



Scoping Literature Review: What Factors Influence the Adoption of HR Analytics in Western Settings?

An investigation of the environmental, technological, organizational, and individual context.

Elin Palklint & Talitha Müller

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Examiner:	Monica Andersson Bäck

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List of Abbreviations

HR	Human Resources
HRA	Human Resource Analytics
HRM	Human Resource Management
TAM	Technology Acceptance Model
TOE	Technology-Organization-Environment

Abstract

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Keywords: HR analytics, Adoption barriers and enablers, Technology–Organization–Environment (TOE) framework, Technology Acceptance Model 3 (TAM3), Data-driven decision-making, Ethics in HR analytics, Western settings, Workforce analytics, People analytics, Scoping review, HR innovation

Purpose: This thesis investigates the factors that influence the adoption of Human Resource Analytics (HRA) in Western settings. Despite the growing strategic relevance of HRA, adoption remains challenging due to fragmented understanding and misalignment with existing structures, processes, and practices. The study aims to provide a consolidated view of the complex landscape shaping HRA adoption by integrating multiple contexts.

Theory: The research is grounded in the Technology–Organization–Environment (TOE) framework and the Technology Acceptance Model 3 (TAM3). These complementary frameworks are applied to examine the technological, organizational, environmental, and individual contexts that collectively shape the adoption of HRA.

Method: A scoping literature review was conducted, leading to the identification of 24 relevant and peer-reviewed articles. An inductive thematic analysis was employed to identify, refine, and organize 30 subthemes under 11 overarching themes, which were then allocated to the four influencing contexts defined by the theoretical models.

Result: The findings reveal a broad set of factors across all four contexts. Key themes include regulatory context, data governance, leadership commitment, and user motivation, among others. The study underscores the importance of ethical considerations, cross-functional collaboration, and layered training strategies. By offering a structured synthesis, the thesis contributes to both academic theory and practical efforts to advance the responsible adoption of HRA in Western settings.

Foreword

Throughout the process of writing this thesis, several individuals have contributed to its development with their support, encouragement, and expertise. First, we would like to thank our peers for their insightful discussions and camaraderie. Knowing that others faced similar challenges along the way was comforting. We are also grateful to our course leaders, Bertil Rolandsson and Ylva Wallinder, for their guidance throughout this journey.

We owe a special thanks to our supervisor, Jing Wu, whose invaluable feedback (and “*balabalabala*”), unwavering support, and remarkable ability to balance between pushing us forward and reminding us to pause and enjoy the sunshine truly made a difference. We are convinced that this thesis is significantly stronger thanks to her insights and dedication.

It has also been a joy to conduct this thesis in a partnership with one another. Our daily iced coffees and shared lunch recipes provided much-needed joyful breaks. A warm thank you to each other—and to our boyfriends who generously shared their homes and offices with us—for the extra emotional support that helped us through this challenging yet inspiring process.

We are sincerely grateful to everyone who contributed to the completion of this work and are proud to present this thesis as the result of our joint efforts. We hope this thesis offers an engaging read and are convinced it provides a meaningful contribution to the academic field of strategic HRM.

Happy reading!

Sincerely,

Elin Palklint & Talitha Müller

1 Introduction

This thesis presents a scoping literature review aimed at mapping the current landscape of factors influencing the adoption of Human Resource Analytics (HRA) in Western settings. The introductory chapter outlines the study's aim, purpose, and scope. By presenting the guiding research questions and providing key background information, it sets the direction for the thesis.

1.1 Research Problem & Purpose

As organizations seek new ways to gain competitive advantage, they are increasingly turning to data-driven approaches to enhance strategic decision-making and operational effectiveness. One notable development in this context is HRA—the use of analytical tools and techniques to process workforce data with the aim of optimizing human capital decisions and aligning Human Resource (HR) strategies with broader business objectives (van der Togt & Rasmussen, 2017; Ekka, 2021). By offering deeper insights into employee performance, turnover prediction, talent management, and organizational development, HRA has the potential to elevate the role of HR from a traditionally administrative support function to a central, strategic partner (Fitz-Enz & Mattox II, 2014; Shet et al., 2021; van der Togt & Rasmussen, 2017).

Despite growing recognition of its strategic potential—evidenced by surveys showing that over 70% of companies worldwide consider HRA a business priority (Collins, et al., 2017)—many organizations continue to face significant adoption challenges (van den Heuvel & Bondarouk, 2017; Angrave et al., 2016). These include poor data quality (Yoon et al., 2023), insufficient analytical capabilities (Angrave et al., 2016), and employee resistance stemming from concerns around transparency, privacy, or conflicting personal beliefs (van den Heuvel & Bondarouk, 2017; Edwards et al., 2024; Vargas et al., 2018). Additional obstacles stem from silo mentalities—which describe departmental fragmentation and reluctance to share data across teams (Angrave, et al., 2016)—and the ambiguity surrounding concepts and terminology within the HRA field (McCartney & Fu, 2022; Shet et al., 2021).

While these barriers are well-documented, they are often explored in isolation, without a unifying framework to integrate the diverse contexts that shape HRA adoption. This fragmented approach can result in single factors or even entire areas being overlooked in practice, leaving organizations unprepared for their influence on the adoption process. In response, both scholars and practitioners have increasingly emphasized the need for more integrated and contextualized

approaches to studying HRA adoption (Coolen et al., 2023; Margherita, 2022; Shet et al., 2021). This thesis addresses that need by systematically identifying, synthesizing, and mapping the factors that influence HRA adoption. Situated within the field of strategic Human Resource Management (HRM), it applies a scoping literature review combined with two complementary theoretical lenses: the Technology–Organization–Environment (TOE) framework and the Technology Acceptance Model 3 (TAM3). Together, these frameworks enable a multidimensional analysis that incorporates four influencing contexts: environmental, technological, organizational, and individual.

To enhance the relevance and interpretability of the findings, this study focuses specifically on organizations in Western countries. The Western context is not strictly defined, as some countries outside the traditional geographic West have become “westernized” through the adoption of Western values and institutions. For example, scholars have argued that countries in Asia, such as Japan and China, exhibit Western characteristics (Gallegos-Riofrío, et al., 2022). However, following the geographic-economic distinction used by Milanovic (2006), this study defines the West as comprising Europe, North America, and Oceania. These regions tend to share institutional characteristics such as robust legal frameworks, advanced technological infrastructures and data protection regulations that shape how HRA is perceived and adopted (World Bank, 2016). The European Union’s General Data Protection Regulation (GDPR) is one example of such a regulatory framework (European Commission, 2018). By narrowing the scope to these specific regions—Europe, North America, and Oceania—the study aims to generate clearer conceptual insights and offer more actionable recommendations tailored to the Western setting.

To guide this review, the study examines four research questions:

RQ1: What factors in the *environmental* context influence the adoption of HR analytics in Western settings?

RQ2: What factors in the *technological* context influence the adoption of HR analytics in Western settings?

RQ3: What factors in the *organizational* context influence the adoption of HR analytics in Western settings?

RQ4: What factors in the *individual* context influence the adoption of HR analytics in Western settings?

By grouping the findings into 11 themes and 30 subthemes across these four contexts, the thesis offers a consolidated overview of current knowledge, highlights underexplored areas, and provides actionable insights for both academics and practitioners. While prior reviews have often focused on isolated factors or single frameworks, this study delivers a more integrative perspective, expanding theoretical understanding of technology innovation adoption and offering practical guidance for organizations seeking to adopt or expand their use of HRA, with a focus on those operating within Western settings.

The findings thereby present valuable insights to a wide range of stakeholders involved in HRA adoption, being especially applicable to medium and large organizations, which typically possess the structural complexity, resource capacity, and formalized HR functions necessary to operationalize the identified factors (Min, 2021). Smaller organizations, by contrast, may find some recommendations less immediately actionable due to more limited resources or less formalized HR structures (Min, 2021). Additionally, researchers in the fields of strategic HRM, technology adoption, and organizational studies may use the synthesized framework as a foundation for further empirical exploration or theory development.

1.2 Background of HR Analytics

Analytics, in general, refers to the process of making decisions based on data, analysis, and systematic reasoning (Davenport, et al., 2010). HRA applies this approach to workforce-related decision-making to enhance the efficiency and effectiveness of HR activities (van den Heuvel & Bondarouk, 2017). By combining intuition and experience with hard facts and evidence, HRA enables decision-makers to make more well-informed, evidence-based people decisions (Gelbard, et al., 2018; van der Togt & Rasmussen, 2017; van den Heuvel & Bondarouk, 2017). In essence, it serves as a tool with the potential to support managers in recognizing strategic opportunities, overcoming challenges, and predicting future trends within the HR field (Fitz-Enz & Mattox II, 2014). It can, if implemented efficiently, be a distinctive advantage for organizations (Sakib, et al., 2024).

Although measurement practices in HR date back to the early 1900s, the term HRA did not appear in the literature until the early 2000s (Marler & Boudreau, 2017). Since then, research on HRA has primarily focused on areas such as training and development, recruitment, performance assessment, and workforce turnover (Bahuguna, et al., 2024). Early practical applications predominantly relied on descriptive statistics, often focusing on employee turnover

and absenteeism. Recently, technological advancements and disruptive innovations—such as artificial intelligence, data mining, machine learning, and the Internet of Things—have enabled better data-driven HR decisions (Shet, et al., 2021). These advancements allow deeper insights into workforce productivity and facilitate HR strategies to support business objectives, thereby improving organizational effectiveness and efficiency (Shet, et al., 2021; van der Togt & Rasmussen, 2017). Contemporary HRA applications include, for example, turnover and attrition prediction (Fitz-Enz & Mattox II, 2014), data-driven candidate selection, and employee mood analysis (Shet, et al., 2021; Gelbard, et al., 2018).

1.3 Thesis Structure

While Chapter 1 provided a background on HRA, establishing the context and purpose of the study, Chapter 2 presents a review of previous research, including definitions on both HRA and the adoption process. Chapter 3 outlines the theoretical foundation of the thesis, which is based on a combination of the TOE framework and TAM3. Chapter 4 describes the research methodology—a scoping literature review—and details the review process, its strengths, limitations, and ethical considerations. Chapter 5 begins by portraying the characteristics of the included articles and presents the results of the scoping review, categorized into environmental, technological, organizational, and individual contexts. Chapter 6 summarizes and interprets the main findings, answers the research questions, highlights contributions to the existing literature, and offers recommendations for future research and practice. Finally, Chapter 7 concludes this thesis by synthesizing the study’s key contributions and takeaways.

2 Previous Research

To chart the fragmented landscape of HRA adoption literature, it is first necessary to understand where the field currently stands. This chapter outlines the terrain of existing research, highlighting key definitions, conceptual boundaries, and uncovers what is known and what remains unclear. By doing so, it establishes the baseline from which this study’s mapping effort departs.

2.1 Literature Overview

In recent years, a growing number of studies have examined the adoption of HRA, exploring its drivers, barriers, and organizational implications—highlighting the increasing strategic relevance of data-driven HR practices (Fernandez & Gallardo-Gallardo, 2021; Bahuguna, et al., 2024). While both quantitative and qualitative research has contributed to this field, a substantial share of the literature remains non-empirical, consisting largely of literature reviews and conceptual viewpoints.

Much of the existing research tends to focus on a relatively narrow set of influencing factors, for instance by emphasizing individual-level elements such as perceived usefulness and behavioral intention (e.g., Vargas, et al., 2018; Bonilla-Chaves, et al., 2024). This focus often overlooks the interplay between environmental, technical, organizational, and human dynamics that collectively shape adoption outcomes. Given that HRA is increasingly understood as a sociotechnical innovation (Wirges & Neyer, 2023; Chen, et al., 2021), its adoption depends on the alignment of technologies, user behavior, internal organizational structures, and broader contextual influences, calling for a more integrated approach.

Although some studies consider multiple perspectives, they typically address only a subset of commonly cited factors, limiting their ability to capture the full complexity within and across contexts (e.g., Andersen, 2017; Angrave, et al., 2016; Madhani, 2023; Rasmussen & Ulrich, 2015; Ratnam & Devi, 2024). Consequently, broad and cohesive syntheses that organize and connect the various strands of existing research remain rare.

