoption of digital tools. dentsu Ukraine has implemented cloud infrastructure, proprietary software solutions, and data analytics platforms to support campaign planning, performance monitoring, and cross-channel analysis. In recent years, AI-based tools have been increasingly integrated into everyday workflows, supporting both routine tasks and more complex analytical and preparatory activities.

Organizational culture emphasizes openness, initiative, and continuous professional development. Employees are encouraged to experiment with new tools and share practices internally, supported by internal learning platforms and knowledge-sharing initiatives. This environment facilitates bottom-up adoption of AI, where usage emerges through everyday practices rather than being solely driven by formal top-down implementation.

Simultaneously, the organization operates in a volatile external environment shaped by economic uncertainty and the ongoing war in Ukraine. This context increases the importance of flexibility, speed, and adaptive decision-making, reinforcing the use of tools that enhance efficiency and analytical capacity.

The combination of intensive AI adoption, decentralized operational practices, and stable hierarchical accountability structures makes dentsu Ukraine a suitable case for examining how AI affects

decision-making autonomy, influence, and governance. While the findings are not intended to be statistically generalizable, the case provides a theoretically informative context for understanding the organizational implications of AI adoption in knowledge-intensive service environments.

The researcher's prior professional involvement with the organization facilitated access to respondents and supported data collection. To mitigate potential bias, the study relies on standardized survey instruments, semi-structured interview protocols, and analysis of anonymized and aggregated data.

### **4.3 Quantitative Survey**

The quantitative component of the study is based on a structured survey conducted among employees of dentsu Ukraine. The survey was designed to capture patterns of AI adoption, its integration into work processes, and its relationship with decision-making autonomy, perceived influence, and organizational governance.

The questionnaire was developed specifically for this study and consisted of seven sections: (A) Respondent Profile, (B) AI Adoption, (C) Workflow Integration, (D) Decision Rights and Authority, (E) Governance and Risk, (F) Outcomes, and (G) Open-ended reflections. A detailed overview of the survey instrument is provided in Appendix A.

The final dataset includes 182 valid responses. Participation was voluntary and anonymous, covering a diverse sample of functional roles and seniority levels, from junior employees to C-level executives, ensuring sufficient variation for statistical analysis.

The survey instrument primarily utilized 7-point Likert scales (1 = Strongly Disagree; 7 = Strongly Agree) for perceptual measures, while behavioral variables such as frequency of AI use and task involvement were captured using categorical scales. To enable statistical analysis, these categorical variables were transformed into ordinal numeric values reflecting increasing intensity. For example, frequency of AI usage was mapped onto a 0–5 scale ranging from “Never” to “Multiple times per day”.

Based on the survey responses, four composite indices were constructed to represent the key analytical variables. The AI adoption index aggregates frequency of use, self-assessed proficiency, level of workflow integration, and the share of tasks supported by AI (Cronbach's  $\alpha = 0.78$ ). The decision-making autonomy index captures independent decision-making and reduced need for escalation. The perceived influence index reflects the extent to which AI-based insights affect participation in decision processes. The governance index measures perceptions of organizational policies, guidance, and risk management related to AI use.

All indices were calculated as the mean of their respective items, allowing multiple dimensions of each construct to be aggregated into continuous variables suitable for regression analysis. Missing

values were handled using pairwise deletion, ensuring that index scores were calculated based on available responses.

Data processing and analysis were conducted using Python, utilizing libraries such as pandas for data manipulation, statsmodels for regression analysis, and pingouin for reliability testing. The relationships between variables were examined using descriptive statistics, correlation analysis, and ordinary least squares (OLS) regression models. Position level and tenure were included as control variables to account for structural differences within the organizational hierarchy.

In addition, moderation analysis was conducted to examine whether governance influences the strength of the relationship between AI adoption and decision-making outcomes. An interaction term between AI adoption and governance was constructed and included in the regression models.

Overall, the quantitative approach provides a systematic and transparent framework for identifying patterns and testing hypotheses regarding the relationship between AI adoption and decision-making dynamics within the organization.

#### 4.4 Qualitative Study

The qualitative component of the study is based on semi-structured interviews conducted with 10 key organizational actors within dentsu Ukraine. The sample includes representatives from marketing, legal, IT, and management functions, allowing coverage of both operational and decision-making perspectives. This cross-functional composition enables the analysis of AI usage and its implications across multiple organizational roles.

An overview of the interview participants is presented in Table 1.

Table 1 Profile of Interview Participants

Code	Role/Level	Decision Domain
Q1	Chair of the Board (holding)	Corporate strategy & oversight
Q2	Head of Legal & Compliance (holding)	Legal risk & compliance decisions
Q3	Chief Technical Officer & Head of In-House Engineering (holding)	Technology architecture & tools
Q4	Director / C-level (agency)	Business & strategic decisions
Q5	Chief of Transformation / C-level (agency)	Process change & client delivery
Q6	Head of Research / Product Development (agency)	Data-driven product decisions
Q7	Head of PPC / Paid Media (agency)	Media spend & optimization decisions
Q8	Head of production & product integration (agency)	Production workflows & integration
Q9	Senior specialist / R&D / digital analytics & AI integration (agency)	AI development & integration
Q10	Senior specialist / functional lead (agency)	Client-facing operational decisions

The use of participant codes (Q1–Q10) ensures anonymity while preserving the organizational context of each statement. The codes are used for interpretative contextualization rather than for comparative analysis across roles or hierarchical levels.

The interviews were conducted using a semi-structured format based on a predefined interview guide (see Appendix B) and were held either in person or remotely via Microsoft Teams. Digital recording tools were used to ensure accurate data capture, and all interviews were subsequently transcribed. Interview duration ranged from approximately 40 to 90 minutes, allowing for an in-depth exploration of organizational practices and decision-making dynamics related to AI use.

The qualitative data were analyzed using thematic analysis. The coding process followed an iterative approach combining both deductive and inductive techniques. Deductive coding was used to map responses onto the core theoretical constructs of the study, including operational autonomy, hierarchical authority, and governance. Inductive coding enabled the identification of emergent patterns not fully captured by the initial framework.

The final coding structure consisted of a set of themes and associated codes reflecting recurring patterns in the data (see Appendix C).

The qualitative component complements the quantitative analysis by providing a deeper understanding of organizational practices, behavioral patterns, and contextual factors shaping the use of AI in decision-making.

#### **4.5 Validity and Reliability**

To ensure the quality and academic rigor of the study, specific measures were taken to address the reliability and validity of both quantitative and qualitative components, as well as the overall research design.

##### **Quantitative Reliability and Validity**

The reliability of the constructed indices was assessed using Cronbach's alpha ( $\alpha$ ), which measures the internal consistency of multi-item scales. The results indicate a satisfactory to high level of reliability across the main constructs. The governance index demonstrates excellent internal consistency ( $\alpha = 0.87$ ), while the perceived influence index ( $\alpha = 0.84$ ) and the AI adoption index ( $\alpha = 0.78$ ) show good reliability. The decision-making autonomy index yields a lower value ( $\alpha = 0.60$ ), which remains acceptable given the exploratory nature of the study and the use of newly constructed measures.

Construct validity was supported through the operationalization of variables based on established theoretical concepts and their consistent measurement across multiple items. In addition, multicollinearity diagnostics were performed using the Variance Inflation Factor (VIF). All VIF values

remained well below the commonly accepted threshold of 5, indicating that the independent variables are not highly correlated and that the regression estimates are stable. The robustness of the results was further supported by the use of standardized coefficients and non-parametric correlation checks (Spearman), which yielded consistent patterns.

### **Qualitative Trustworthiness**

The validity of the qualitative findings, referred to as trustworthiness, was ensured through several complementary strategies. First, triangulation was applied by integrating qualitative insights with quantitative findings. Patterns identified in the statistical analysis were interpreted and supported through detailed interview evidence, allowing for cross-validation of results across methods.

Second, purposive sampling was used to include participants from diverse functional areas and hierarchical levels, ensuring a broad range of perspectives on AI adoption and decision-making processes. This approach enhances the credibility of the findings by capturing variation across organizational roles.

Third, rich qualitative data were obtained through in-depth interviews, with durations ranging from 40 to 90 minutes. This enabled the collection of detailed and contextually grounded insights into organizational practices, decision dynamics, and behavioral patterns associated with AI usage.

### **Methodological Consistency and Transparency**

The study follows an explanatory sequential mixed-methods design, where qualitative findings are used to interpret and contextualize quantitative results. This integration enhances internal validity by linking statistical relationships to underlying mechanisms.

The survey instrument was developed based on existing literature and pre-tested for clarity and consistency. Quantitative data processing and analysis were conducted using Python, ensuring transparency and reproducibility of the analytical procedures.

### **Generalizability and Research Scope**

Given the use of a single-case study design, the findings of this research are not intended to be statistically generalizable to a broader population. Instead, the study provides analytical generalization by offering theoretically informed insights into how AI adoption affects decision-making processes within knowledge-intensive organizations. The selected case represents an information-rich context characterized by intensive AI usage, allowing for the development of insights that may be transferable to similar organizational settings.

Overall, the combination of reliable quantitative measures, rigorous qualitative analysis, and a coherent mixed-methods design ensures a robust and internally consistent research framework.

#### **4.6 Ethical Considerations**

This study was conducted in accordance with general ethical principles for academic research, including voluntary participation, informed consent, confidentiality, and responsible data handling.

Participation in both the survey and interviews was entirely voluntary. Respondents were informed about the purpose of the study, the use of the data for academic research, and their right to withdraw at any stage without any consequences.

To ensure confidentiality, no personally identifiable information was collected or disclosed. Survey responses were anonymized, and interview participants were assigned codes (Q1–Q10) to prevent identification while preserving the organizational context of their statements.

All data were used exclusively for research purposes and reported in aggregated form. Interview recordings and transcripts were handled securely and were not shared beyond the scope of the research.

The researcher's prior professional affiliation with the organization was taken into account. To mitigate potential bias, the study relied on standardized data collection instruments and focused on objective analysis of anonymized data.

Overall, the research design ensured that participants were not exposed to harm, and that the study complied with ethical standards for confidentiality, transparency, and academic integrity.

## CHAPTER 5. EMPIRICAL FINDINGS

This chapter presents the empirical findings of the study, examining how AI adoption shapes decision-making autonomy, influence, and governance dynamics within dentsu Ukraine. The findings are structured around key themes emerging from the quantitative and qualitative analyses.