Moreover, existing studies are not specifying what part of the adoption process their research applies to—using terms as adoption and implementation interchangeably—which may cause confusion hindering full understanding (e.g., Ratnam & Devi, 2024; Fernandez & Gallardo-Gallardo, 2021). This contributes to a continued fragmentation of the field and hinders the development of a more cohesive, system-level understanding of HRA adoption. While this provided a brief overview of the research landscape, a detailed analysis of empirical studies is presented in the results section through the scoping literature review.

2.2 Definition & Demarcation

2.2.1 Defining HR Analytics

This thesis defines HRA as an HR practice facilitated by information technology to systematically enhance people-related decision-making (van den Heuvel & Bondarouk, 2017).

It does so by utilizing “descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making” (Marler & Boudreau, 2017, p. 15).

HRA is often used interchangeably with related terms such as people analytics, workforce analytics, human capital analytics, and talent analytics, though each carries distinct nuances (van den Heuvel & Bondarouk, 2017; Yoon, et al., 2023). For instance, workforce analytics primarily focuses on the application of statistical tools and quantitative methods to generate evidence-based insights for decision-making (Sakib, et al., 2024), while people analytics emphasizes the broader business value derived from data-driven HR practices (Yoon, et al., 2023). Nevertheless, these terms all describe the process of analyzing and communicating data to inform employee-related decisions, with the aim of enhancing outcomes on both individual and organizational levels (Fernandez & Gallardo-Gallardo, 2021). Given that HRA is the most widely used term in the literature (Marler & Boudreau, 2017), this thesis adopts the same terminology.

2.2.2 HR Analytics as an Innovation

HRA remains a relatively novel concept in many organizations and is frequently described as an innovation within the field of HRM (Marler & Boudreau, 2017; Opatha & Dayarathna, 2024; Ratnam & Devi, 2024; Shet, et al., 2021; Vargas, et al., 2018; Pongpisutsopa, et al., 2020). As defined by Rogers (1962), an innovation is “an idea, practice, or object that is perceived as new by an individual or other unit of adoption” (p. 11). From this perspective, the novelty of HRA lies not in its absolute originality, but in the subjective perception of those adopting it (Hameed, et al., 2012; Marler & Boudreau, 2017). Thus, even when HRA has been widely discussed or implemented in other settings, it may still be experienced as an innovation by those organizations or individuals encountering it for the first time, regardless of their classification as early or late adopters (Marler & Boudreau, 2017). This perception-based definition of innovation justifies the application of theories and models from the domain of technological innovation adoption to the study of HRA.

2.2.3 Framing the HR Analytics Adoption Process

Understanding HRA as an innovation also informs how the adoption process is conceptualized as a technology innovation adoption process. Although various interpretations of the technology innovation adoption process exist, Hameed et al. (2012) observe that scholars widely recognize three core stages in the adoption process: initiation, adoption decision, and implementation—commonly referred to as pre-adoption, adoption-decision, and post-adoption, as shown in Figure 1. For consistency, the term *adoption* is used throughout this thesis to denote the entire process across all three stages.

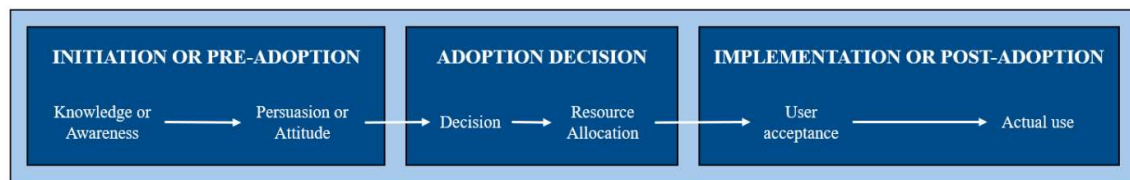


Figure 1: Stages of Innovation Adoption. Adapted from Hameed et al. (2012) and Pongpisutsopa et al. (2020)

Combining the descriptions of Hameed et al. (2012) and Pongpisutsopa et al. (2020), the stages can be defined as follows: the initiation or pre-adoption stage involves recognizing a need or opportunity, developing awareness and knowledge, forming attitudes toward the innovation, and engaging in early planning and proposal activities. This is followed by the adoption decision stage, in which organizations assess the innovation from technical, financial, and strategic perspectives and decide whether to proceed. If the decision is affirmative, the necessary resources for implementation are allocated. The final stage, implementation or post-adoption, centers on actual use, where individual users engage with the innovation and integrate it into routine practice. Successful adoption is therefore not only a matter of organizational approval but also of sustained user engagement and acceptance (Hameed, et al., 2012).

This stage-based framing is central to the thesis. It supports a comprehensive understanding of HRA adoption that extends beyond the moment of decision-making to include the broader socio-technical process through which analytics becomes part of organizational practice.

3 Theory

Any attempt to map the multifaceted terrain of HRA adoption requires strong navigational tools. This chapter introduces two complementary frameworks that guide this exploration: the Technology–Organization–Environment (TOE) framework and the Technology Acceptance Model 3 (TAM3). Together, they serve as the study’s conceptual compass, which is used to orient the investigation of influencing factors and organize diverse findings.

3.1 Technology-Organization-Environment (TOE) Framework

3.1.1 Overview of the TOE Framework

The Technology–Organization–Environment (TOE) framework was developed by Tornatzky and Fleischer (1990) to analyze the adoption of technological innovations at the organizational level. Grounded in the Contingency Theory of Organizations, which was first introduced in 1967 as the contingency model of leadership effectiveness (Fiedler, 1967), the TOE framework emphasizes that technology adoption is influenced by the specific context in which an organization operates (Awa, et al., 2017). This includes both internal and external factors, which shape the organization’s decisions and capacities related to technological innovation.

The TOE framework identifies three key contextual dimensions that affect the adoption of technological innovations: the technological context, the organizational context, and the environmental context (Tornatzky & Fleischer, 1990). Since its introduction, the TOE framework has been validated across a wide range of industries and research domains, examining diverse technologies and organizational settings (Bryan & Zuva, 2021; Gangwar, et al., 2014). While the framework’s core structure remains consistent, the specific variables associated with each context vary across studies (e.g., Zhu, et al., 2003; Ramdani, et al., 2009).

3.1.2 Description of the TOE Framework

Technological context

The technological context refers to the technologies available to an organization, encompassing both existing internal technologies and externally accessible technologies relevant to its operations (Zhu et al., 2003). Key variables identified by studies applying the TOE framework include complexity (Wang, et al., 2010), compatibility (Malik, et al., 2021), relative advantage (Alam, et al., 2016; Ramdani, et al., 2009), trialability (Ramdani, et al., 2009), ICT

infrastructure (Awa, et al., 2016), and the availability of technological resources (Lin & Lin, 2008).

Organizational context

The organizational context encompasses the internal conditions that shape an organization's readiness to adopt and implement innovations, including both formal and informal communication and control mechanisms, as well as available resources and creative capacity (Gangwar, et al., 2014; Bryan & Zuva, 2021). Prior research using the TOE framework has identified variables such as firm scope (Zhu, et al., 2003), firm size (Low, et al., 2011; Ramdani, et al., 2009), top management support (Alam, et al., 2016; Ramdani, et al., 2009), innovativeness (Malik, et al., 2021), and organizational learning capabilities (Malik, et al., 2021) to be significant within the organizational context.

Environmental context

The environmental context refers to the external setting in which an organization operates. It includes factors such as industry characteristics, regulatory pressure, access to external resources, and relationships with business partners and government institutions (Bryan & Zuva, 2021; Gangwar, et al., 2014). Key environmental variables identified in TOE-based studies include competitive (Zhu, et al., 2003; Low, et al., 2011; Lin & Lin, 2008), trading partner (Low, et al., 2011; Wang, et al., 2010), and customer (Scupola, 2009) pressure, vendor support (Alam, et al., 2016), and government regulation and support (Alam, et al., 2016).

3.1.3 Discussion of the TOE Framework

The TOE framework offers several advantages that make it particularly suitable for studying the adoption of HRA within organizations. Its comprehensive structure enables the TOE framework to capture the multifaceted influences on innovation adoption processes, including not only technical aspects but also organizational dynamics and external pressures, aligning with the socio-technical nature of HRA (Di Lauro, et al., 2025; Wirges & Neyer, 2023; Chen, et al., 2021). Another important strength of the TOE framework is its generic nature: it is not restricted by industry type or firm size, making it applicable across diverse organizational contexts (Wen & Chen, 2010). Moreover, the TOE framework has consistently received

empirical support (Zhu, et al., 2003), reinforcing its credibility as a guiding framework for this research.

Despite its strengths, the TOE framework is criticized for functioning more as a taxonomy for categorizing variables than as an integrated or dynamic model (Dedrick & West, 2003; Bryan & Zuva, 2021). In addition, the framework has seen relatively little theoretical advancement over time and may overlook important aspects such as sociological and cognitive variables (Awa, et al., 2015; Bryan & Zuva, 2021). Given these limitations, the TOE framework benefits from being complemented by an additional theoretical perspective that captures individual-level determinants of technology acceptance.

3.2 Technology Acceptance Model 3 (TAM3)

3.2.1 Overview of the TAM3

The Technology Acceptance Model (TAM) was originally developed by Davis (1986) to explain individual acceptance and use of information systems across a wide range of end-user technologies (Davis, et al., 1989). Drawing on Fishbein and Ajzen's (1975) socio-psychological Theory of Reasoned Action (TRA), TAM proposes that two key constructs—perceived usefulness and perceived ease of use—shape an individual's attitude toward a system. Perceived usefulness thereby refers to how strongly a person believes that using a particular system will enhance their job performance (Venkatesh & Davis, 2000). In contrast, perceived ease of use captures the individual's belief about how effortless the system will be to operate (Venkatesh & Davis, 2000). Together, these beliefs influence behavioral intentions and, ultimately, actual system use (Davis, et al., 1989; Xu, et al., 2014).

By highlighting the role of internal beliefs and attitudes in driving technology adoption, TAM has become one of the most influential and widely applied models for predicting user acceptance of technology (Venkatesh & Davis, 2000; Xu, et al., 2014; Yousafzai, et al., 2007) (Venkatesh & Davis, 2000; Xu, et al., 2014; Yousafzai, et al., 2007). Since its original development, the model has undergone several extensions, including TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008). While these versions incorporate additional external factors, moderators, and outcome measures, they all retain the core structure linking beliefs, attitudes, intentions, and behavior (Wu, 2011; Bryan & Zuva, 2021). This thesis adopts TAM3, the most comprehensive version of the model, as it offers a richer understanding of individual-level technology adoption, making it particularly well-suited to the research objective.

3.2.2 Description of the TAM3

TAM3, developed by Venkatesh and Bala (2008), retains the key constructs of the original TAM by Davis (1986): perceived usefulness and perceived ease of use. It extends the model by incorporating a comprehensive set of antecedents and moderating factors to more robustly account for these constructs (Venkatesh & Davis, 2000). Building on Venkatesh and Davis's (2000) earlier work, TAM3 explains perceived ease of use by distinguishing between anchor and adjustment variables. Anchor variables include initial beliefs such as computer self-efficacy, perceptions of external control, computer playfulness, and computer anxiety, while adjustment variables encompass perceived enjoyment and objective usability (Venkatesh & Bala, 2008).

In relation to perceived usefulness, TAM3 integrates both social influence determinants, such as subjective norm and image, and cognitive instrumental processes. Subjective norm refers to the perceived social pressure from important others to use or not use the system, whereas image reflects the perception that system use enhances one's status (Venkatesh & Bala, 2008). Cognitive instrumental processes include job relevance, output quality, result demonstrability, as well as perceived ease of use (Venkatesh & Bala, 2008). The effects of these determinants on perceived usefulness are moderated by both user experience and voluntariness, the latter referring to whether system use is perceived as mandatory (Venkatesh & Davis, 2000).

A central contribution of TAM3 is its emphasis on experience as a moderating variable. Experience strengthens the relationship between perceived ease of use and perceived usefulness, suggesting that as users become more familiar with a system, ease of use becomes more influential in shaping their perceptions of its usefulness (Venkatesh & Bala, 2008). At the same time, experience reduces the impact of computer anxiety on perceived ease of use and gradually diminishes the direct effect of perceived ease of use on behavioral intention (Venkatesh & Bala, 2008).

3.2.3 Discussion of the TAM3

TAM3 provides a comprehensive lens for understanding individual-level determinants of technology adoption. Its extended structure helps identify a wide range of cognitive and perceptual factors influencing user acceptance, making it particularly well-suited for studying such influences in the context of HRA (Venkatesh & Bala, 2008). The model has received strong empirical support across various organizational contexts and technologies, explaining a significant proportion of variance in its key constructs, addressing earlier theoretical gaps such

as the moderating role of user experience, and maintaining widespread popularity due to its simplicity and consistent validation (Venkatesh & Bala, 2008; Yousafzai, et al., 2007; Bryan & Zuva, 2021; Wu, 2011).

However, while TAM3 expands upon the original model, several authors argue that it remains relatively parsimonious—meaning it focuses on a limited set of core variables—and may not fully capture broader organizational, social, or contextual influences on technology adoption (Wu, 2011; Gangwar, et al., 2014). This limitation, combined with the model’s adaptable nature, has established it as a common theoretical basis for subsequent modifications and integrations with other frameworks (Xu, et al., 2014).

3.3 Integration of TOE Framework & TAM3

To comprehensively analyze the factors influencing the adoption of HRA, this study integrates the TOE framework with TAM3. While the TOE framework effectively captures technological, organizational, and environmental influences, it traditionally considers individual characteristics under technological or organizational contexts. However, extant research emphasizes the critical role of individual decision-makers’ perceptions, attitudes, and motivations in shaping organizational strategies and technology adoption outcomes (Hambrick & Mason, 1984; Awa, et al., 2015; Thong, 1999). Recognizing this, an explicit individual context is introduced alongside the three TOE dimensions, drawing on TAM3’s comprehensive treatment of user acceptance behaviors (Venkatesh & Bala, 2008).

The combination of TOE and TAM3 is particularly suitable for HRA adoption, as both models were originally developed to study technology acceptance (Awa, et al., 2017). TOE offers a robust structure for assessing organizational and external drivers, while TAM3 complements it by capturing internal, psychological determinants of adoption. Several scholars have also encouraged combining these models to enhance explanatory value in technology adoption research (Gangwar, et al., 2014; Bryan & Zuva, 2021). By extracting individual-level factors from the broader organizational context of the TOE framework and integrating TAM3, a richer, multi-level perspective for understanding the factors influencing HRA adoption is provided.

4 Method

Constructing a comprehensive map of the factors influencing HRA adoption requires a well-defined and rigorous methodology. This chapter outlines the systematic procedures used to identify, extract, and analyze relevant literature, forming the foundation for the structured mapping of influencing factors presented in the subsequent chapters. It further addresses ethical considerations and offers a critical reflection on the study's limitations.

4.1 Research Design

4.1.1 Overview Scoping Review

To answer the research questions, this study employed a scoping literature review, which is a method of systematically mapping key concepts and types of evidence within a specific field (Colquhoun, et al., 2014). Unlike systematic reviews, scoping reviews are particularly useful for exploring emerging or under-researched topics, as they allow for a broad synthesis of literature rather than an exhaustive evaluation of study quality (Arksey & O'Malley, 2005). The flexibility of this approach makes it particularly suited for answering the research questions: "What environmental (1), technological (2), organizational (3), and individual (4) factors influence HRA adoption in Western settings?". Since research on this topic remains limited, a scoping review provides a structured yet exploratory method to identify existing knowledge and develop an overview of the factors influencing HRA adoption.

Following the methodological approach used by Wu et al. (2025), this study systematically collected, reviewed, and categorized literature to create a comprehensive mapping of the field. The review is conducted in accordance with the five-stage framework developed by Arksey and O'Malley (2005) and later refined by Levac et al. (2010), ensuring a rigorous and replicable research process: 1) identifying the research question; 2) identifying relevant studies; 3) selecting studies; 4) charting the data; 5) organizing, analyzing, and reporting the results. Additionally, this study adheres to the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) guidelines, which provide best practices for reporting scoping reviews and enhance the transparency of the study (Tricco, et al., 2018).

4.1.2 Search Strategy

Following Levac et al.'s (2010) second stage of the scoping review process—identifying relevant studies—a four-step search strategy was employed. Initially, relevant known articles were scanned to identify key terminology frequently used in discussions of HRA adoption, implementation, and moderating factors. Based on these findings, a Boolean search string was developed following the approach outlined by Kugley et al. (2017). This keyword-based search was applied to identify relevant article titles and abstracts across selected databases. Finally, after the screening, the reference lists of selected articles were assessed to distinguish further important studies that might have been missed in the database search.

While this thesis adopts the term HRA, it acknowledges that authors often use related terms—such as workforce analytics, people analytics, and talent analytics—interchangeably. Recognizing this, the Boolean search string used in the database search was carefully designed to capture the broadest possible range of studies relevant to the topic: ("HR analytics" OR "human resource analytics" OR "people analytics" OR "workforce analytics" OR "talent analytics" OR "employee analytics" OR "human capital analytics" OR "workforce intelligence") AND ("adoption factors" OR "barriers" OR "drivers" OR "determinants" OR "challenges" OR "facilitators" OR "enablers" OR "obstacles" OR "success factors" OR "implementation factors" OR "motivators" OR "influencing factors" OR "moderating factors" OR "moderators" OR "requirements" OR "legitimation") AND ("organization*" OR "business*" OR "enterprise*" OR "company*" OR "corporate sector" OR "industry" OR "firm*" OR "workplace*" OR "HR department*"). The literature search was conducted across five major academic databases: Scopus (210 results), Business Source Premier (101 results), Web of Science (78 results), ProQuest Social Science Collection (48 results), and IEEE Xplore (34 results), leading to a total of 471 articles.

4.1.3 Screening & Study Selection

As part of the third stage of Levac et al.'s (2010) scoping review framework—study selection—the 471 articles were systematically screened and iteratively filtered. The first step involved removing 150 duplicate articles, leaving 321 studies for further review. The second step consisted of title and abstract screening. This process led to the exclusion of 204 studies that did not directly address moderating factors of HRA adoption or were focused on unrelated HR technologies and big data.

Following this, a full-text screening of the remaining 117 articles was conducted, leading to the selection of 20 studies that were directly relevant to the research question. This second part of the selection process was guided by clear inclusion criteria. Papers related to specific HRA cases such as talent analytics or absenteeism minimization were excluded as they do not focus on the general adoption of HRA. Furthermore, to maintain a credible yet manageable scope, this thesis only included peer-reviewed journal articles published in English and excluded grey literature.

While the primary focus of this review is on factors influencing HRA adoption within Western settings, articles originating from non-Western regions were also considered when they mainly reviewed, synthesized, or engaged with Western academic literature and addressed themes relevant to the research objectives. The decision to include such studies was based on the thematic relevance and focus of the work, rather than the geographic location of the authors or publication outlet, allowing for a thorough representation of literature contributing insights into Western settings. To ensure comprehensiveness, the reference lists of the selected 20 articles were examined, leading to the identification of 4 additional relevant studies, resulting in a total of 24 studies included in the scoping review.

To ensure transparency and replicability, the screening process followed the recommendations of Levac et al. (2010), which emphasize the importance of maintaining a clear and rigorous study selection process. Screening was conducted independently by two researchers, and any disagreements regarding inclusion were resolved through discussion. The full study selection process is visually represented in the PRISMA-ScR flow diagram (see Figure 2).

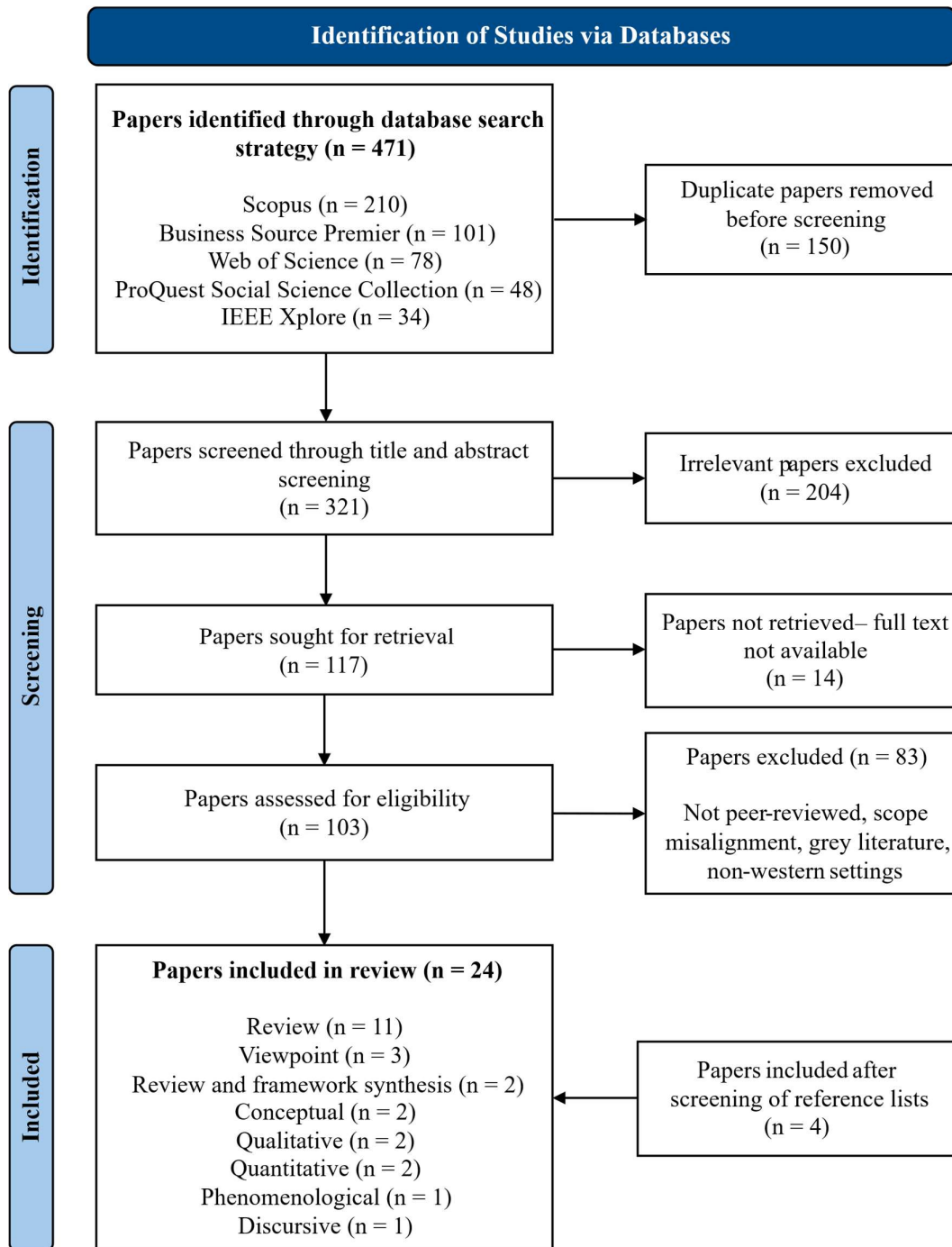


Figure 2: PRISMA-ScR Flow Diagram. Adapted from Page et al. (2021)

4.1.4 Data Extraction, Coding & Thematic Analysis

Following stage four of the scoping review process by Levac et al. (2010), a structured data extraction framework was created to systematically chart the key information from the final included studies. This approach ensures that the review not only synthesizes findings but also provides a clear characterization of the existing research landscape. To synthesize the data in the final stage of the scoping review process (Levac, et al., 2010), a thematic analysis was conducted. The analysis followed the phases outlined by Braun et al. (2019): becoming familiar with the data, generating codes, constructing, revising, and defining themes, and lastly producing the report. Thematic analysis is particularly useful in scoping reviews as it enables researchers to identify recurring patterns and themes across diverse studies while allowing for the emergence of new, previously unrecognized themes (Braun, et al., 2019).