The chapter is organized around the key dimensions of decision-making affected by AI, focusing on changes in individual autonomy, perceived influence, and the practical role of governance. Section 5.1 establishes the baseline patterns of AI adoption and its distribution across marketing domains. Sections 5.2 and 5.3 examine the relationship between AI usage and decision-making autonomy and influence, respectively, combining statistical evidence with thematic insights to uncover the underlying mechanisms of these effects. Section 5.4 evaluates the role of governance as a contextual layer, highlighting the gap between formal policies and everyday operational practices. Section 5.5 explores the emergence of informal AI-driven influence within the organization.

Together, these findings provide a comprehensive, evidence-based account of how AI reconfigures decision-making processes while leaving formal authority structures largely unchanged.

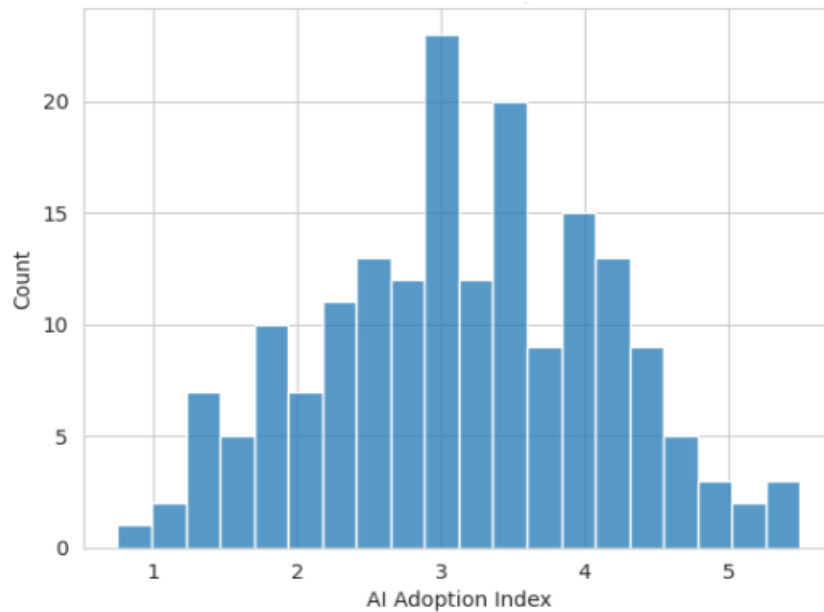
### 5.1 AI Adoption Patterns

This section provides an overview of AI adoption within the organization, focusing on its prevalence, distribution, and areas of application in decision-making processes.

The dataset consists of 182 observations. The mean value of the AI adoption index is 3.15 (SD = 1.04), indicating a moderate level of AI usage among employees. This suggests that AI tools are widely integrated into everyday work practices, although the intensity of use varies across individuals.

As shown in Figure 2, the distribution of AI adoption is relatively symmetric, with a clear concentration around moderate levels of usage, providing a solid basis for the subsequent regression analysis.

Descriptive statistics further show that employees report moderate levels of decision-making autonomy ( $M = 3.12$ ,  $SD = 1.12$ ), while perceived influence over final decisions is lower ( $M = 2.48$ ,  $SD = 1.26$ ). In contrast, the governance index demonstrates a relatively high mean ( $M = 5.11$ ,  $SD = 1.33$ ), indicating a strong perceived presence of formal structures regulating AI use.



**Figure 2 Distribution of AI Adoption Index (N = 182)**

*Source: Author's calculations based on survey data*

This distribution points to an initial pattern: AI is actively used in day-to-day work, while formal governance structures are perceived as more developed than employees' actual decision authority. This suggests a potential gap between formal organizational frameworks and the practical role of AI in decision-making processes.

Additional analysis of domain-specific responses indicates that AI is primarily embedded in analytical and operational activities. The most frequently reported areas of impact include reporting and analytics, internal process improvements, and the preparation of pitches and proposals. In contrast, high-stakes domains such as budget allocation, vendor selection, and media planning show significantly lower levels of AI-related influence.

This pattern suggests that AI is predominantly used in decision preparation rather than in final decision-making stages. Employees actively rely on AI to structure information, generate insights, and accelerate workflows, while responsibility for high-risk or strategic decisions remains more constrained.

Finally, analysis of decision-making roles indicates that AI-supported decisions are most frequently made at the level of individual contributors, followed by team leads and collective decision-making formats. Senior leadership appears less frequently as the primary decision-maker in these contexts. This reflects a partial decentralization of decision processes at the operational level, while not necessarily implying a shift in formal authority.

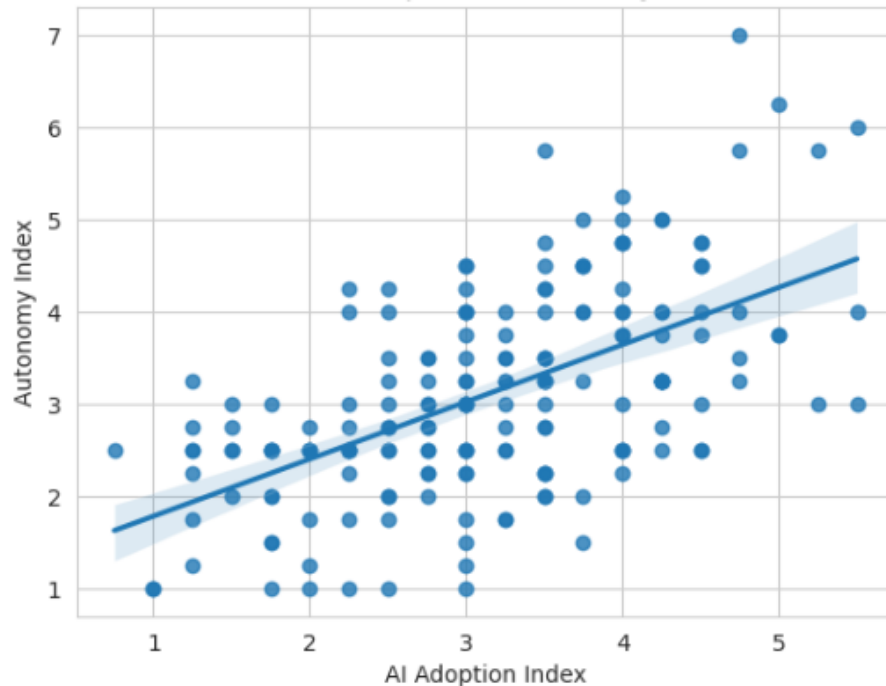
Overall, the findings indicate that AI adoption is widespread and embedded in routine work processes, particularly in analytical and preparatory tasks. Nevertheless, its impact remains concentrated

in domains characterized by lower risk and higher standardization, providing an important foundation for understanding its effects on autonomy, influence, and governance explored in the following sections.

## 5.2 Effects on Decision-Making Autonomy

This section examines the impact of AI adoption on decision-making autonomy, combining quantitative results with qualitative insights to provide a comprehensive understanding of the observed effects.

Regression analysis indicates a strong and statistically significant positive relationship between AI adoption and decision-making autonomy ( $\beta = 0.64$ ,  $p < 0.001$ ; see Table 2). The model explains a substantial share of the variance in autonomy ( $R^2 = 0.35$ ), supporting Hypothesis 1. The relationship remains robust when controlling for position and tenure, neither of which emerge as statistically significant predictors of autonomy. This suggests that the autonomy-enhancing effect of AI is not strongly dependent on an employee's formal role or experience. Higher levels of AI usage are associated with increased independence in the preparation and structuring of decisions, suggesting that employees who actively use AI tools are better able to perform analytical tasks, generate insights, and develop decision alternatives without extensive managerial involvement. The relationship between AI adoption and decision-making autonomy is illustrated in Figure 3.



**Figure 3 Relationship Between AI Adoption and Decision-Making Autonomy**

*Source: Author's calculations based on survey data*

Table 2 OLS Regression Results: AI Adoption and Decision-Making Autonomy

Variable	Coefficient ( $\beta$ )	Std. Error	p-value
AI Adoption Index	0.644	0.069	<0.001
Position (role)	0.028	0.056	0.616
Tenure	0.131	0.079	0.099
Constant	0.586	0.333	0.080

*Note.* Dependent variable: Decision-Making Autonomy. OLS regression including controls for position and tenure.  $R^2 = .353$ , Adjusted  $R^2 = .342$ ,  $N = 182$ .

Qualitative findings provide further insight into the mechanisms underlying this effect. Across interviews, respondents consistently described AI as a tool that reduces routine work, accelerates task execution, and enables more independent problem-solving. A key mechanism is the reduction of manual and repetitive tasks. As one participant noted, “instead of three days of manual categorization - 20–30 minutes.” (Q9) Similarly, another respondent explained that “previously, 90% of my time was spent making slides... now the amount of manual work is decreasing,” (Q8), while others highlighted that “boilerplate code and documentation - AI remove a lot of the boring work.” (Q3)

AI is also widely used to support standardized tasks, particularly in communication and analytical preparation. Respondents reported that “presentations, Excel, emails - all of this is now much faster,” (Q7), and that AI “helps with information gathering and standard analysis.” (Q1) In addition, AI enables more independent problem-solving by allowing employees to resolve minor uncertainties without external input. As one respondent described, “if you don’t know how to name a slide - you just ask Claude.” (Q4)

These changes are closely linked to the overall acceleration of work processes. While the nature of work remains largely unchanged, its execution becomes significantly faster. As one participant summarized, “the work itself hasn’t changed, only the speed of execution has increased,” (Q7), with another adding that “the main task is saving human time through the machine.” (Q3)

In parallel, the increase in autonomy appears to be bounded and does not extend to shifts in formal decision authority. AI supports better argumentation and idea development, with respondents describing it as “an intelligence amplifier” (Q3) and “a fast way to test hypotheses” (Q1). It also reduces the need for escalation in routine situations, as “you can get an answer instantly instead of waiting for someone to reply to an email” (Q10). However, these effects remain within the scope of task execution and preparation rather than affecting final decision authority.