After familiarization with the selected articles, inductive coding was employed to allow insights and themes to emerge naturally from the data, uninfluenced by prior theories or predefined frameworks. To ensure rigor and mitigate individual bias, the initial coding process was carried out independently by both authors. Inconsistencies in codes were subsequently reviewed and resolved through discussion to achieve consensus. Based on the initial codes, 16 preliminary thematic categories were constructed. Following this initial theme construction, each theme's scope and title were further refined and defined, leading to a final set of 11 overarching themes. Building on the study's theoretical foundation, the themes were then allocated to the four contexts influencing the adoption of HRA. For improved comprehension, the initial codes were additionally clustered into a total of 30 subthemes, each presenting distinct yet interconnected aspects of HRA adoption. The final set of themes and associated subthemes along with supporting quotes from the included articles are presented in Appendix 1.

4.2 Ethical Considerations

Although this thesis did not involve primary data collection, several ethical considerations remained relevant. First, it was essential to ensure transparency and integrity throughout the research process. According to the European Code of Conduct for Research Integrity, researchers must uphold honesty, accountability, and rigor in their work (ALLEA, 2017). This included maintaining clear documentation of methodological choices, particularly in the literature selection process, to avoid bias in data interpretation. As Suri (2019) highlights, publication and selection biases can influence research outcomes, potentially leading to an overrepresentation of widely cited frameworks while neglecting less prominent but valuable

studies. Second, ethical responsibility in data management is crucial, even when using secondary data. The European Code of Conduct for Research Integrity emphasizes proper data handling and citation to ensure the traceability and accountability of research findings (ALLEA, 2017). In this thesis, all sources were properly acknowledged to distinguish original contributions from prior work.

Third, ethical interpretation and communication of findings were prioritized to avoid misrepresentation, exaggeration, or overgeneralization. Researchers must ensure that findings are communicated accurately and without distortion (ALLEA, 2017). This was particularly important in this thesis, as the scoping review involved synthesizing diverse sources, which required careful representation to maintain the integrity and context of the original studies. Finally, AI tools were used to improve the language and readability of this study while maintaining the originality and validity of the research findings. By adhering to these ethical values, this study aimed to ensure that its contributions to HRA research were rigorous, responsible, and aligned with best research practices.

4.3 Limitations

This study is subject to several limitations, primarily stemming from its reliance on secondary data and the methodological choices inherent in conducting a scoping review. The use of secondary data means that insights are shaped by the scope, depth, and possible biases of the original studies (Diatta & Berchtold, 2023). This risk is amplified by the fact that most of the articles included in the scoping review are themselves literature reviews, adding an additional layer of interpretation and potential bias. As the scoping review does not apply a formal quality assessment beyond peer-reviewed status, there is also a risk that some findings reflect incomplete or distorted representations of the phenomenon. This risk is further underscored by concerns raised in academic literature about the peer review process itself, which has been criticized as biased, inconsistent, and lacking transparency—raising questions about the reliability of peer-reviewed sources (Velterop, 2015). By focusing exclusively on peer-reviewed literature, the review may also exclude valuable insights found in grey literature or less frequently cited works.

In addition, the study's selection process introduces another potential source of bias (Diatta & Berchtold, 2023; Suri, 2019). While the screening was conducted collaboratively and with attention to consistency, the inclusion and exclusion decisions ultimately relied on the

subjective judgment of two researchers. This may influence the comprehensiveness and neutrality of the final dataset and, consequently, the scope of the resulting synthesis.

Furthermore, the theoretical frameworks applied—TOE and TAM3—carry inherent limitations. While their integration offers a more holistic view than either model alone, both remain limited in their ability to fully capture the complexity of real-world adoption processes. They present a largely static view, focusing on influencing factors rather than on how these factors interact and evolve over time. This constrains their explanatory power in relation to iterative adoption and long-term dynamics. TOE's flexibility, although useful for contextual adaptation, also poses challenges due to its loosely defined constructs, which may result in inconsistent interpretation across studies (Prakash, 2025).

5 Results

This chapter presents the results of the scoping review, beginning with an overview of the characteristics of the included articles, followed by a systematic mapping of the diverse factors influencing the adoption of HRA in Western settings. To navigate this complex landscape, the findings are organized according to the four contexts derived from the combination of TOE and TAM3: environmental, technological, organizational, and individual.

5.1 Study Characteristics

The extracted data encompasses author(s), year, region, publication source, population, research methods, and the themes influencing HRA adoption identified in each article. Region refers to the authors' location, while population—applicable only to the empirical studies—refers to the group of individuals or organizations that were surveyed. The extracted data are presented in Table 1.

The selected 24 articles include a diverse range of methodological approaches and geographic coverage. Among them, two studies employed quantitative methods (Bonilla-Chaves, et al., 2024; Vargas, et al., 2018), while two used qualitative approaches (Dahlbom, et al., 2020; Wirges & Neyer, 2023), and one adopted a phenomenological design (Minbaeva, 2018). A notable number of articles were review-based, including 11 reviews (Cho et al., 2023; Coolen et al., 2023; Fernandez & Gallardo-Gallardo, 2021; Levenson & Fink, 2017; Marler & Boudreau, 2017; McCartney & Fu, 2022; Moraes & Damian, 2021; Opatha & Dayarathna,

2024; Peeters et al., 2020; Ratnam & Devi, 2024; Wang et al., 2024), and two combined review and framework synthesis (Kurikala & Parvathi, 2023; Shet et al., 2021). In addition, three articles presented viewpoint perspectives (Andersen, 2017; Green, 2017; Rasmussen & Ulrich, 2015), one was discursive (Angrave et al., 2016), and two were conceptual (Gal, et al., 2020; Madhani, 2023).

Geographically, the studies originate from diverse regions: ten from Europe (Andersen, 2017; Angrave, et al., 2016; Coolen, et al., 2023; Dahlbom, et al., 2020; Fernandez & Gallardo-Gallardo, 2021; Green, 2017; McCartney & Fu, 2022; Minbaeva, 2018; Peeters, et al., 2020; Wirges & Neyer, 2023), four from Asia (Kurikala & Parvathi, 2023; Madhani, 2023; Opatha & Dayarathna, 2024; Ratnam & Devi, 2024), three from the USA (Levenson & Fink, 2017; Marler & Boudreau, 2017; Vargas, et al., 2018), and one from Brazil (Moraes & Damian, 2021). Several studies were co-authored by researchers from different countries (Bonilla-Chaves, et al., 2024; Rasmussen & Ulrich, 2015; Shet, et al., 2021), also including New Zealand (Cho, et al., 2023) and Australia (Gal, et al., 2020; Wang, et al., 2024). The publication years range from 2015 to 2024.

Table 1: Data Extraction: Factors Influencing the Adoption of HR Analytics in Western Settings

Author(s)	Year	Region	Publication Source	Population	Research Method	Themes Influencing HRA Adoption
Andersen	2017	Denmark	Journal of Organizational Effectiveness		Viewpoint	Data Governance; External Influences; Organizational Culture; Organizational Structure; Skills, Capabilities & Expertise; Strategic Focus & Insights; Technology & Digital Infrastructure
Angrave et al.	2016	UK	Human Resource Management Journal		Discursive	External Influences; Organizational Culture; Skills, Capabilities & Expertise; Strategic Focus & Insights
Bonilla-Chaves et al.	2024	Costa Rica and Spain	Electronic Research Archive	Valid questionnaire responses were collected from 554 HR analytics users via an American crowdsourcing platform	Quantitative	Individual Motivation & Beliefs; Organizational Culture
Cho et al.	2023	New Zealand and South Korea	Administrative Sciences		Review	Data Governance; Ethics; External Influences; Leadership; Organizational Culture; Organizational Structure; Organizational Resources & Readiness; Skills, Capabilities & Expertise; Strategic Focus & Insights; Technology & Digital Infrastructure
Coolen et al.	2023	Netherlands	Human Resource Management Review		Review	Data Governance; Ethics; External Influences; Individual Motivation & Beliefs; Leadership; Organizational Culture; Organizational Resources & Readiness; Skills, Capabilities & Expertise; Strategic Focus & Insights; Technology & Digital Infrastructure
Dahlbom et al.	2020	Finland	Baltic Journal of Management	HR and analytics professionals from nine of Finland's largest globally operating companies across diverse industries participated in the study	Qualitative	Data Governance; Ethics; Individual Motivation & Beliefs; Leadership; Organizational Culture; Organizational Structure; Skills, Capabilities & Expertise; Strategic Focus & Insights
Fernandez & Gallardo-Gallardo	2021	Spain	Competitiveness Review		Review	Data Governance; External Influences; Leadership; Organizational Culture; Organizational Structure; Skills, Capabilities & Expertise; Strategic Focus & Insights; Technology & Digital Infrastructure
Gal et al.	2020	Australia and Denmark	Information and Organization		Conceptual	Ethics
Green	2017	UK	Journal of Organizational Effectiveness		Viewpoint	Data Governance; Ethics; External Influences; Leadership; Organizational Culture; Organizational Resources & Readiness; Skills, Capabilities & Expertise; Strategic Focus & Insights

Table 1: (continued)

Author(s)	Year	Region	Publication Source	Population	Research Method	Themes Influencing HRA Adoption
Kurikala & Parvathi	2023	India	Journal of Chinese Human Resource Management		Review and framework synthesis	Data Governance; Ethics; External Influences; Individual Motivation & Beliefs; Leadership; Organizational Culture; Organizational Resources & Readiness; Skills, Capabilities & Expertise; Strategic Focus & Insights; Technology & Digital Infrastructure
Levenson & Fink	2017	USA	Journal of Organizational Effectiveness		Review	Data Governance; Leadership; Organizational Resources & Readiness; Organizational Structure; Strategic Focus & Insights
Madhani	2023	India	Compensation and Benefits Review		Conceptual	Data Governance; Ethics; Individual Motivation & Beliefs; Leadership; Organizational Culture; Organizational Resources & Readiness; Skills, Capabilities & Expertise; Strategic Focus & Insights; Technology & Digital Infrastructure
Marler & Boudreau	2017	USA	International Journal of Human Resource Management		Review	External Influences; Individual Motivation & Beliefs; Leadership; Organizational Culture; Organizational Structure; Skills, Capabilities & Expertise; Technology & Digital Infrastructure
McCartney & Fu	2022	Ireland	Journal of Organizational Effectiveness		Review	Data Governance; Ethics; External Influences; Organizational Culture; Skills, Capabilities & Expertise; Technology & Digital Infrastructure
Minbaeva	2018	Denmark	Human Resource Management		Phenomenological	Data Governance; Ethics; External Influences; Individual Motivation & Beliefs; Leadership; Organizational Culture; Organizational Resources & Readiness; Skills, Capabilities & Expertise; Strategic Focus & Insights; Technology & Digital Infrastructure
Moraes & Damian	2021	Brazil	AtoZ		Review	Data Governance; Ethics; External Influences; Individual Motivation & Beliefs; Leadership; Organizational Culture; Organizational Resources & Readiness; Skills, Capabilities & Expertise; Strategic Focus & Insights; Technology & Digital Infrastructure
Opatha & Dayarathna	2024	Sri Lanka	South Asian Journal of Management		Review	Data Governance; Ethics; External Influences; Leadership; Organizational Culture; Organizational Resources & Readiness; Skills, Capabilities & Expertise; Strategic Focus & Insights; Technology & Digital Infrastructure
Peeters et al.	2020	Netherlands	Journal of Organizational Effectiveness		Review	Data Governance; Ethics; External Influences; Leadership; Organizational Culture; Organizational Resources & Readiness; Organizational Structure; Skills, Capabilities & Expertise; Strategic Focus & Insights; Technology & Digital Infrastructure

Table 1: (continued)