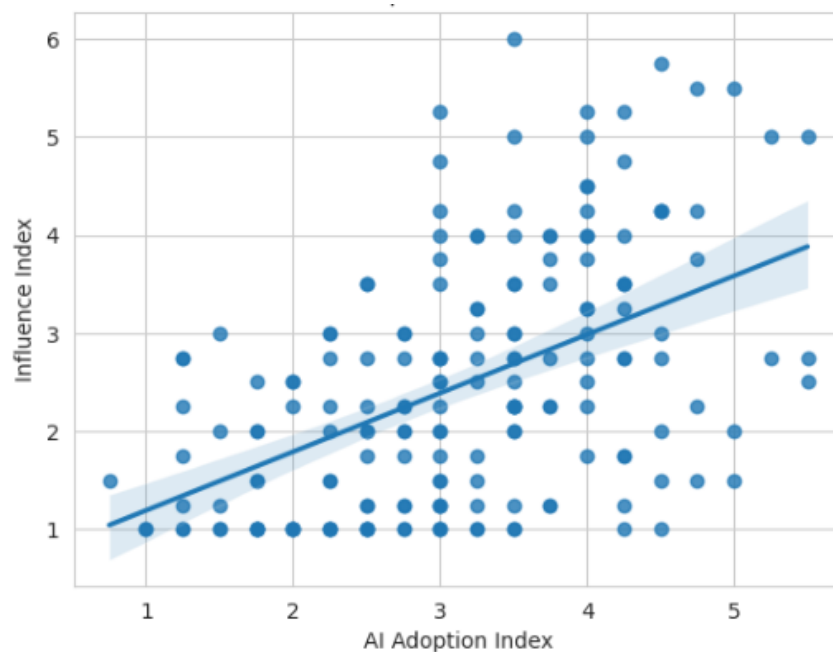
Overall, the findings demonstrate that AI adoption leads to a substantial increase in decision-making autonomy by enabling faster execution, reducing reliance on others for routine inputs, and supporting more self-sufficient task performance. This effect represents a key mechanism through which

AI reshapes organizational decision-making processes and provides the foundation for its influence on perceived decision impact, examined in the following section.

### 5.3 Effects on Decision-Making Influence

This section examines the impact of AI adoption on employees' perceived influence over decision-making, combining quantitative results with qualitative insights to capture both the magnitude and the mechanisms of this effect.

Regression analysis indicates a positive and statistically significant relationship between AI adoption and perceived decision-making influence ( $\beta = 0.58$ ,  $p < 0.001$ ). The model explains a meaningful share of the variance in influence ( $R^2 = 0.30$ ), providing support for Hypothesis 2. Compared to autonomy, however, the strength of this relationship is more moderate, suggesting that while AI enhances employees' capacity to contribute to decisions, its effect on actual influence is more constrained (Figure 4).



**Figure 4 Relationship Between AI Adoption and Decision-Making Influence**

*Source: Author's calculations based on survey data.*

Importantly, unlike the autonomy model, position emerges as a statistically significant predictor of influence ( $\beta = 0.18$ ,  $p = 0.007$ ; see Table 3), indicating that formal hierarchy continues to play a role in shaping whose input affects final decisions. In contrast, tenure does not appear to significantly influence perceived decision impact. These findings suggest that, while AI expands access to analytical capabilities, their impact on influence remains partially dependent on formal organizational structures.

Table 3 OLS Regression Results: AI Adoption and Decision-Making Influence

Variable	Coefficient ( $\beta$ )	Std. Error	p-value
AI Adoption Index	0.582	0.081	< .001
Position (role)	0.179	0.065	.007
Tenure	0.074	0.092	.425
Constant	-0.178	0.390	.649

*Note.* Dependent variable: Decision-Making Influence. OLS regression including controls for position and tenure.  $R^2 = .301$ , Adjusted  $R^2 = .290$ ,  $N = 182$ .

Qualitative evidence provides further insight into this dynamic. While AI enhances employees' ability to contribute to decision-making processes, respondents consistently emphasized that formal authority structures remain unchanged. As one participant noted, "the approval hierarchy remains exactly the same," (Q6), while another stated, "I don't see AI giving anyone more authority or taking it away." (Q2).

This limitation is further reflected in how AI is perceived within the organization. Rather than acting as a decision-maker, AI is described as a supporting instrument - "a doorbell, not a manager" (Q5) and "a calculator for knowledge" (Q3). These metaphors highlight that AI contributes to decision preparation without displacing human judgment or authority.

Respondents also emphasized the continued primacy of human evaluation in decision-making processes. As one participant noted, "AI knows more than me, but I am smarter than AI" (Q2), underscoring the perception that, despite its analytical capabilities, AI does not replace human judgment. As a result, final decisions continue to be made by those who hold formal authority, as "decisions are made by those who are authorized to make them... and who bear responsibility" (Q9).

These findings indicate that although AI enhances employees' analytical and argumentative capacity and broadens their participation in decision-making processes, its effect on actual decision influence remains limited, as it continues to be shaped by hierarchical structures and behavioral dynamics such as trust and interpretation (Logg et al., 2019; Glikson & Woolley, 2020).

#### 5.4 Governance: Limited Practical Role

This section examines the role of organizational governance in shaping the relationship between AI adoption and decision-making outcomes. Contrary to expectations, the results do not support Hypothesis 3, which proposed that governance mechanisms moderate the relationship between AI use and decision-making autonomy and influence.

Moderation analysis indicates that governance does not have a statistically significant moderating effect on this relationship ( $p = .671$  for autonomy and  $p = .679$  for influence; see Table 4). This suggests that, despite the presence of formal governance structures, they do not substantially alter how AI adoption

influences decision-making processes in practice. The result remains consistent when using centered variables, confirming the absence of a moderating effect.

Table 4 Moderation Analysis: Governance as a Moderator of AI Adoption Effects

<b>Outcome Variable</b>	<b>Interaction Term (AI × Governance)</b>	<b>p-value</b>
Decision-Making Autonomy	-0.020	.671
Decision-Making Influence	-0.023	.679

*Note.* No statistically significant moderating effect of governance on the relationship between AI adoption and decision-making outcomes is observed. N = 181.

Qualitative findings provide important insights into this result. A key pattern emerging from the interviews is a misalignment between formal governance frameworks and everyday organizational practices. Respondents consistently emphasized that governance mechanisms lag behind the rapid pace of AI adoption. As one participant noted, “governance definitely does not keep up with the speed of AI adoption,” (Q8), while another observed that “regulation is lagging behind - and that is normal.” (Q1)

This lag is further reinforced by the limited operationalization of existing policies. Even where formal rules are in place, they are often not actively enforced or embedded in daily workflows. As one respondent explained, “formally, policies exist, but no one controls self-usage,” (Q3), while another added, “policies exist, but in reality you know how it actually works.” (Q9)

In addition, governance is not consistently accessible or clearly communicated to employees. Several respondents reported uncertainty regarding the existence or location of relevant policies, indicating that governance frameworks are not fully integrated into routine work practices. For example, “there are no policies... I don’t know where to find such a document,” (Q10), and “to say that we have a clear instruction - I do not have that.” (Q6)

As a result, employees rely more on informal learning and experimentation than on structured governance mechanisms. AI usage is often developed through “learning by doing,” rather than guided by formal training or standardized procedures. This dynamic reflects a broader shift in which governance functions less as an active moderator of behavior and more as a background constraint.

In addition, the findings indicate that governance does play a role in defining boundaries of acceptable AI use, particularly in relation to risk and accountability. Respondents highlighted clear limitations regarding the use of sensitive data and emphasized the need for human responsibility. As one participant stated, “you cannot include sensitive information, commissions, or client names,” (Q10), while another noted that “AI does not take responsibility.” (Q2)

Trust in AI is therefore conditional and mediated by human oversight. Respondents consistently described the need to verify AI-generated outputs, particularly in high-risk contexts. For example, “AI needs to be double-checked, especially budgets,” (Q4), and “verification is our superpower.” (Q6)

Taken together, these findings suggest that governance operates primarily as a contextual boundary rather than an active driver of decision-making dynamics. While formal structures define what is permissible, they do not significantly shape how AI is used in practice or how it influences autonomy and perceived influence.

Overall, the results indicate that governance mechanisms currently play a limited and indirect role in moderating the effects of AI adoption. Instead of actively structuring behavior, governance provides a safety perimeter within which employees experiment, learn, and integrate AI into their workflows.

### **5.5 Emergence of Informal AI-Driven Influence**

This section explores an emergent pattern that complements the quantitative findings by explaining how influence evolves in the absence of formal structural change. While governance mechanisms do not significantly moderate the effects of AI adoption, and formal decision rights remain stable, the qualitative analysis reveals the development of informal influence structures associated with AI usage.

A key pattern is the emergence of informal “AI champions” - individuals perceived as more advanced or knowledgeable in using AI tools. These actors gain visibility within the organization and are increasingly approached for advice by both peers and managers. As one participant noted, “there are informal AI experts... whom management turns to for advice,” (Q10), while another added, “there are people who simply understand it better.” (Q6).

This dynamic is reinforced through informal consultation practices. Employees reported relying on colleagues with stronger AI skills when facing unfamiliar tasks or tools. For example, “I go to this designer and consult with him... he understands it better than I do,” (Q6), and “people turn to such individuals more often for advice.” (Q4). These interactions indicate that AI-related expertise becomes a resource that shapes internal collaboration patterns.

As a result, AI proficiency contributes to increased individual credibility and recognition within teams. Respondents associated strong AI skills with professionalism and progressiveness. As one participant noted, “they are respected more... it is a sign that a person is progressive,” (Q7), while another emphasized that “champions are people others rely on.” (Q9). This suggests that AI capability functions as a source of reputational advantage within the organization.

Notably, these shifts in influence do not correspond to changes in formal authority. Respondents consistently emphasized that decision-making remains anchored in existing hierarchical structures. As one participant stated, “decisions still follow the formal hierarchy,” (Q6), while another noted that “ideas

may come from these people, but decisions do not.” (Q9). This finding provides a qualitative explanation for the moderate correlation observed in the quantitative analysis of influence in Section 5.3.

Overall, the findings indicate that AI adoption contributes to the emergence of informal influence structures based on expertise and usage capability. While these actors gain visibility and advisory influence, their impact remains bounded within existing organizational hierarchies. This suggests that AI reshapes influence not by redistributing formal authority, but by enabling new forms of expertise-based recognition and participation in decision-making processes.

## **5.6 Thematic Synthesis: Mechanisms and Boundary Conditions**

### **5.6.1 Purpose and Analytical Approach**

This subsection provides a thematic synthesis of the qualitative findings presented in Sections 5.2–5.5. Rather than introducing new empirical results, it integrates the interview evidence to clarify how AI adoption shapes decision-making dynamics and to explain the observed patterns of autonomy, influence, and governance.

The analysis is based on thematic coding (see Appendix C) and focuses on recurring patterns across roles, as well as contextual factors that shape how AI is used in practice. The aim is to consolidate the qualitative insights into a coherent explanation of the mechanisms underlying the quantitative relationships identified earlier in this chapter.

### **5.6.2 Time Compression and the Expansion of Autonomy**

Across interviews, AI is consistently described as a tool that accelerates routine cognitive work. Respondents note that it reduces the time required for tasks such as drafting, summarizing, structuring information, and performing standard analytical activities. As participants observed, “work that used to take hours is now done much faster” (Q4), and “AI reduces minutes and hours for specific tasks” (Q7).

This observation is consistent with the strong positive relationship between AI adoption and autonomy identified in Section 5.2. By reducing time spent on routine tasks, AI allows employees to prepare decisions more independently and with less reliance on others. The effect is concentrated at the level of decision preparation rather than formal decision rights.

### **5.6.3 AI-Related Expertise and Informal Influence**

The qualitative evidence also highlights the growing importance of AI-related expertise as a source of informal influence. As discussed in Section 5.5, individuals with stronger AI capabilities increasingly become reference points within teams and are more frequently approached for advice on tools, workflows, and interpretation of outputs.

Respondents noted that “if you know how to build agents, you gain more influence” (Q8) and that such individuals “have a greater influence on decision-making.” (Q7) This reflects a broader shift in

how credibility is established: employees who are able to effectively use AI and translate outputs into structured insights are more likely to shape discussions and contribute to how decisions are framed.

At the same time, this influence remains advisory. Formal decisions continue to be made by those who hold accountability and responsibility, indicating that increased participation in decision-making does not translate into changes in formal authority structures.

#### **5.6.4 Verification Practices and the Stability of Authority**

A third recurring pattern concerns the role of verification and accountability in maintaining existing authority structures. Despite increased reliance on AI-generated outputs, respondents consistently emphasized the need for human validation, particularly in high-risk or client-facing contexts.

In practice, this includes selective verification, human-in-the-loop control, and clear assignment of responsibility for final outputs. As one participant noted, “where money is involved, everything must be clearly defined in terms of responsibility,” (Q9) while another emphasized that “AI is a supporting tool, not a tool for making decisions.” (Q6) More broadly, responsibility is understood as inherently human, as “a person remains the one who takes ultimate responsibility.”

These practices help explain why formal authority remains stable. While AI expands capabilities in decision preparation, decision rights continue to be anchored in accountability and risk-bearing roles.

#### **5.6.5 Governance and Contextual Constraints**

The qualitative findings also provide a more nuanced understanding of governance. As shown in Section 5.4, formal governance structures exist, but their visibility and integration into daily workflows vary across teams.

A key pattern is the gap between formal policies and their practical application. Some respondents described governance as clearly defined, while others emphasized reactive dynamics, where rules become salient only after specific incidents. As one participant noted, “if we only scare people with policies, we will not survive,” (Q1) highlighting the limited role of formal regulation in everyday practice.

In addition, governance constraints are often shaped by external factors, particularly client requirements. In some cases, clients restrict the use of AI in final deliverables, effectively turning governance into a boundary that limits application rather than actively guiding behavior.

Overall, governance operates less as a direct driver of decision-making and more as a contextual constraint, shaping the boundaries within which AI is used.

#### **5.6.6 Implications for the Core Argument**

Taken together, these qualitative findings help explain the patterns identified in the quantitative analysis. AI adoption increases autonomy by accelerating routine work and expanding individual

capabilities in decision preparation. It also enhances perceived influence by strengthening expertise-based credibility and participation in discussions. At the same time, formal authority remains stable, as decision rights continue to be anchored in accountability and responsibility.

Governance, in turn, functions primarily as a contextual constraint, shaping the boundaries of acceptable AI use without consistently influencing day-to-day decision-making dynamics. This helps explain the absence of a significant moderating effect in the quantitative analysis.

Overall, the findings support the interpretation that AI adoption leads to an asymmetric transformation of decision-making: preparatory processes become more distributed and AI-enabled, while formal authority structures remain largely unchanged.

The key mechanisms and contextual constraints identified in the qualitative analysis are summarized in Table 5.

Table 5 Mechanisms and Boundary Conditions in AI-Enabled Decision-Making

<b>Mechanism</b>	<b>Description</b>	<b>Implications for Decision-Making</b>
Time compression	AI reduces time required for routine cognitive and analytical tasks	Increased autonomy in decision preparation
AI-related expertise	Advanced AI use enhances credibility and problem-solving capacity	Increased informal influence in decision processes
Verification and accountability practices	Human validation, cross-checking, and responsibility for outcomes	Stability of formal decision authority
Governance and contextual constraints	Organizational policies and client-imposed limitations on AI use	Context-dependent boundaries of AI application

## CHAPTER 6. DISCUSSION

This chapter interprets the empirical findings in relation to the conceptual model, hypotheses, and prior literature. The results point to a consistent pattern: AI adoption significantly changes how decisions are prepared but does not fundamentally alter how decision rights are structured within the organization. It creates a persistent gap between operational capabilities and formal authority, referred to in this study as the Adoption-Authority Gap.

The findings show that AI expands employees' ability to independently generate analyses, structure problems, and develop decision alternatives. In this sense, individuals gain greater real authority, as they increasingly control the informational inputs that shape decisions. On the other hand, formal authority remains anchored in accountability, risk, and responsibility, which continue to be concentrated at higher levels of the hierarchy. As a result, decision-making becomes more decentralized in practice, while authority remains centralized.

This pattern is consistent with existing organizational theory. The distinction between formal and real authority (Aghion & Tirole, 1997) helps explain why increased informational capacity does not lead to a redistribution of decision rights. Similarly, the information-processing perspective (Tushman & Nadler, 1978) suggests that organizations adapt to increased complexity by expanding their capacity to process information, without necessarily changing their structural foundations.

The results also highlight the limited role of governance in shaping day-to-day decision-making. Governance mechanisms define the boundaries of acceptable AI use, particularly in relation to risk and accountability, but do not directly determine how AI is applied in practice. In several cases, governance appears deliberately underdeveloped, allowing organizations to experiment and learn before formalizing rules and structures.

Additionally, the current configuration reflects an early stage of AI adoption. Initial signs of structural adaptation are already visible, including the emergence of AI-related roles and changes in how expertise is recognized within organizations. This suggests that while authority structures remain stable in the short term, they may gradually evolve as AI becomes more deeply embedded in organizational processes.

The chapter also considers the broader regulatory context, particularly the implications of the EU AI Act. As formal requirements around risk classification and accountability become more defined, the current balance between autonomy and control may shift, raising questions about how organizations will maintain flexibility while complying with stricter governance frameworks.

The remainder of the chapter elaborates on these themes. Section 6.1 introduces the Adoption-Authority Gap and explains the underlying mechanism linking real authority and accountability. Section 6.2 discusses the theoretical implications of the findings. Section 6.3 examines governance as a boundary condition. Section 6.4 situates the results within the evolving regulatory landscape.

### **6.1 AI Reconfigures Decision Rights Without Transforming Hierarchy**

The empirical results show a clear asymmetry in how AI adoption affects decision-making. The strongest effect is observed at the level of decision preparation, where employees gain greater independence in generating analysis, structuring problems, and developing alternatives. This confirms that AI reduces reliance on hierarchical input in day-to-day work and increases autonomy in operational tasks.

Such pattern is consistent with recent evidence showing that AI systems significantly enhance productivity in knowledge-intensive work, particularly in tasks involving information synthesis and communication (Brynjolfsson et al., 2023). By lowering the cost of accessing and processing information, AI enables individuals to perform activities that previously required coordination across hierarchical levels.

At the same time, the effect on influence is more limited. While employees who actively use AI contribute more to discussions and are more frequently consulted, this influence remains bounded by existing decision structures. The results suggest that AI enhances participation in decision processes, but does not redefine who makes final decisions.

This asymmetry can be explained through the distinction between informational capacity and decision rights. AI expands access to analytical capabilities and allows individuals to exercise greater control over the inputs that shape decisions. However, this shift does not extend to the formal allocation of authority. Decision rights remain anchored in accountability, particularly in contexts involving financial, legal, or reputational risks.

The persistence of this structure reflects the fundamental role of accountability as a coordinating mechanism. Even when analytical work is effectively performed at lower levels of the organization, final approval remains concentrated at higher levels. In this sense, authority is determined not by who produces the analysis, but by who bears responsibility for the outcome.

These findings are consistent with research on human–AI collaboration, which emphasizes that AI primarily augments rather than replaces human decision-making, leaving final judgment with accountable actors (Jarrahi, 2018; Raisch & Krakowski, 2021). As a result, organizations broaden participation in decision preparation without transferring formal decision rights.

The qualitative evidence reinforces this interpretation. AI is consistently used as a tool for generating and structuring inputs, while final judgments remain subject to human validation. Employees can act more independently, but their outputs must still be justified and approved within existing structures.

Overall, AI reconfigures how decisions are produced without transforming how authority is structured. It enables more decentralized preparation and broader participation, while hierarchical control over final decisions remains largely intact. This explains why organizations experience significant operational change without corresponding structural transformation.

## **6.2 Theoretical Implications in Management Studies**

The findings of this study contribute to several strands of organizational theory by clarifying how AI adoption affects the relationship between information, authority, and decision-making. These insights also have direct implications for management studies, particularly in understanding how organizations adapt decision-making structures and managerial roles in response to emerging technologies.

The results are consistent with the distinction between formal and real authority (Aghion & Tirole, 1997). Employees who actively use AI gain greater control over information and analytical inputs, which increases their ability to shape decisions in practice. Formal decision rights, however, remain unchanged, as they continue to be tied to accountability and risk. This supports the view that expanded access to information strengthens real authority without necessarily altering formal control. From a management perspective, this highlights the continued centrality of accountability as a coordinating mechanism in organizational decision-making.

The evidence also refines the information-processing perspective on organizations (Tushman & Nadler, 1978). AI increases the capacity to process information by accelerating analysis and reducing cognitive effort. This expanded capacity is absorbed within existing organizational structures rather than leading to immediate structural change. Decision-making structures therefore appear to be shaped not only by information-processing needs, but also by accountability requirements and the need to maintain legitimacy. For managers, this suggests that improvements in information access do not eliminate the need for hierarchical coordination but rather coexist with it.

The findings align with the augmentation perspective in human–AI collaboration (Raisch & Krakowski, 2021; Dellermann et al., 2019). AI is primarily used to support decision preparation, enabling individuals to work more independently and contribute more effectively. Final decisions remain with human actors, indicating that AI complements rather than replaces managerial judgment. This reinforces the role of managers as final integrators of information, responsible for validating and legitimizing decisions.