Author(s)	Year	Region	Publication Source	Population	Research Method	Themes Influencing HRA Adoption
Rasmussen & Ulrich	2015	Netherlands and USA	Organizational Dynamics		Viewpoint	Ethics; External Influences; Individual Motivation & Beliefs; Leadership; Organizational Culture; Organizational Resources & Readiness; Organizational Structure; Skills, Capabilities & Expertise; Strategic Focus & Insights
Ratnam & Devi	2024	India	Human Resource Development International		Review	Data Governance; Ethics; External Influences; Individual Motivation & Beliefs; Leadership; Organizational Culture; Organizational Resources & Readiness; Skills, Capabilities & Expertise; Strategic Focus & Insights; Technology & Digital Infrastructure
Shet et al.	2021	India, France, and UK	Journal of Business Research		Review and framework synthesis	Data Governance; Ethics; External Influences; Individual Motivation & Beliefs; Leadership; Organizational Culture; Organizational Resources & Readiness; Organizational Structure; Skills, Capabilities & Expertise; Strategic Focus & Insights; Technology & Digital Infrastructure
Vargas et al.	2018	USA	International Journal of Human Resource Management	Valid questionnaire responses were collected from 123 HR professionals employed in companies across various industries that have adopted HR analytics	Quantitative	Data Governance; External Influences; Individual Motivation & Beliefs; Leadership; Organizational Culture; Organizational Resources & Readiness
Wang et al.	2024	China, Australia, and USA	Journal of Business Research		Review	Data Governance; Ethics; External Influences; Individual Motivation & Beliefs; Leadership; Organizational Culture; Skills, Capabilities & Expertise; Strategic Focus & Insights; Technology & Digital Infrastructure
Wirges & Neyer	2023	Germany	Review of Managerial Science	Seventeen HR analytics experts from the DACH region (Germany, Austria, and Switzerland) participated in the study	Qualitative	Data Governance; External Influences; Leadership; Organizational Culture; Organizational Resources & Readiness; Organizational Structure; Skills, Capabilities & Expertise; Strategic Focus & Insights; Technology & Digital Infrastructure

Based on the scoping literature review, a broad range of factors influencing the adoption of HRA was identified. These factors have been organized using the analytical lens of the TOE framework, complemented by the individual-level perspective of TAM3. While these frameworks provided the conceptual foundation for our study, the results are not presented in strict alignment with their sequence of contexts. Instead, the findings are introduced in an order that moves from the broader external context toward the more specific, internal aspects of adoption. Accordingly, the environmental factors are presented first, followed by technological, organizational, and finally individual-level influences. This progression—from macro to micro—was chosen to improve readability and support a more intuitive understanding of the multi-layered nature of HRA adoption. The contexts are broken down into 11 distinctive themes and 30 subthemes. Figure 3 illustrates the thematic structure.

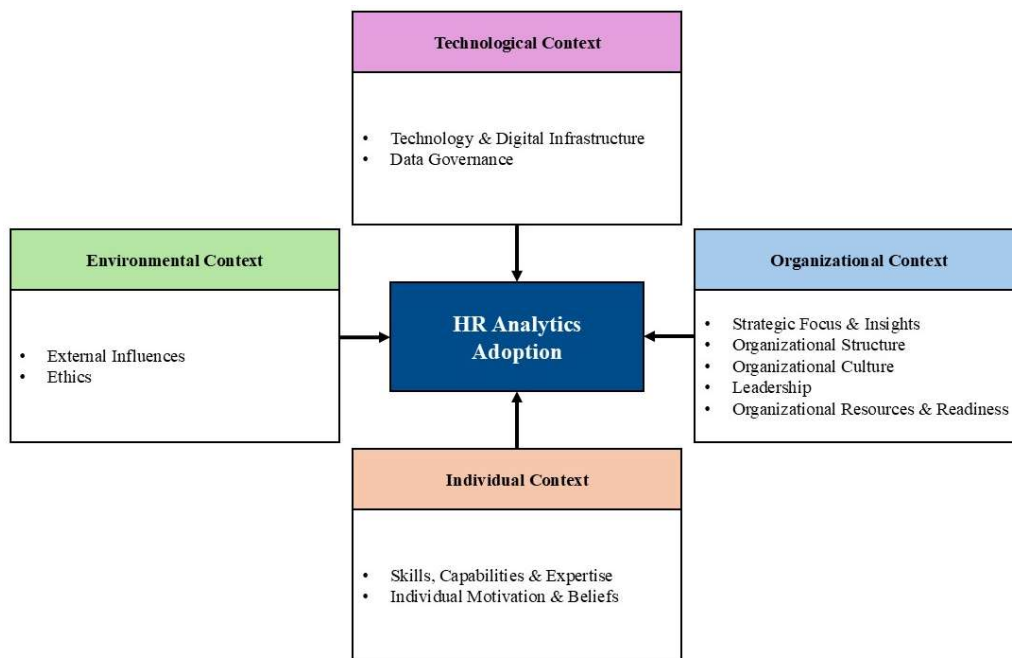


Figure 3: Contexts and Themes Influencing HR Analytics Adoption

At the beginning of each subtheme, the relevant articles addressing that area are listed.

If a specific factor is mentioned without further attribution, it was discussed in at least three of the listed sources; for factors mentioned in only one or two articles, the source(s) are named directly. To further enhance readability, the **most essential factors are printed in bold** within the text, facilitating a quick identification of the core aspects. Additionally, each context chapter

begins with a visual overview in the form of a partial map (Figures 4 to 7), illustrating the included themes and subthemes before they are discussed in detail in the text.

5.2 Factors Influencing HR Analytics Adoption: Environmental Context

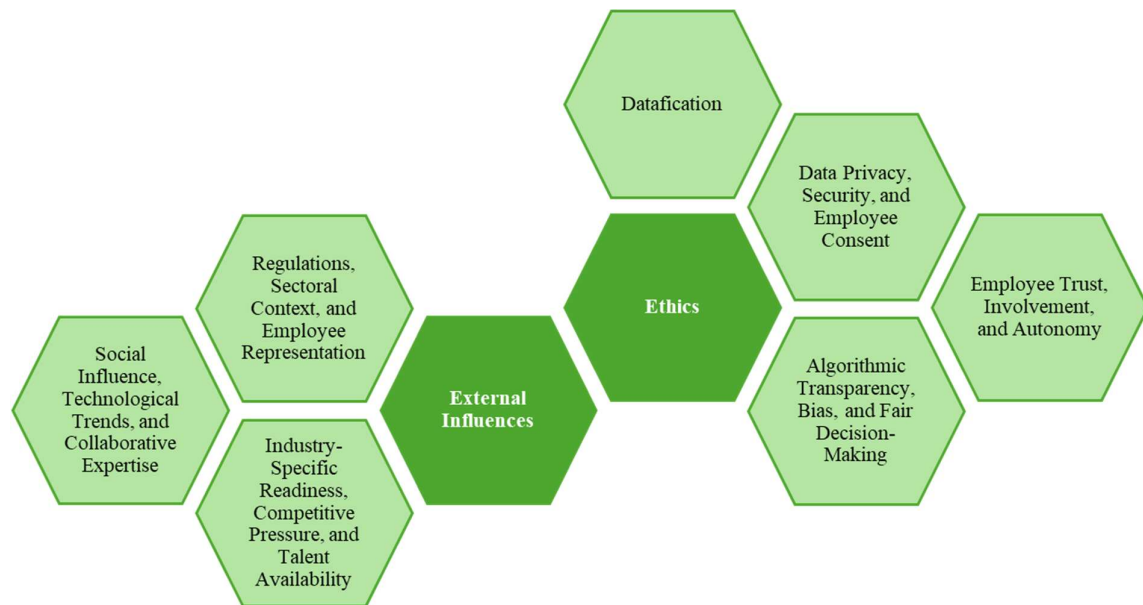


Figure 4: Mapping the Environmental Context

5.2.1 External Influences

Regulations, Sectoral Context, and Employee Representation

This subtheme draws on insights from eight studies (Cho, et al., 2023; Coolen, et al., 2023; Fernandez & Gallardo-Gallardo, 2021; McCartney & Fu, 2022; Opatha & Dayarathna, 2024; Peeters, et al., 2020; Shet, et al., 2021; Wang, et al., 2024), which identify the following influencing factors.

Whether an organization operates in the **public or private sector** impacts its adoption of HRA. Cho et al. (2023) particularly emphasize that public organizations often face political interference, budget constraints, and stricter regulatory requirements due to the public nature of their data. Moreover, all organizations are required to ensure full compliance with **regulatory frameworks** related to data usage and analytics, which may encourage or limit HRA practices. In addition, the **involvement of employee representatives**, such as works councils and trade

unions may impact HRA adoption, especially in countries where these actors hold substantial power.

Industry-Specific Readiness, Competitive Pressure, and Talent Availability

Seven studies (Andersen, 2017; Coolen, et al., 2023; Fernandez & Gallardo-Gallardo, 2021; Kurikala & Parvathi, 2023; Marler & Boudreau, 2017; Opatha & Dayarathna, 2024; Shet, et al., 2021) identify a range of influencing factors associated with this subtheme.

Competitive pressure may compel organizations to adopt HRA to keep pace with rivals or avoid falling behind. In some cases, the use of HRA becomes a necessity rather than a choice, driven by economic rationality and the need to maintain a competitive edge. The **type of industry** further influences the readiness for HRA adoption. Certain sectors are better positioned to implement these practices due to more advanced data and technological infrastructures. In contrast, industries with limited digital maturity may face greater barriers. Furthermore, the **availability of analytically and technically skilled HR professionals** on the labor market affects the ability of organizations to recruit individuals with the necessary competencies to carry out effective HRA.

Social Influence, Technological Trends, and Collaborative Expertise

A total of 13 articles (Angrave, et al., 2016; Coolen, et al., 2023; Fernandez & Gallardo-Gallardo, 2021; Green, 2017; Minbaeva, 2018; Moraes & Damian, 2021; Opatha & Dayarathna, 2024; Peeters, et al., 2020; Rasmussen & Ulrich, 2015; Ratnam & Devi, 2024; Vargas, et al., 2018; Wang, et al., 2024; Wirges & Neyer, 2023) highlight key factors relevant to this subtheme.

Social influence emerges from various external sources, such as professional networks, peers, vendors, and even family and friends. These influences shape how HRA is perceived and approached within organizations and can affect whether specific HRA practices are adopted or dismissed. Another influencing factor is the **availability of technology** in the external market—specifically its maturity, accessibility, and alignment with organizational needs. Green (2017) further highlights that **staying attuned to the rapidly evolving technological landscape** enables organizations to identify new opportunities and adopt emerging tools, thereby advancing HRA adoption. Moreover, **collaboration with external specialists**, including consultancies, HR vendors, and academics can accelerate adoption efforts and bring in expertise

that enhances the credibility of HRA initiatives. Such external engagement offers opportunities for benchmarking and shared learning. Academic partnerships, in particular, provide impartial guidance on necessary skills, evolving research findings, and the application of specific terminology.

5.2.2 Ethics

Data Privacy, Security, and Employee Consent

14 of the reviewed articles (Cho et al., 2023; Coolen et al., 2023; Dahlbom et al., 2020; Green, 2017; Kurikala & Parvathi, 2023; Madhani, 2023; McCartney & Fu, 2022; Moraes & Damian, 2021; Opatha & Dayarathna, 2024; Peeters et al., 2020; Rasmussen & Ulrich, 2015; Ratnam & Devi, 2024; Shet et al., 2021; Wang et al., 2024) identify factors relevant to this subtheme.

Compliance with **data privacy legislation** such as the GDPR and other country-specific regulations is crucial. Peeters et al. (2020) encourage organizations to seek guidance from data privacy specialists to navigate this regulatory landscape. Beyond legal compliance, organizations should be guided by moral responsibility in handling employee data. Ensuring **data security**, including protection against external intrusions such as cyber-attacks and viruses, is essential for building stakeholder trust and gaining broader support for HRA initiatives. Furthermore, **transparency** is central to ensure ethical data practices. This encompasses clearly communicating how data will be used, determining who has access, and whether they are authorized to view it. It also involves being conscious of the level of detail shared—for example, ensuring that data cannot be traced back to specific individuals and maintaining **confidentiality** in reports or surveys. **Consent management** is an integral part of this process, requiring that data is only used when explicit consent has been granted. According to Wang et al. (2024), this also includes allowing employees to opt out.

Additionally, McCartney and Fu (2022) highlight that **organizational data collection** increasingly extends beyond the workplace, capturing aspects of employees' personal lives through tools like mobile devices and network monitoring—raising significant ethical and privacy concerns. These developments underscore the need for organizations to continuously reflect on what data is truly necessary to collect and where the line should be drawn to avoid overly invasive practices. McCartney and Fu (2022) and Ratnam and Devi (2024) therefore advise establishing **control mechanisms**, such as appointing a Chief Data Officer or creating a data governance board to review analytics initiatives before their adoption. Shet et al. (2021) similarly stress the need for caution when sharing employee data with third parties, such as HR

vendors. Measures like document classification, internal data policies, and organization-specific agreements are recommended to preserve privacy. Furthermore, **data storage location** and **retention periods** should be considered in regard to ethical data governance.

Algorithmic Transparency, Bias, and Fair Decision-Making

Ten studies (Coolen et al., 2023; Dahlbom et al., 2020; Gal et al., 2020; McCartney & Fu, 2022; Minbaeva, 2018; Moraes & Damian, 2021; Opatha & Dayarathna, 2024; Peeters et al., 2020; Shet et al., 2021; Wang et al., 2024) reflect on a variety of factors connected to this subtheme.

When algorithmic systems become so complex that their inner workings are difficult to grasp, there is a central concern about the presence of **algorithmic bias**, resulting in unjust and biased decisions, potentially reinforcing self-fulfilling prophecies (Peeters et al., 2020) or even resulting in discriminatory outcomes (Wang et al., 2024). **Algorithmic transparency** involves making clear how analytics-based decisions are made, including the logic that drives them, what data is used, and how employees are assessed. Being open about the purpose, processes, and outcomes of analytics is key to increasing understanding and achieving buy-in. Gal et al. (2020) stress that without the necessary skills to understand and work with the information provided, employees may experience confusion or lose confidence in the system. They further advise communicating not only the decision logic but also the limitations and uncertainties associated with algorithmic outputs (Gal, et al., 2020).

Employee Trust, Involvement, and Autonomy

Nine articles (Cho, et al., 2023; Coolen, et al., 2023; Gal, et al., 2020; Green, 2017; Minbaeva, 2018; Opatha & Dayarathna, 2024; Peeters, et al., 2020; Ratnam & Devi, 2024; Wang, et al., 2024) recognize factors within this subtheme.

Employee trust in ethical data collection and usage influences the adoption of HRA. A lack of trust can lead to employee discomfort and may result in resistance or even the intentional sabotage of analytics efforts, for example by providing inaccurate data. To reduce this risk and strengthen the buy-in, it is important to actively **involve employees** in the process, enabling them to engage with the data and understand its purpose. Gal et al. (2020) also explore the ethical implications of using HRA to **nudge** individuals toward specific behaviors. While such practices may be intended to support organizational goals, they can also manipulate individual

decisions, potentially conflicting with personal interests. This raises ethical concerns about autonomy and informed decision-making.

Datafication

One article (Gal, et al., 2020) identifies **datafication** as an ethical challenge regarding HRA adoption, referring to the reduction of individuals to data points. Datafication risks reinforcing oversimplified categorization, potentially limiting the ability to reflect on an individual’s actions and their broader impact. Moreover, providing one-sided, data-driven feedback may hinder the development of practical organizational wisdom, including insights into workplace culture and shared values. Gal et al. (2020) emphasize the need to move beyond metrics and incorporate a more ethically sensitive approach. They argue that HRA should balance algorithmic insights with human interpretation and judgment to better reflect the complexity and nuance of real-world work environments (Gal, et al., 2020).

5.3 Factors Influencing HR Analytics Adoption: Technological Context

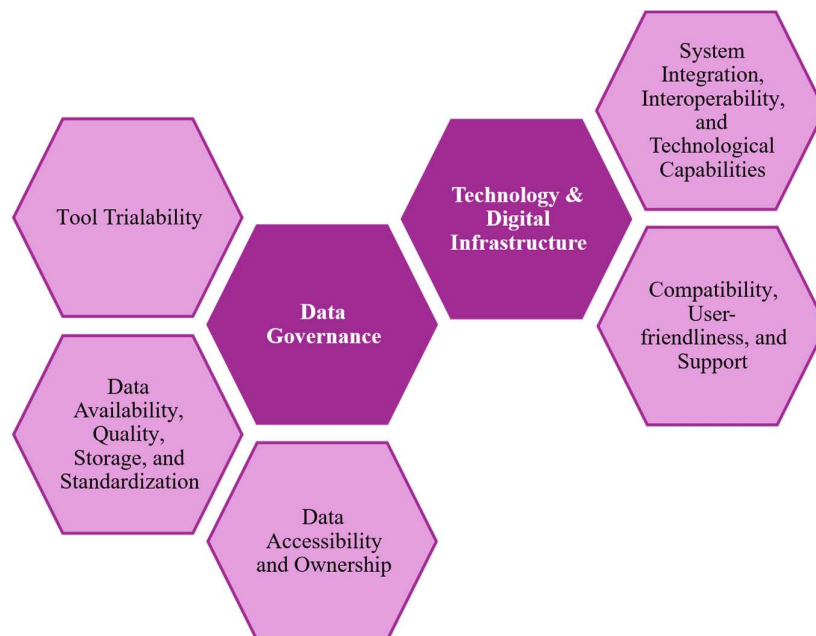


Figure 5: Mapping the Technological Context

5.3.1 Technology & Digital Infrastructure

System Integration, Interoperability, and Technological Capabilities

13 articles (Andersen, 2017; Cho, et al., 2023; Coolen, et al., 2023; Kurikala & Parvathi, 2023; Marler & Boudreau, 2017; McCartney & Fu, 2022; Minbaeva, 2018; Moraes & Damian, 2021; Opatha & Dayarathna, 2024; Peeters, et al., 2020; Ratnam & Devi, 2024; Shet, et al., 2021; Wang, et al., 2024) highlight key factors relevant to this subtheme.

System **integration** is one core factor that influences HRA adoption. Part of that is ensuring **interoperability** between systems—meaning the seamless connection and exchange of information across different platforms—which is critical to overcome siloed data environments. However, integration becomes significantly more challenging when technologies are complex (Kurikala & Parvathi, 2023) or poorly aligned. Moreover, the **capability** of employed technologies, such as capturing, storing, accessing, processing, and visualizing data, along with the available analytical methods, impact the analytical level that can be realized with HRA.

Compatibility, User-friendliness, and Support

Eight studies (Coolen, et al., 2023; Fernandez & Gallardo-Gallardo, 2021; Kurikala & Parvathi, 2023; Madhani, 2023; McCartney & Fu, 2022; Shet, et al., 2021; Wang, et al., 2024; Wirges & Neyer, 2023) identify factors within this subtheme.

Central for the adoption of HRA is the **compatibility** of systems with organizational goals and values, so that technological solutions align closely with strategic aims. At the same time, IT systems must be scalable and flexible enough to adapt to evolving business needs (Coolen et al., 2023). Furthermore, when analytics systems are deemed difficult to understand or operate, their adoption is likely to fail. A **user-centric design**, tailored to the needs and knowledge levels of various stakeholders, can enhance ease of use and perceived relevance. In addition to design considerations, Madhani (2023) highlights the importance of providing sufficient **technical support** to users. Ongoing support services play a crucial role in facilitating user engagement, resolving technical issues, and sustaining the adoption of HRA tools.

5.3.2 Data Governance

Data Availability, Quality, Storage, and Standardization

18 articles (Andersen, 2017; Cho, et al., 2023; Coolen et al., 2023; Dahlbom et al., 2020; Fernandez & Gallardo-Gallardo, 2021; Green, 2017; Kurikala & Parvathi, 2023; Levenson & Fink, 2017; Madhani, 2023; McCartney & Fu, 2022; Minbaeva, 2018; Moraes & Damian, 2021; Opatha & Dayarathna, 2024; Peeters et al., 2020; Ratnam & Devi, 2024; Shet et al., 2021; Wang et al., 2024; Wirges & Neyer, 2023) explore a range of factors contributing to this subtheme.

To enable meaningful analyses, data must first be available in sufficient quantity and collected from appropriate sources. However, **data availability** alone is not enough; ensuring high **data quality** is also critical, as the quality of analytics outcomes directly depends on the quality of the underlying data. High-quality data must be complete, accurate, reliable, up to date, and consistent. Within organizations, workforce data is often scattered across fragmented systems and silos, leading to duplication, inconsistencies, and integration challenges. Consolidating data into a centralized **storage system** helps overcome these issues by eliminating duplicate entries, standardizing metrics, coding, and time frames, as well as providing a clearer overview of existing data assets.

Standardization plays a crucial role in supporting data quality and integration. Organizations should establish consistent definitions and terminology for key HR metrics, such as headcount, and apply these standards uniformly across different functions, divisions, and regions. Minbaeva (2018) suggests that academic publications can serve as useful references when setting such standards. Levenson and Fink (2017) further emphasize that standardization should extend to defining which analytical methods are most appropriate for specific variables and analytical situations. Additionally, developing a standardized process specifically aimed toward generating actionable insights can enhance the effectiveness of analytics projects.

Manual data input also affects the reliability of HRA efforts. Incorrect or incomplete entries can introduce errors that undermine analysis quality, making careful attention to data input processes essential. Even with thorough data validation and cleaning, it is generally accepted that perfect data quality is unachievable. Therefore, Levenson and Fink (2017) recommend proceeding once further efforts yield diminishing added value. Finally, rather than relying solely on existing datasets that may only indirectly address the analysis objective, Levenson and Fink (2017) recommend the collection of new, targeted data from relevant sample groups to ensure closer alignment with specific analytical goals.

Tool Trialability

Four articles (Coolen, et al., 2023; Minbaeva, 2018; Ratnam & Devi, 2024; Vargas, et al., 2018) detect the opportunity for employees to become familiar and experiment with HRA—referred to as **tool trialability**—as an important factor shaping individual attitudes toward HRA adoption. Providing opportunities for hands-on engagement with HRA technologies, for instance through training, helps build confidence in employees’ capabilities and encourages broader use of HRA.

Data Accessibility and Ownership

11 studies (Cho, et al., 2023; Coolen, et al., 2023; Dahlbom, et al., 2020; Kurikala & Parvathi, 2023; Madhani, 2023; Moraes & Damian, 2021; Opatha & Dayarathna, 2024; Peeters, et al., 2020; Ratnam & Devi, 2024; Shet, et al., 2021; Wang, et al., 2024) examine aspects of this subtheme.

As access to data is fundamental for the adoption of HRA, data silos that restrict **access** across functions can significantly delimit the potential to generate valuable insights. Additionally, clear **data ownership**, as emphasized by Shet et al. (2021) and Kurikala and Parvathi (2023), is essential for assigning responsibility for maintaining data quality, ensuring accuracy, and monitoring usage. This becomes particularly important as HRA often relies on data from multiple functions beyond HR, making cross-functional data sharing and access agreements necessary. Cho et al. (2023) recommend establishing formal data-sharing regulations to address these challenges and promote seamless collaboration.