In contrast to more transformative expectations in the literature, the results suggest a more constrained impact of AI on organizational control. While prior research highlights the potential for algorithmic systems to reshape authority structures (Kellogg et al., 2020; Shrestha et al., 2019), the evidence here indicates that their effect is more limited. AI primarily changes how decisions are prepared and who contributes to them, while hierarchical authority remains largely intact. Structural change appears gradual and context-dependent, as the impact of AI depends on how technological capabilities are integrated into existing organizational structures and practices (Bankins et al., 2024). Rather than driving abrupt redesign, AI becomes embedded in organizational routines and is shaped by established coordination and accountability mechanisms.

The persistence of formal authority structures can be further explained through an institutional lens. Organizations tend to preserve existing arrangements due to pressures for legitimacy and consistency (DiMaggio & Powell, 1983). As a result, new technologies are integrated into established governance systems rather than used to redesign them. Managers therefore operate within existing institutional constraints, balancing innovation with the need for stability and legitimacy.

Overall, these insights reinforce the central contribution of the study. The findings demonstrate that AI adoption creates an Adoption-Authority Gap, where decision-making becomes more decentralized in preparation but remains centralized in approval. This gap reflects a structural separation between informational capacity and formal authority, confirming that increased access to information enhances autonomy and influence without redistributing decision rights. For management research, this highlights a key tension between technological capability and organizational control that is likely to shape future organizational design.

### **6.3 Governance as a Boundary Condition**

The empirical results indicate that governance plays a more limited and indirect role in shaping AI-driven decision-making than often assumed. While formal policies, guidelines, and risk controls are present to varying degrees, they do not appear to significantly influence how AI is used in everyday work processes. Instead, governance defines the outer limits of acceptable use rather than actively directing behavior.

This pattern is reflected in the absence of a significant moderating effect of governance in the quantitative analysis. The relationship between AI adoption and decision-making outcomes remains stable across different levels of perceived governance. In practice, employees rely more on their own judgment, team norms, and task requirements than on formal rules when deciding how to apply AI tools.

Qualitative evidence provides further insight into this dynamic. In many cases, governance mechanisms are either loosely defined or intentionally underdeveloped. Rather than introducing strict

controls at early stages of adoption, organizations allow employees to experiment with AI tools and learn through practice. This pattern can be described as a form of strategic lag, where governance deliberately evolves more slowly than technological adoption in order to preserve flexibility and support learning.

In this context, governance operates as a safety perimeter. It sets implicit boundaries around risk, data sensitivity, and accountability, but does not prescribe detailed rules for day-to-day usage. Employees remain aware of what is acceptable and where caution is required, even in the absence of formalized procedures. This creates a form of distributed responsibility, where individuals are expected to balance initiative with risk awareness.

Simultaneously, this configuration is not static. Early signs of formalization are already visible, including the introduction of AI-related roles, the gradual development of internal guidelines, and increased attention to data protection and compliance. These developments suggest that governance is likely to become more structured as AI adoption matures.

This evolution highlights a key tension. Informal experimentation supports rapid learning and capability development, but it also creates uncertainty and potential exposure to risk. As governance mechanisms become more formalized, they may reduce this uncertainty but also constrain the autonomy that currently enables flexible and efficient use of AI.

These findings suggest that governance should be understood as a boundary condition rather than a direct lever of control. It shapes the conditions under which AI can be used, but does not determine how it is used in practice. This perspective aligns with recent research on responsible AI governance, which emphasizes the role of high-level principles and risk frameworks rather than detailed operational rules (Papagiannidis et al., 2025).

#### **6.4 Regulatory Context and the EU AI Act in a Global Management Perspective**

The findings of this study reflect an early stage of AI adoption, where organizational practices evolve faster than formal governance structures. This creates conditions for experimentation, flexible use of AI tools, and the emergence of informal influence. However, this balance is unlikely to remain stable as regulatory requirements become more clearly defined. From a global management perspective, such transitions are particularly significant, as regulatory developments increasingly shape organizational practices across national boundaries.

The relevance of these regulatory developments is particularly pronounced in the Ukrainian context. As Ukraine advances along its EU integration path, national legislation and organizational practices are increasingly aligned with European regulatory frameworks, often ahead of formal accession. This process of legal harmonization extends to digital regulation and data governance, including emerging requirements related to artificial intelligence.

As a result, the implications of the EU AI Act are not limited to future compliance but already shape expectations, risk perceptions, and governance practices within Ukrainian organizations. Firms operating in international environments or serving EU-based clients are likely to anticipate and gradually adopt elements of these standards, even in the absence of full regulatory enforcement. This highlights how global regulatory frameworks influence organizational behavior beyond their formal jurisdiction.

The EU AI Act introduces a structured approach to AI governance based on risk classification, documentation requirements, and accountability obligations (European Union, 2024). These provisions are expected to increase the level of formalization in how AI is deployed within organizations, particularly in areas involving sensitive data, automated decision support, and client-facing applications.

Under these conditions, the current pattern of relatively flexible and loosely structured governance is likely to shift toward more formalized control. Organizations that currently rely on internal judgment and evolving practices will need to introduce clearer procedures, validation steps, and accountability frameworks.

This transition may directly affect the dynamics identified in this study. Increased requirements for validation, documentation, and risk management are likely to constrain the level of autonomy currently observed in decision preparation. Tasks that are now performed independently with AI support may require additional checks, approvals, or compliance procedures, potentially reducing speed and flexibility.

At the same time, regulatory frameworks may reinforce the role of formal authority. By explicitly linking responsibility for AI-related outcomes to designated roles, regulation strengthens the accountability-based allocation of decision rights identified in this study. This may further stabilize hierarchical structures, even as AI capabilities continue to expand.

These developments point to a growing tension between autonomy and compliance. While AI enables more decentralized and efficient decision preparation, regulatory requirements may reintroduce elements of centralization through oversight and control mechanisms. The challenge for organizations will be to preserve the benefits of AI-enabled flexibility while ensuring compliance with evolving legal standards.

In this sense, the findings of this study provide a baseline for understanding how AI affects decision-making in a relatively unconstrained environment. As regulatory frameworks become more embedded, future research may examine whether the Adoption-Authority Gap narrows, persists, or becomes more pronounced under conditions of increased formalization.

## CHAPTER 7. PRACTICAL IMPLICATIONS

This chapter operationalizes the empirical findings into a practical AI governance strategy tailored to knowledge-intensive, project-based organizations. The results of the study indicate a clear pattern: while AI tools are widely used across the organization, the depth of adoption remains limited, with most employees applying AI only to a small share of their daily tasks. This creates a gap between nominal adoption and actual productivity gains, highlighting the need for more structured and systematic implementation, effectively moving from experimentation toward the industrialization of AI.

Furthermore, the findings confirm that AI increases autonomy and individual contribution to decision-making, while formal authority remains anchored in accountability and risk. Governance, in this context, operates primarily as a boundary rather than a direct driver of behavior, and its relatively limited formalization reflects a deliberate choice to prioritize experimentation and learning.

Building on these insights, the chapter develops an integrated AI governance strategy that shifts the focus from isolated experimentation to scalable adoption. The proposed approach balances two competing priorities. On the one hand, organizations need to preserve flexibility, bottom-up innovation, and rapid learning. On the other hand, they must gradually introduce structure, clear boundaries, and accountability mechanisms to ensure consistent and safe use of AI across all roles and functions.

The strategy reflects the operating realities of organizations such as dentsu Ukraine, where innovation is driven by decentralized initiative, internal competition, and a strong learning culture, while key functions such as legal and finance remain centralized to ensure stability and risk control.

The chapter is structured across three interconnected levels: strategic orientation, organizational structure, and operational implementation.

### **7.1 AI Governance Strategy: Balancing Learning and Control**

AI governance at early stages of adoption should not be designed as a system of control, but as a framework for managing uncertainty. Rather than focusing on restricting the use of AI tools, organizations need to define how experimentation, learning, and responsibility are balanced in everyday work.

In this context, governance becomes a mechanism for guiding behavior without limiting initiative. The challenge is to create conditions that allow AI capabilities to scale across the organization, while maintaining clarity around accountability and risk.

The proposed governance strategy is therefore based on balancing two objectives. It preserves the conditions that enable rapid experimentation and bottom-up innovation, while gradually introducing

structure, clarity, and accountability. This balance reflects the broader transition from exploratory use of AI toward more consistent and organization-wide deployment.

### **7.1.1 Sandbox Logic and Intentional Governance Lag**

The empirical findings suggest that the current stage of AI adoption is characterized by uneven and relatively shallow integration into daily work processes. While AI tools are widely accessible, their application remains concentrated in specific tasks and driven by individual initiative. Under such conditions, strict governance frameworks are unlikely to be effective and may even constrain learning.

A learning-by-doing approach is therefore both practical and necessary. AI tools evolve rapidly, use cases are highly context-dependent, and widely accepted best practices are still emerging. Early formalization carries the risk of locking organizations into suboptimal processes or discouraging experimentation before sufficient experience has been accumulated.

In this context, delayed formalization should not be interpreted as a weakness. It can be understood as a deliberate governance choice aimed at preserving flexibility. Organizations such as dentsu Ukraine already demonstrate this logic in practice through internal experimentation, idea-driven initiatives, and strong support for bottom-up innovation, including internal AI idea contests and continuous knowledge sharing.

This approach allows employees to explore the capabilities of AI tools, identify relevant use cases, and build practical expertise before formal rules are introduced. It also aligns with the organizational need for adaptability in uncertain environments, where rigid structures may be less effective than iterative learning.

Concurrently, this phase is inherently transitional. As AI use becomes more embedded in core processes, the need for coordination, consistency, and risk management increases. The challenge is therefore not to eliminate experimentation, but to gradually complement it with more structured governance mechanisms.

### **7.1.2 Decision Boundaries as a Governance Mechanism**

The findings of Chapter 6 indicate that authority in AI-supported environments remains tied to accountability rather than access to information. This has direct implications for governance design. Instead of defining rigid rules around whether AI can or cannot be used, governance should focus on clarifying where AI can inform decisions and where human judgment remains decisive.

Decision boundaries provide a practical way to operationalize this principle. They distinguish between stages of the decision-making process rather than attempting to regulate tools themselves. Tasks related to information gathering, analysis, and preparation can be widely decentralized and supported by

AI. In contrast, decisions that involve client impact, financial commitments, legal implications, or reputational risk require escalation and human validation.

This approach allows organizations to maintain high levels of autonomy in routine and preparatory work while preserving control over high-stakes outcomes. It also reduces ambiguity for employees, who are often less concerned with abstract policies than with understanding where responsibility begins and ends.

Importantly, decision boundaries are compatible with evolving regulatory requirements. As discussed in Chapter 6, emerging frameworks such as the EU AI Act emphasize accountability, risk classification, and human oversight. By structuring governance around decision points rather than tool restrictions, organizations can align internal practices with external requirements without disrupting established workflows.

Taken together, the sandbox logic and the use of decision boundaries form the foundation of a governance strategy that supports both learning and control. Rather than limiting AI adoption, this approach enables its gradual scaling while maintaining clarity around responsibility and risk.

## **7.2 Structural Adaptation: Oversight and Expertise**

As AI adoption scales, organizations require a governance architecture that can support growing complexity without disrupting existing operations. Rather than redesigning formal structures, effective adaptation emerges through the integration of new coordination mechanisms, distributed expertise, and selective role formalization. This approach can be described as an adaptive governance architecture, where structure evolves incrementally to support AI-enabled work.

This architecture develops along two interconnected dimensions. The first is the establishment of oversight mechanisms that provide coordination and risk visibility. The second is the recognition and organization of AI-related expertise, both formal and informal. Together, these elements enable organizations to scale AI adoption while maintaining coherence across functions and teams.

### **7.2.1 AI Oversight Architecture**

As AI becomes more embedded in organizational processes, the need for coordination and risk visibility increases. However, this does not require the creation of new centralized decision-making structures. Instead, organizations can build on existing functions to provide oversight without disrupting established authority.

In the case of dentsu Ukraine, key support functions such as legal, finance, IT, and HR are already centralized and operate across multiple agencies, providing coordination and control over critical aspects of business activity. These units are well positioned to extend their role to AI-related risks, including data

protection, contractual obligations, and financial exposure. Their function is not to replace decision-makers, but to ensure that decisions are taken within acceptable risk boundaries.

Oversight in this model serves several purposes. It provides visibility into how AI is used across the organization, supports risk identification and mitigation, and creates legitimacy for external stakeholders such as clients and regulators. At the same time, it avoids excessive centralization by leaving operational decision-making within teams.

This approach allows organizations to strengthen governance without undermining autonomy. It also ensures that AI-related risks are addressed systematically while preserving the flexibility required for experimentation and innovation.

### **7.2.2 Role of AI Director and Specialized AI Leads**

The emergence of AI-related roles represents an important step in structuring AI adoption. However, these roles should be designed as integrative rather than directive.

In the case of dentsu Ukraine, formalization remains uneven. A dedicated AI & Digital Analytics Director role has been introduced at the agency level (Carat), while in most other units AI-related responsibilities are embedded within existing roles or added as extensions to functional responsibilities. This reflects an early stage of structural development, where coordination is still distributed rather than centralized.

Within this context, the role of AI leadership is to connect, bridge, and scale. AI Directors and specialized leads act as integrative nodes within the organization. They consolidate knowledge from different teams, identify transferable practices, support tool selection, and help convert technical capabilities into business applications.

Their effectiveness depends on their ability to operate across boundaries rather than control them. They connect functions horizontally and link management with operational teams, ensuring that local experimentation feeds into broader organizational learning.

Over time, as AI adoption deepens, a more structured approach to role definition may become necessary. Selective formalization of such roles can support coordination, capability development, and cross-unit integration without introducing unnecessary rigidity.

### **7.2.3 Recognition of Informal AI Expertise**

Alongside formal roles, AI adoption is driven by the emergence of informal expertise within teams. Individuals who actively experiment with AI tools and demonstrate practical results become internal reference points and play a key role in diffusing knowledge.

Rather than leaving this process entirely informal, organizations can strengthen it through the development of an AI Champions Network. This network connects individuals across teams who are

actively engaged in AI use, creating a distributed layer of expertise that supports learning and adoption at scale.

In practice, such a network operates through existing communication channels, including internal discussions, collaborative platforms, and knowledge-sharing initiatives. It enables rapid exchange of experience, dissemination of successful use cases, and peer-to-peer support without requiring formal hierarchical structures.

The interaction between integrative leadership and the champions network is particularly important. While AI Directors and leads provide coordination and strategic direction, champions drive experimentation and implementation at the operational level. Together, they form a complementary system that connects top-down alignment with bottom-up innovation.

As AI becomes more embedded in organizational processes, supporting this network in a more systematic way may become necessary. This can include recognizing contributions, providing development opportunities, and defining clearer responsibilities, while preserving the flexibility that makes such networks effective.

### **7.3 Operational Frameworks: Risk, Legal, and Workflows**

The governance strategy outlined in the previous sections requires operationalization into practical mechanisms that can be applied in everyday work. At this stage, the focus shifts from organizational design to execution. Governance becomes effective only when it is embedded into workflows, decision processes, and routine interactions.

Rather than relying on formal policies alone, organizations need operational frameworks that provide clarity at the point of use. These frameworks should support employees in making informed decisions about when and how to apply AI, while ensuring that risks are identified and managed in proportion to their impact.

The following sections outline key components of such an approach, including a governance risk map, models of legal involvement, and mechanisms for embedding governance into workflows.

#### **7.3.1 Governance Risk Map for AI Use**

As AI adoption expands across different functions, the range of associated risks becomes more diverse and context-dependent. A practical governance approach therefore requires a structured way to identify, interpret, and prioritize these risks without limiting experimentation.

A governance risk map provides such a mechanism. Instead of functioning as a restrictive checklist, it serves as a navigation tool that helps employees understand the types of risks associated with different use cases and adjust their behavior accordingly. The objective is not to prohibit AI use, but to guide it based on the level of potential impact.

In the context of a marketing and communications organization such as dentsu Ukraine, four main categories of risk are particularly relevant. These categories and their corresponding governance responses are summarized in Table 6

Table 6 Governance Risk Map for AI Use

<b>Risk Category</b>	<b>Typical AI Use Cases</b>	<b>Key Risk Drivers</b>	<b>Governance Response</b>
Reputational	AI-assisted content, creative ideation	Accuracy, tone, cultural sensitivity	Human review before external release; escalation for sensitive or public-facing content
Legal	Client data use, AI-generated content	Compliance, IP ownership, data protection	Legal validation for high-risk use cases; predefined escalation triggers
Client Trust	Strategic proposals, client deliverables	Transparency, reliability, accountability	Disclosure of AI use; validation checkpoints for client-critical outputs
Operational	Analysis, forecasting, task automation	Over-reliance, lack of verification	Human-in-the-loop checks; limits on scope of automation

Reputational risk arises when AI-generated content is used in client-facing materials or public communication. This includes the risk of inaccurate, misleading, or culturally insensitive outputs that may affect brand perception.

Legal risk is associated with the use of data, intellectual property, and compliance with contractual obligations. This includes the potential misuse of client data, unclear ownership of AI-generated content, and violations of regulatory requirements.

Client trust risk reflects the expectations of clients regarding transparency, quality, and control over deliverables. The use of AI may create uncertainty if not properly communicated or validated, particularly in high-value or strategic projects.

Operational risk relates to over-reliance on AI-generated outputs without sufficient verification. This includes errors in analysis, hallucinated information, or inappropriate automation of tasks that require human judgment.

Rather than treating these risks equally, the governance framework should distinguish between different levels of impact. Low-risk use cases, such as internal drafts or exploratory analysis, can remain largely decentralized and require minimal oversight. In contrast, high-risk applications, particularly those

involving external stakeholders or sensitive data, require validation, escalation, and potentially involvement of specialized functions.

This risk-based approach aligns with emerging regulatory frameworks, including the EU AI Act, which emphasizes classification and proportionality rather than blanket restrictions (European Union, 2024). It also complements the decision boundary logic introduced earlier, by linking risk levels to appropriate forms of control.

In practice, a governance risk map allows organizations to preserve flexibility while increasing awareness. It enables employees to make context-sensitive decisions, reduces uncertainty, and supports consistent behavior across teams without imposing rigid rules.

### **7.3.2 Legal Involvement Model: Early, Embedded, and Proportionate**

As AI becomes more deeply integrated into organizational processes, the role of legal functions evolves from ex-post control to continuous participation in decision-making. Rather than acting as gatekeepers who intervene only at the final stage, legal teams need to be positioned as advisors and enablers who support responsible use of AI throughout the workflow.

An effective legal involvement model is based on three principles: early engagement, embedded presence, and proportional response.

Early engagement ensures that legal considerations are addressed at the stage where AI use cases are being defined, rather than after risks have already materialized. This is particularly important in areas involving client data, intellectual property, and contractual obligations. By being involved at the outset, legal teams can help shape how AI is applied, reducing the likelihood of downstream issues.

Embedded presence refers to the integration of legal expertise into everyday processes rather than isolating it within a separate approval function. In practice, this means that legal guidance is accessible at key decision points, either through direct interaction or through predefined escalation mechanisms. This approach reflects a governance logic in which support functions act as service providers, supporting teams without centralizing decision-making.

Proportional response ensures that legal involvement is calibrated to the level of risk. Not all AI use cases require the same level of scrutiny. Low-risk applications, such as internal drafts or exploratory analysis, can proceed with minimal involvement, while high-risk scenarios, particularly those involving external stakeholders or sensitive data, require more formal review. This reduces unnecessary friction while maintaining adequate safeguards. Such approach can be operationalized through a structured model of legal involvement, as illustrated in Table 7

Table 7 Legal Involvement Model for AI Use

AI Use Context	Risk Level	Timing of Legal Involvement	Form of Involvement
Internal drafts, exploratory analysis	Low	No formal involvement	Guidance via general principles & self-service FAQs
Internal decision support	Medium	Early / on escalation	Advisory input, template-based checks
Client-facing deliverables	High	Early and mandatory	Formal review, validation, and documentation
Sensitive data / IP use	Very High	Embedded throughout workflow	Continuous legal support and dedicated oversight

In the context of dentsu Ukraine, this model builds on an already centralized legal function that supports multiple agencies. Extending this function to AI-related activities does not require the creation of new structures, but rather the refinement of existing practices and the introduction of clearer escalation triggers.

Importantly, the role of legal teams in this model is not limited to risk prevention. It also includes clarifying acceptable use, supporting internal alignment, and strengthening trust in AI-enabled processes. By contributing to the development of shared understanding, legal functions help ensure that AI is used consistently and responsibly across the organization.

Over time, as regulatory requirements become more formalized, particularly in relation to the EU AI Act, the importance of structured legal involvement will increase. Organizations that establish such models early will be better positioned to adapt without disrupting operational efficiency.

### 7.3.3 Embedding Governance into Workflows

For governance to be effective, it must be embedded into everyday workflows rather than defined solely through formal policies. Employees make decisions in the context of specific tasks, deadlines, and client expectations. As a result, governance needs to operate at the point of action, providing clear signals on when additional validation, escalation, or documentation is required.