5.4 Factors Influencing HR Analytics Adoption: Organizational Context

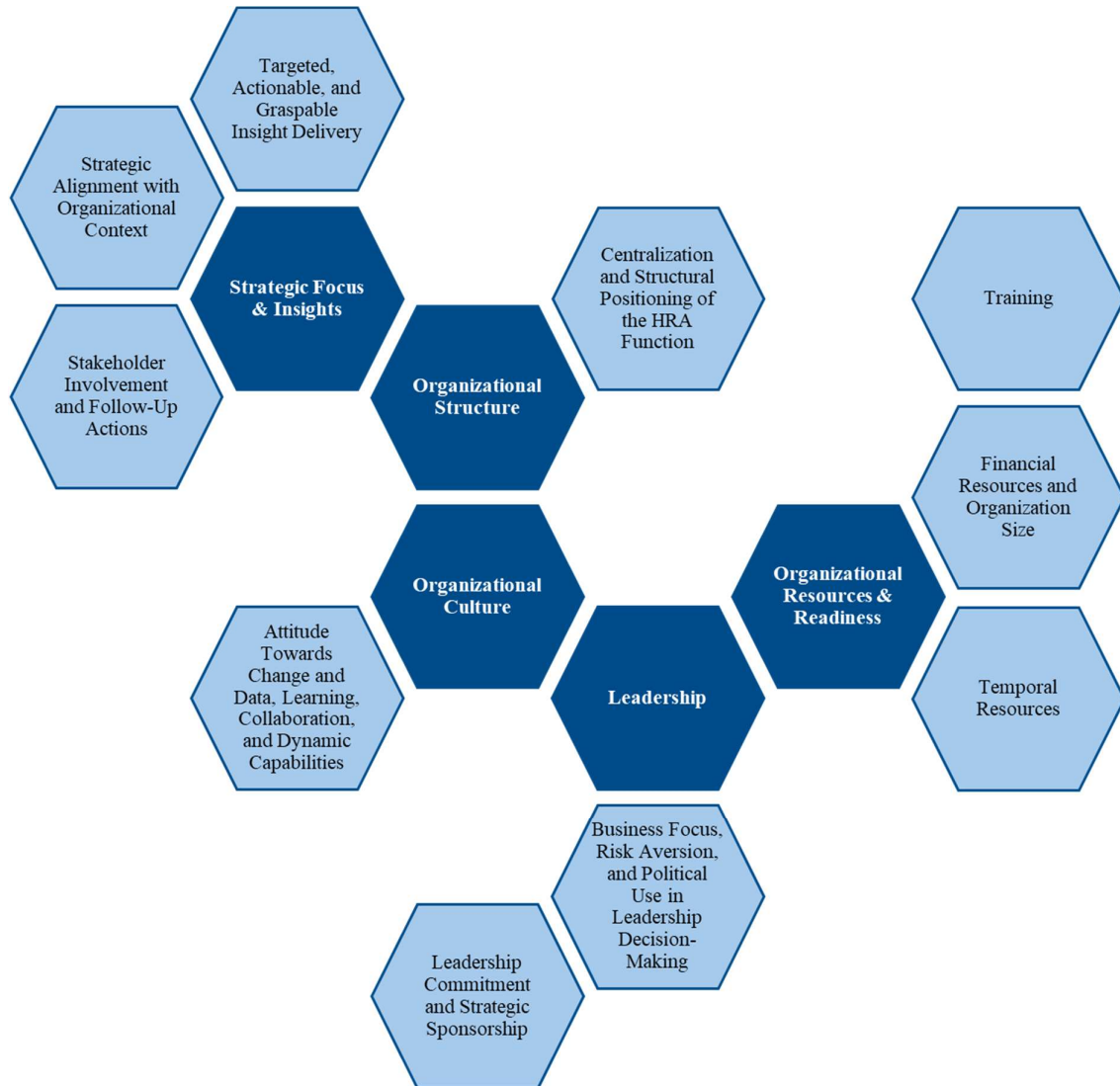


Figure 6: Mapping the Organizational Context

5.4.1 Strategic Focus & Insights

Strategic Alignment with Organizational Context

16 studies (Andersen, 2017; Angrave, et al., 2016; Coolen, et al., 2023; Dahlbom, et al., 2020; Fernandez & Gallardo-Gallardo, 2021; Green, 2017; Levenson & Fink, 2017; Madhani, 2023; Minbaeva, 2018; Moraes & Damian, 2021; Opatha & Dayarathna, 2024; Peeters, et al., 2020; Rasmussen & Ulrich, 2015; Shet, et al., 2021; Wang, et al., 2024; Wirges & Neyer, 2023) distinguish a variety of factors within this subtheme.

The adoption of HRA is influenced by its alignment with the organization's broader strategic context, including linking it to **organizational needs, values, and business drivers**. This requires a thorough understanding of the business model, stakeholder interests, strategic objectives, and barriers to performance. HRA initiatives should be guided by clearly framed problems based on current and future business challenges rather than existing datasets and should focus on areas where it can generate the most value. Particularly, Green (2017) stresses that organizations should assess the potential value of insights before committing resources, focusing on high-impact, cost-effective projects. A strong emphasis should be placed on how employees contribute to overall organizational success, ensuring that HRA supports informed strategic decision-making.

Alignment must also extend to **existing resources, processes, and practices**. Integrating HRA with current HR practices, such as recruitment or learning, as well as decision-making processes, technologies, skills, and culture is essential, as misalignment can hinder the adoption process. Organizations should focus their analytic resources selectively on a few strategically important areas rather than dispersing efforts across numerous less impactful projects (Levenson & Fink, 2017).

A clear **HR strategy** provides essential direction for positioning HRA within the broader HR agenda. This strategy must be tightly connected to the organization's overall business strategy to strengthen adoption. Furthermore, having a defined **HRA strategy and vision** helps guide the development and institutionalization of analytics within the organization, establishing it as a core component of the HR function and reinforcing its strategic value over time. Finally, Wirges and Neyer (2023) note that strategic clarity around the **scope** of HRA—including roles, responsibilities, and task allocation—is essential for effective adoption. Positioning HRA as a **strategic priority** promotes organization-wide buy-in and sustained commitment, which can be further reinforced by communicating successful use cases across the organization (Peeters et al., 2020).

Stakeholder Involvement and Follow-Up Actions

This subtheme encompasses factors discussed in eight articles (Coolen, et al., 2023; Levenson & Fink, 2017; Madhani, 2023; Minbaeva, 2018; Opatha & Dayarathna, 2024; Peeters, et al., 2020; Wang, et al., 2024; Wirges & Neyer, 2023).

The **acknowledgement and involvement of stakeholders** promotes acceptance, strengthens organization-wide buy-in, and increases the likelihood of successful adoption. Stakeholders of HRA adoption include employees, their representatives, functional stakeholders such as IT and finance, HR professionals, management, and relevant external actors. Additionally, addressing the needs of and collaborating with those responsible for enacting changes—typically line managers—is particularly important (Peeters et al., 2020) to foster a sense of ownership and further enhance motivation (Wang et al., 2024).

Ensuring that insights are **followed up by concrete actions** is another factor impacting HRA adoption highlighted by Levenson (2017) and Minbaeva (2018). Analytical results should lead to meaningful change, particularly as employees may expect visible efforts once insights are communicated. Continuous monitoring of these follow-up measures is necessary to track progress and ensure impact. Subsequently, evaluating the effectiveness and efficiency of HRA initiatives is essential for legitimization (Wirges & Neyer, 2023).

Targeted, Actionable, and Graspable Insight Delivery

12 studies (Andersen, 2017; Cho, et al., 2023; Coolen, et al., 2023; Dahlbom, et al., 2020; Kurikala & Parvathi, 2023; Minbaeva, 2018; Moraes & Damian, 2021; Peeters, et al., 2020; Ratnam & Devi, 2024; Shet, et al., 2021; Wang, et al., 2024; Wirges & Neyer, 2023) discover a collection of factors within this subtheme.

How insights are delivered plays a crucial role in the adoption of HRA. To ensure relevance and usability, insights must be **actionable**, meaning they can be translated into concrete actions (Andersen, 2017; Minbaeva, 2018). They should also be **tailored to the intended audience**, considering the specific implications for different stakeholders, and presented in a way that is **graspable** and easy to interpret. To further enhance understanding, results should be **contextualized** by relating them to the end user's specific situation and background (Wang et al., 2024). Insights also need to be considered from **multiple perspectives**, such as individual, team and unit level, to avoid oversimplified conclusions and enable a more comprehensive understanding (Minbaeva, 2018). Maintaining **consistent communication and using metrics** are essential when working with data across departments and cultural contexts (Dahlbom et al., 2020). In addition, **visualization** techniques and **storytelling** help structure insights in an engaging and accessible format, further enhancing their clarity and impact.

5.4.2 Organizational Structure

Centralization and Structural Positioning of the HRA Function

11 articles (Andersen, 2017; Cho, et al., 2023; Dahlbom, et al., 2020; Fernandez & Gallardo-Gallardo, 2021; Levenson & Fink, 2017; Marler & Boudreau, 2017; Minbaeva, 2018; Peeters, et al., 2020; Rasmussen & Ulrich, 2015; Shet, et al., 2021; Wirges & Neyer, 2023) highlight factors within this subtheme.

A central consideration is the **placement of the HRA function** within the organization. While some scholars advocate for embedding it within the HR department, others support positioning it outside. Despite differing views, there is a broad consensus on the value of a **centralized HRA function**, which can coordinate efforts and support the organization during adoption. Each structural choice carries implications for integration, collaboration, and visibility, and organizations are advised to consider these carefully, as the literature does not point to a single dominant model. Regardless, Peeters et al. (2020) propose dividing the HRA function into **specialized sub-teams**—such as reporting and analytics—while stressing the importance of collaborating closely and coordinating efforts. Additionally, structural changes within organizations, such as business unit reorganizations, may hinder the effectiveness of HRA if such changes are not properly reflected in the underlying data systems (Minbaeva, 2018).

5.4.3 Organizational Culture

Attitude Towards Change and Data, Learning, Collaboration, and Dynamic Capabilities

A total of 22 studies (Andersen, 2017; Angrave, et al., 2016; Bonilla-Chaves, et al., 2024; Cho, et al., 2023; Coolen, et al., 2023; Dahlbom, et al., 2020; Fernandez & Gallardo-Gallardo, 2021; Green, 2017; Kurikala & Parvathi, 2023; Madhani, 2023; Marler & Boudreau, 2017; McCartney & Fu, 2022; Minbaeva, 2018; Moraes & Damian, 2021; Opatha & Dayarathna, 2024; Peeters, et al., 2020; Rasmussen & Ulrich, 2015; Ratnam & Devi, 2024; Shet, et al., 2021; Vargas, et al., 2018; Wang, et al., 2024; Wirges & Neyer, 2023) emphasize an array of factors within this subtheme.

A culture characterized by openness to change, continuous learning, and data-driven thinking is essential for HRA adoption. **Acceptance, commitment, and support** from both employees and management play a crucial role in this process. Connected to that is **social influence**, as individuals tend to adjust their perceptions of HRA in response to perceived approval or endorsement by peers and organizational leaders.

A part of that culture should be valuing **evidence-based** decision-making and data sharing, as this increases the likelihood that insights derived from analytics will be trusted and applied. Familiarity with data concepts, ease in working with metrics, and a shared belief in the value of HRA are foundational to its adoption. Furthermore, organizations that encourage curiosity, promote knowledge sharing, and treat mistakes as opportunities for learning are more likely to embrace new technologies like HRA. Such a culture of learning also reflects open-mindedness toward new ideas and a willingness to re-evaluate established practices and assumptions. This can further be strengthened by fostering agility and ensuring **dynamic capabilities**, meaning the organization's ability to flexibly reconfigure and reallocate resources in response to shifting needs and priorities.

Moreover, the **collaborative and communicative** culture is influential to HRA adoption. Cross-functional collaboration—both formal and informal—between HRA professionals and other departments such as finance, IT, and operations promotes the exchange of perspectives, skills, and domain knowledge. Avoiding isolated working structures helps mitigate organizational silos. Opatha and Dayarathna (2024) highlight that a culture of **trust** further encourages open information sharing.

5.4.4 Leadership

Leadership Commitment and Strategic Sponsorship

16 studies (Cho, et al., 2023; Coolen, et al., 2023; Dahlbom, et al., 2020; Green, 2017; Kurikala & Parvathi, 2023; Madhani, 2023; Marler & Boudreau, 2017; Minbaeva, 2018; Moraes & Damian, 2021; Opatha & Dayarathna, 2024; Peeters, et al., 2020; Ratnam & Devi, 2024; Shet, et al., 2021; Vargas, et al., 2018; Wang, et al., 2024; Wirges & Neyer, 2023) discuss factors within this subtheme.

Support from top management is critical for HRA adoption—not only in terms of signaling the importance of HRA to the wider organization, but also in providing access to necessary financial, political, and technological resources as well as securing buy-in from other stakeholders. Active **leadership engagement** includes ongoing communication with the HRA team, regular consultation to align analytics with business objectives, and close involvement throughout the adoption process. This enables leaders to better understand the insights generated and to act on them effectively. Vargas et al. (2018) and Wang et al. (2024) further highlight the positive impact managers have on HRA adoption by serving as **change agents**

who encourage the use of analytics, drive adoption through example, and help embed HRA practices into strategic decision-making.