A practical way to achieve this is through the use of workflow triggers that activate governance mechanisms in specific situations. These triggers do not restrict the use of AI tools, but define when additional oversight becomes necessary. Typical triggers include the use of AI outputs in client-facing materials, the involvement of sensitive or proprietary data, the automation of decisions with measurable business impact, and the generation of outputs that may affect financial, legal, or reputational outcomes.

Once a trigger is activated, the corresponding response should be predefined and proportionate. This may involve peer review within the team, validation by a manager, or the involvement of support functions such as legal, finance, or IT. The objective is to ensure that the level of control matches the level of risk, while avoiding unnecessary friction in low-risk scenarios.

Embedding governance into workflows also requires standardization of a limited set of practices. This includes the use of simple documentation templates for AI-assisted work, basic validation routines for outputs, and clearly defined escalation pathways. These mechanisms should be lightweight and easy to apply, allowing teams to integrate them into existing processes without disrupting productivity.

Information technology functions play a critical role in enabling this model. While governance defines when and how AI should be used, IT determines where and under what conditions it can be used. This includes managing access to approved tools, ensuring data security, integrating AI capabilities into existing systems, and supporting compliance with internal and external requirements. In practice, governance and IT operate as complementary layers: one defines decision logic, the other provides the technical environment in which it can be consistently applied.

An important aspect of this approach is visibility. Governance mechanisms should make the use of AI more transparent within the organization. This can be achieved through clear signaling of AI usage, internal tracking of higher-risk applications, and shared understanding of acceptable practices. Increased visibility supports accountability while reinforcing trust between teams and with external stakeholders.

Over time, as AI adoption becomes more systematic, these workflow-based mechanisms can be refined and formalized. However, their initial design should prioritize usability and adaptability. Overly complex procedures are likely to be bypassed, while simple and well-integrated practices are more likely to be consistently applied.

By embedding governance directly into workflows, organizations can ensure that control mechanisms operate in parallel with everyday work rather than in opposition to it. This allows AI adoption to scale while maintaining alignment with organizational standards, risk tolerance, and external requirements.

The governance approach proposed in this chapter reflects a shift from static control mechanisms to adaptive, workflow-integrated practices. Rather than relying on rigid policies or centralized decision-making, organizations can manage AI adoption through a combination of strategic guidance, distributed expertise, and context-dependent controls. This enables a transition from isolated experimentation toward more consistent and scalable use of AI, while preserving flexibility and initiative at the operational level.

Importantly, the model does not seek to eliminate uncertainty, but to structure it. By aligning governance mechanisms with actual work processes, organizations can ensure that AI is applied

responsibly without constraining its potential. This balance between learning and control becomes the central condition for sustainable AI integration.

These elements form an integrated AI governance loop, in which risk identification, decision boundaries, role-based oversight, and workflow triggers reinforce each other. Together, they create a system that supports both control and adaptability, allowing organizations to scale AI use without losing coherence or accountability.

The frameworks outlined in this chapter provide a practical foundation for organizations navigating early-stage AI adoption. However, their effectiveness depends on context, scale, and regulatory environment. These limitations, along with the broader implications of the findings, are discussed in the concluding chapter.

## CHAPTER 8. CONCLUSION

This concluding chapter synthesizes the research findings to provide a comprehensive answer to the research question of how AI adoption influences organizational decision-making. It reflects on the empirical evidence obtained through the case study of dentsu Ukraine and examines the implications of the identified Adoption-Authority Gap. The chapter is structured to summarize the key findings, outline the study's theoretical and practical contributions, acknowledge its limitations, and suggest directions for future research in the evolving field of AI governance.

### 8.1 Summary of Findings

This study examined how AI adoption influences decision-making within organizations, with a particular focus on the relationship between autonomy, influence, and formal authority. Drawing on a mixed-methods case study of dentsu Ukraine, the findings reveal a consistent pattern across both quantitative and qualitative evidence.

The empirical analysis reveals that integrating AI significantly increases individual autonomy in decision preparation. Employees are able to independently perform tasks that previously required consultation or approval, particularly in areas such as information gathering, analysis, and content development. This effect is robust and observed across different roles and levels of seniority.

AI adoption also contributes to increased perceived influence. Individuals who actively use AI tools are more likely to shape discussions, propose solutions, and contribute to decision-making processes. However, this influence remains informal and is primarily driven by demonstrated competence rather than formal authority.

At the same time, formal decision rights remain largely unchanged. Final decisions continue to be anchored in hierarchical structures, reflecting the persistence of accountability and organizational responsibility. This results in a structural gap between expanding capabilities and stable authority, referred to in this study as the Adoption-Authority Gap.

The role of governance in this relationship is limited and primarily contextual. While governance mechanisms define acceptable boundaries for AI use, they do not significantly alter the relationship between AI adoption and decision-making outcomes. Instead, governance functions as a boundary condition that shapes how AI is applied rather than how authority is distributed.

### 8.2 Contributions

This study contributes to the literature on AI and organizational decision-making in several ways.

First, it provides empirical evidence on how AI adoption affects decision-making autonomy and influence in a real organizational setting. While much of the existing literature remains conceptual, this study offers data-driven insights based on both survey analysis and qualitative interviews.

Second, it introduces the concept of the Adoption-Authority Gap, highlighting the divergence between technological capabilities and formal organizational structures. This concept helps explain why increased access to information does not automatically lead to redistribution of decision rights.

Third, the study extends existing theoretical perspectives, particularly the work of Aghion and Tirole (1997), by demonstrating that increases in informational capacity do not necessarily alter formal authority. It also contributes to information processing theory by showing that improvements in information handling can be absorbed within existing hierarchical structures.

Furthermore, the findings align with and extend the knowledge-based view of the firm (Grant, 1996), as AI adoption enhances the organization's ability to generate, access, and apply knowledge at the individual level. The emergence of informal AI expertise and distributed knowledge networks suggests that competitive advantage increasingly depends not only on access to information, but on the capability to effectively integrate and utilize it across the organization.

Fourth, the study offers a practical contribution by developing an integrated AI governance framework. This framework combines strategic orientation, adaptive organizational structures, and workflow-based mechanisms, providing organizations with a structured approach to managing AI adoption.

### **8.3 Limitations**

This study is subject to several limitations that should be considered when interpreting its findings.

The research is based on a single case organization within the marketing and communications industry. While this enables a detailed and context-rich analysis, it limits the extent to which the results can be generalized to other organizational settings, particularly those with different structures or levels of technological maturity.

The analysis reflects an early stage of AI adoption, characterized by experimentation, uneven integration, and limited formalization. The patterns identified in this study may therefore evolve as organizations move toward more mature and standardized use of AI.

Key variables such as autonomy and perceived influence are measured through self-reported data. Although this approach captures individual experience and perception, it may introduce bias related to interpretation, overestimation of capabilities, or differences in understanding across respondents.

The study focuses primarily on internal decision-making processes. External factors, including regulatory developments, client expectations, and competitive dynamics, are not examined in depth, despite their potential influence on how organizations structure AI use and governance.

Finally, the research design does not fully capture the role of technological infrastructure in shaping AI adoption. While the importance of IT functions is acknowledged, further analysis would be required to understand how access to tools, system integration, and platform choices affect decision-making dynamics.

#### **8.4 Future Research Directions**

The findings of this study open several avenues for future research.

One important direction is the examination of how the Adoption–Authority Gap evolves over time. Longitudinal studies could provide insight into whether continued AI adoption leads to gradual changes in formal structures or reinforces existing hierarchies.

Further research could explore the role of governance in more mature stages of AI adoption. As regulatory frameworks such as the EU AI Act become more widely implemented, it will be important to assess how increased formalization affects autonomy, influence, and organizational flexibility.

Comparative studies across industries and organizational types would also be valuable. The dynamics observed in a knowledge-intensive, project-based organization may differ significantly from those in more standardized or operational environments.

Another promising direction involves deeper analysis of informal expertise and its organizational implications. The emergence of AI champions and distributed knowledge networks raises questions about how expertise is recognized, developed, and integrated into formal structures.

Finally, future research could investigate the interaction between technological infrastructure and governance. In particular, the role of IT systems in shaping access, control, and scalability of AI use remains an important but underexplored area.

## APPENDIX A. SURVEY INSTRUMENT

This appendix presents the structured survey instrument used for the quantitative component of the study. The questionnaire was designed to measure AI adoption, workflow integration, decision-making autonomy and influence, governance practices, and perceived outcomes. The survey was administered online and completed anonymously by employees of dentsu Ukraine. The estimated completion time was 10-12 minutes.

The instrument consists of seven thematic sections, as outlined below.

### **Section A - Professional Profile**

A1. Your agency / department within dentsu Ukraine:

- Carat
- dentsu X
- iProspect
- Vizeum
- Posterscope
- Isobar
- Maker
- Other (please specify)

A2. Your primary function:

- Client Service / Account Management
- Strategy / Planning
- Media Planning
- Media Buying
- Performance / Digital Marketing
- Creative / Content / Production
- Analytics / Data / BI
- PR / Communications
- Finance / Operations
- HR
- Legal / Compliance
- IT / Engineering

- Other (please specify)

A3. Your position level:

- Junior / Assistant

- Specialist

- Senior Specialist

- Team Lead / Manager

- Head of Department

- Director / C-level

A4. Tenure in dentsu Ukraine:

- Less than 1 year

- 1-3 years

- 3-5 years

- More than 5 years

A5. Size of your immediate team:

- 1-3 people

- 4-7 people

- 8-15 people

- 16+ people

### **Section B - AI Adoption**

B1. Which AI tools do you use for work? (multiple choice)

- ChatGPT

- Gemini

- Microsoft Copilot

- Claude

- Perplexity

- MidJourney

- Adobe Firefly

- ElevenLabs

- NotebookLM

- Local LLM models

- Other (please specify)

B2. How frequently do you use AI tools for work?

- Never
- Less than once per month
- A few times per month
- A few times per week
- Once per day
- Multiple times per day / continuously

B3. Access to paid AI tools for work:

- No access
- I pay for tools personally
- Company reimburses specific tools upon request
- Company provides centralized access to AI tools
- Both company-provided and personal subscriptions

B4. Self-assessment of your AI proficiency

Scale: 1-7, where 1 = Beginner; 7 = Advanced user

B5. If AI tools suddenly became unavailable, how would it affect your work?

- No significant impact
- Some tasks would become slower
- Noticeable disruption
- Many tasks would become difficult
- Major productivity loss

Section C - AI Use Cases and Workflow Integration

C1. For which tasks do you use AI in your work? (multiple choice)

- Research and information search
- Document summarization / brief extraction
- Copywriting / text generation
- Translation or editing
- Preparing presentations or pitch decks
- Data analysis / Excel / analytics support
- Idea generation / brainstorming
- Image or video generation
- Coding / scripts / automation

- Workflow automation or bots
- Other (please specify)

C2. To what extent are AI tools integrated into your personal workflow?

Scale: 1-7, where 1 = Rarely used; 7 = A standard part of my work process

C3. How is AI adoption occurring in your team? (multiple choice)

- Individual initiative (bottom-up)
- Encouraged by manager
- Supported through internal best practices
- Formalized in workflows or SOPs
- Expected as part of job performance

C4. Which of the following do you use? (multiple choice)

- Personal prompt templates
- Custom GPTs or AI assistants
- Team prompt libraries or shared AI workflows
- None of the above

C5. Approximately what share of your work tasks involve AI assistance?

- 0–10%
- 10–30%
- 30–50%
- 50–70%
- More than 70%

C6. In one or two sentences, how do you typically use AI in your daily work?

(Open-ended, short answer)

#### Section D - Decision Rights and Authority

Please indicate your level of agreement with the following statements.

Scale: 1-7, where 1 = Strongly disagree; 7 = Strongly agree

D1. AI allows me to make more decisions independently without escalating to a manager.

D2. AI has reduced the need to escalate tasks for approval.

D3. AI has increased my responsibility for decision outcomes.

D4. Access to AI-based analysis has changed who actually influences decisions in my team.

D5. Managers are more likely to accept decisions when they are supported by AI-generated analysis.

D6. In time-sensitive situations, the person with the strongest AI or data analysis often drives the decision.

D7. AI-generated insights increasingly influence important decisions in my department.

D8. In which areas have you observed the most noticeable change in decision-making authority?  
(multiple choice)

- Media planning / channel mix
- Budget allocation
- Creative approvals
- Client communication strategies
- Reporting and analytics
- Vendor selection
- Pitch or proposal development
- Internal process improvements
- Other (please specify)

D9. Who typically makes the final decision when AI analysis is involved?

- Mostly individual specialist
- Mostly team lead / manager
- Mostly department head / director
- Usually a collaborative decision

D10. How much autonomy do you personally have to experiment with new AI tools or automation solutions?

Scale: 1-7, where 1 = No autonomy; 7 = Full autonomy

#### Section E - Governance and Risk

Please indicate your level of agreement.

Scale: 1-7

E1. dentsu Ukraine has clear policies regarding the use of AI tools in work tasks.

E2. I understand the rules regarding the use of client or confidential data when using AI tools.

E3. The company provides guidance on which AI tools are recommended or approved for work.

E3b. My organization provides training or guidance on responsible AI use.

E4. AI-generated outputs are expected to be verified before being used in deliverables.

E5. There are processes for escalating issues if AI generates incorrect or risky outputs.

E6. Risks such as hallucinations, bias, or data leakage are actively considered in our workflows.

E7. Employees in my team clearly understand the rules for using AI in work tasks.

E8. In the last three months, have you experienced an issue related to AI use in your work?

- No
- Yes, minor error without consequences
- Yes, error affecting work quality
- Yes, potential compliance or data risk

E9. When working with sensitive information, how do you typically use AI tools?

- I never include sensitive information
- I anonymize or generalize the data
- I only use approved enterprise tools
- I sometimes include sensitive data directly
- Not sure / depends on the situation

#### Section F - Outcomes

Scale: 1-7

F1. AI has increased my productivity.

F2. AI has improved the quality of my work outputs.

F3. AI has accelerated decision-making in my team.

F4. AI has reduced the number of mistakes in my work.

F5. AI outputs are generally reliable and require minimal verification.

#### Section G - Open Reflections

G1. What is the most valuable AI use case in your work today? (short answer)

G2. What is the biggest barrier to AI adoption in your team? (short answer)

G3. If you had unlimited access to AI tools, which subscriptions or services would you add to your work toolkit and why? (short answer)

G4. Do you have any ideas or suggestions for how dentsu Ukraine could improve the use of AI in the organization? (short answer)

G5. What work or type of information would you never trust to AI tools? (short answer)

## **APPENDIX B. INTERVIEW GUIDE**

This appendix presents the semi-structured interview guide used for the qualitative component of the study. The guide was designed to explore how AI adoption affects decision-making processes, autonomy, influence, and governance within the organization. The structure combines thematic blocks aligned with the research framework while allowing flexibility for probing and follow-up questions.

### **1. Introduction (3–5 minutes)**

Q1. Please briefly describe your role at dentsu, including your area of responsibility and the types of decisions you are involved in.

Q2. How did your work look before the active use of AI (2–3 years ago)?

### **2. AI Adoption and Evolution (5–10 minutes)**

Q3. When and how did you start actively using AI in your work?

Q4. Was this driven by your own initiative or by management?

Q5. What are 2–3 of the most significant use cases of AI in your work?

Q6. Are there tasks you now rarely perform without AI?

### **3. Information as a Source of Influence (Core Analytical Block) (8–10 minutes)**

Q7. Has AI changed your ability to access or process information and analytics more quickly or deeply?

Q8. Can you recall a situation where, with the help of AI, you were able to:

- defend your position?
- influence a manager's decision?
- introduce a new approach?

Q9. Have there been situations where AI-based analysis contradicted the opinion or decision of a manager or team? How was this resolved, and who ultimately made the final decision?

Q9a. To what extent do you trust AI-generated recommendations in such situations? Do you verify them?

### **4. Decision Rights (Key Analytical Block) (8–10 minutes)**

Q10. Has the distribution of decision-making authority changed in your unit?

Q11. Has the number of approvals or escalation steps decreased due to AI?

Q12. Are there decisions that are now effectively made at lower levels of the organization?

Q13. Conversely, are there decisions that have become more centralized due to AI (e.g., due to risk or control considerations)?

Q14. Overall, would you say that AI is decentralizing or centralizing decision-making authority?  
Why?

### **5. Formal vs Real Authority (Theoretical Block)**

Q15. Has AI changed who actually influences decisions, even if the formal structure remains unchanged?

Q16. In the context of AI use, are there individuals in your team who have significant influence over decisions despite not holding formal managerial roles? If so, what drives this influence?

Q17. Does AI-supported analysis increase the weight of arguments in discussions, or does it not significantly affect outcomes?

### **6. Governance and Risk (5–8 minutes)**

Q18. How is the use of AI governed within dentsu?

- Are there formal policies (e.g., regarding client data usage)?
- Have there been cases of AI-related errors? If so, who is held accountable?
- Does governance keep pace with the speed of AI adoption?

### **7. Organizational Dynamics (5–8 minutes)**

Q19. How has AI affected interactions between teams or roles within the organization?

- Have informal AI experts emerged?
- Do certain groups (by role, experience, or age) use AI more actively than others?
- Has the need for junior or support roles changed due to AI?

### **8. Strategic Perspective (3–5 minutes)**

Q20. In your view, how might AI influence the management of the company over the next 2–3 years?

- Is there a risk of over-reliance on AI?
- What governance changes may be required?
- What would need to change for AI to have a more direct impact on decision-making rather than just supporting it?

### **Closing Question**

Q21. Is there anything important regarding the use of AI in decision-making that we have not discussed?

## APPENDIX C. CODING FRAMEWORK AND THEMATIC STRUCTURE

This appendix presents the coding framework and thematic structure developed for the qualitative analysis.

The codebook was used to analyze interview data and to identify recurring patterns related to AI adoption, decision-making autonomy, influence, and governance.

The themes were derived through an iterative coding process combining theory-informed categories with inductively emerging codes. Together, these themes support the interpretation of qualitative findings discussed in Chapters 5 and 6.

### **Theme 1: AI as an Enabler of Operational Autonomy**

Codes:

- reduction\_of\_routine\_tasks
- support\_for\_standardized\_tasks
- independent\_problem\_solving
- acceleration\_of\_work\_processes

Boundary codes (related to autonomy but not directly affecting authority):

- improved\_argumentation\_with\_ai\_support
- reduced\_need\_for\_escalation

### **Theme 2: Persistence of Hierarchical Decision Authority**

Codes:

- final\_decision\_retained\_by\_management
- strategic\_decisions\_not\_delegated\_to\_ai
- escalation\_required\_for\_high\_risk\_decisions
- formal\_responsibility\_cannot\_be\_delegated\_to\_ai
- ai\_not\_perceived\_as\_decision\_maker

### **Theme 3: AI as an Advisory, Not Decision-Making Actor**

Codes:

- ai\_as\_advisory\_support
- human\_judgment\_override

- inability\_of\_ai\_to\_assume\_responsibility
- perceived\_lack\_of\_context\_in\_ai

#### **Theme 4: Misalignment Between Formal Governance and Actual AI Use**

Codes:

- governance\_frameworks\_lag\_behind\_practice
- formal\_policies\_not\_operationalized
- lack\_of\_practical\_guidelines\_for\_ai\_use
- learning\_by\_doing\_instead\_of\_structured\_guidance
- governance\_handled\_outside\_tech\_function

#### **Theme 5: Boundaries of Trust and Risk Awareness**

Codes:

- restriction\_on\_sharing\_confidential\_data
- legal\_accountability\_cannot\_be\_delegated
- trust\_requires\_output\_validation
- multi\_model\_verification
- risk\_sensitive\_use\_of\_ai
- ai\_induced\_technical\_debt

#### **Theme 6 (Emergent): Informal AI-Driven Influence**

Codes:

- presence\_of\_ai\_champions
- informal\_consultation\_on\_ai\_use
- credibility\_gained\_through\_ai\_usage
- no\_direct\_authority\_shift\_due\_to\_ai

The coding framework illustrates how qualitative data were systematically categorized to identify recurring patterns in AI usage, decision-making dynamics, and governance practices. The distinction between primary and boundary codes allows for a more nuanced interpretation of how AI affects autonomy without necessarily altering formal authority structures.

## **APPENDIX D. DATA PROCESSING AND ANALYSIS SCRIPTS (PYTHON)**

This appendix provides access to the code used for data preparation, descriptive statistics, and regression analysis presented in this study.

Due to its length and to ensure readability of the main document, the code is provided externally and is available via the following Google Drive link:

<https://drive.google.com/file/d/1zK-aADMPwPoptZymyd2l0ZirmuMwfpqJ/view?usp=sharing>

The code was used to generate the empirical findings reported in Chapter 5 and supports the replication and transparency of the analysis. No proprietary or sensitive data are included in the shared materials. Access is provided for academic review purposes only.

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