Business Focus, Risk Aversion, and Political Use in Leadership Decision-Making

Eight studies (Coolen, et al., 2023; Dahlbom, et al., 2020; Fernandez & Gallardo-Gallardo, 2021; Green, 2017; Levenson & Fink, 2017; Madhani, 2023; Marler & Boudreau, 2017; Rasmussen & Ulrich, 2015) underline a mixture of factors within this subtheme.

Managers with a clear **business focus** and a **data-driven decision-making** approach—characterized by a willingness to rely on analytics even when insights contradict personal beliefs or past experience—are essential and positively influence HRA adoption. Coolen et al. (2023) note that managerial **risk aversion** may impact adoption decisions, as some leaders may avoid committing to new technologies due to uncertainty. Furthermore, Levenson and Fink (2017) and Rasmussen and Ulrich (2015) warn of potential **political use** of analytics, where data is leveraged to reinforce personal agendas or shift power dynamics, rather than generate objective insights. **Sunk-cost pressure** is another risk highlighted by Levenson and Fink (2017), who caution that leaders may feel compelled to overuse analytics technologies to justify large initial investments, even if the insights produced add no additional value.

5.4.5 Organizational Resources & Readiness

Financial Resources and Organization Size

Eight studies (Cho, et al., 2023; Coolen, et al., 2023; Green, 2017; Kurikala & Parvathi, 2023; Minbaeva, 2018; Opatha & Dayarathna, 2024; Ratnam & Devi, 2024; Shet, et al., 2021) discuss factors central to this subtheme.

Both initial HRA adoption and long-term operational success depend on the availability of sufficient financial means, requiring adequate **investment** across several areas. For instance, investments in talent include the ability to offer competitive compensation and employee training as well as ensuring a sufficiently staffed HRA team (Kurikala & Parvathi, 2023). Additional financial commitments relate to ensuring compliance with data privacy and security regulations, as well as covering the costs of system integration and ongoing technological support. **Organization size** may also be a relevant factor as larger organizations typically have

greater access to financial, technical, and human resources, which can facilitate the adoption and scaling of HRA initiatives (Coolen et al., 2023; Opatha & Dayarathna, 2024).

Temporal Resources

Six studies (Cho, et al., 2023; Levenson & Fink, 2017; Opatha & Dayarathna, 2024; Ratnam & Devi, 2024; Vargas, et al., 2018; Wirges & Neyer, 2023) highlight the influence of this subtheme.

HRA adoption is widely recognized as a time-intensive process that may not generate immediate results, but instead requires long-term commitment. Organizations should therefore invest not only financial but also **temporal resources**. This includes allowing time for professional training and enabling teams to experiment with analytics approaches (Vargas et al., 2018). Additionally, Opatha and Dayarathna (2024) stress that investments in HRA must be made at the right time to maximize their effectiveness.

Training

Nine studies (Cho, et al., 2023; Kurikala & Parvathi, 2023; Madhani, 2023; Moraes & Damian, 2021; Opatha & Dayarathna, 2024; Rasmussen & Ulrich, 2015; Ratnam & Devi, 2024; Shet, et al., 2021; Vargas, et al., 2018) identify the availability of appropriate training resources as a key factor influencing the adoption of HRA.

Kurikala and Parvathi (2023) emphasize the value of **practical, on-the-job training**, while Opatha and Dayarathna (2024) and Ratnam and Devi (2024) highlight the importance of complementary **virtual or online learning** opportunities, which allow employees to train independently and at their own pace. In addition to the in-depth training for dedicated HRA teams, Ratnam and Devi (2024) advocate for foundational data literacy **training across the wider workforce** to improve data comprehension and support accurate data entry. Training related to data privacy and security is also essential. Cho et al. (2023) further suggest training **data experts** within various departments to build broader organizational competence.

5.5 Factors Influencing HR Analytics Adoption: Individual Context

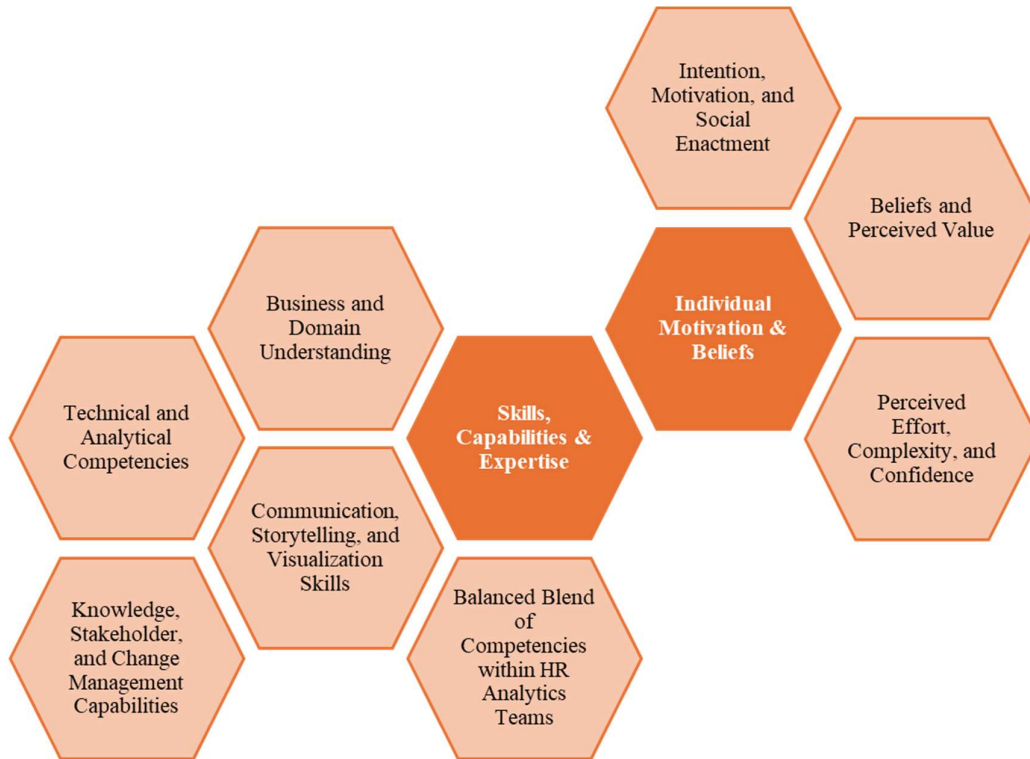


Figure 7: Mapping the Individual Context

5.5.1 Skills, Capabilities & Expertise

Business and Domain Understanding

14 articles (Andersen, 2017; Angrave, et al., 2016; Cho, et al., 2023; Coolen, et al., 2023; Fernandez & Gallardo-Gallardo, 2021; Green, 2017; Madhani, 2023; McCartney & Fu, 2022; Minbaeva, 2018; Moraes & Damian, 2021; Opatha & Dayarathna, 2024; Peeters, et al., 2020; Ratnam & Devi, 2024; Shet, et al., 2021) emphasize competencies within this subtheme.

Business understanding is crucial and includes knowledge of the organization’s customers, products, services, processes, financial situation, and strategy. Specifically, Fernandez and Gallardo-Gallardo (2021) stress the ability to link analytics to business outcomes, while Angrave et al. (2016) highlight the need for awareness of the context in which data is collected to ensure accurate interpretation of results. **Domain expertise in HR**, meaning an understanding of HR-specific contexts and practices, is also essential as not all HR processes can be fully or accurately captured in numerical terms. In a similar vein, strong **psychological**

skills are essential for linking data to human behavior and for mitigating risks such as bias and overconfidence in interpretation.

Technical and Analytical Competencies

19 articles (Andersen, 2017; Angrave, et al., 2016; Coolen, et al., 2023; Dahlbom, et al., 2020; Fernandez & Gallardo-Gallardo, 2021; Green, 2017; Kurikala & Parvathi, 2023; Madhani, 2023; Marler & Boudreau, 2017; McCartney & Fu, 2022; Minbaeva, 2018; Moraes & Damian, 2021; Opatha & Dayarathna, 2024; Peeters, et al., 2020; Rasmussen & Ulrich, 2015; Ratnam & Devi, 2024; Shet, et al., 2021; Wang, et al., 2024; Wirges & Neyer, 2023) reveal multiple skills within this subtheme.

Statistical and mathematical skills—often used interchangeably with analytical competence—are vital for HRA adoption. They encompass familiarity with various statistical methods, the ability to select and apply them appropriately, and the capacity to identify interconnections between variables in order to generate valuable insights. Influential is also the proficiency in **programming languages** (Fernandez & Gallardo-Gallardo, 2021; Ratnam & Devi, 2024), along with knowledge of **scientific methodology** to support robust research design. Furthermore, **technological competence**—particularly in using IT systems and analytics software tools—is essential, as well as the ability to adapt these standard tools to organizational needs. **Data management skills** are required to capture, organize, transform, and share data effectively. Essential are also **research skills**, including the ability to engage with academic literature and follow methodological developments (Minbaeva, 2018). Collectively, these competencies are not only vital for conducting analyses, but also for collecting and preparing data, interpreting results, and communicating findings effectively.

Communication, Storytelling, and Visualization Skills

16 articles (Andersen, 2017; Cho, et al., 2023; Fernandez & Gallardo-Gallardo, 2021; Green, 2017; Kurikala & Parvathi, 2023; Madhani, 2023; McCartney & Fu, 2022; Minbaeva, 2018; Moraes & Damian, 2021; Opatha & Dayarathna, 2024; Peeters, et al., 2020; Rasmussen & Ulrich, 2015; Ratnam & Devi, 2024; Shet, et al., 2021; Wang, et al., 2024; Wirges & Neyer, 2023) underline skills relevant to this subtheme.

The ability to translate complex data into a **clear and compelling narrative** is critical to support decision-making. This includes understanding the audience, tailoring insights to their needs, and giving data a contextual frame that makes it accessible and meaningful. **Storytelling** should target relevant business challenges and engage decision-makers, thereby ensuring a shared understanding of analytical outcomes. Rasmussen and Ulrich (2015) further highlight the value of co-creating the narrative with stakeholders. **Visualization** skills are also essential for avoiding information overload and focusing attention on key findings. Finally, the ability to **communicate results consistently** and meaningfully—both internally and externally—is regarded to build awareness, promote engagement, and increase motivation around HRA initiatives.

Knowledge, Stakeholder, and Change Management Capabilities

Insights drawn from 15 studies (Cho, et al., 2023; Coolen, et al., 2023; Dahlbom, et al., 2020; Fernandez & Gallardo-Gallardo, 2021; Green, 2017; Kurikala & Parvathi, 2023; McCartney & Fu, 2022; Minbaeva, 2018; Moraes & Damian, 2021; Opatha & Dayarathna, 2024; Peeters, et al., 2020; Rasmussen & Ulrich, 2015; Ratnam & Devi, 2024; Shet, et al., 2021; Wirges & Neyer, 2023) point to a variety of abilities within this subtheme.

Boundary-spanning skills, referring to the ability to build and leverage networks across internal and external boundaries to gain relevant insights, are crucial for HRA adoption. In addition, **consulting skills**—specifically the ability to formulate actionable recommendations—are important for translating analytics into practice. Effective **stakeholder management** is likewise key to sharing insights, managing expectations, and securing acceptance of HRA among different groups. Moreover, **knowledge management** skills, including the ability to document and disseminate insights across the organization, help ensure that critical knowledge remains accessible even when key actors leave the organization. Finally, **change management** capabilities are necessary for supporting transitions related to HRA initiatives. This involves guiding adoption processes and managing projects to ensure that insights are translated into action.

Balanced Blend of Competencies within HR Analytics Teams

Three studies (Coolen et al., 2023; Fernandez & Gallardo-Gallardo, 2021; Minbaeva, 2018) emphasize the importance of assembling HRA teams with a **balanced blend** of the presented

competencies. Rather than expecting all skills to be concentrated in a single individual, Fernandez and Gallardo-Gallardo (2021) highlight the value of combining business, analytical, and communication expertise across team members. Minbaeva (2018) further suggests that **diverse professional backgrounds** can be advantageous in building such complementary capabilities within the team.

5.5.2 Individual Motivation & Beliefs

Intention, Motivation, and Social Enactment

Five studies (Bonilla-Chaves, et al., 2024; Minbaeva, 2018; Ratnam & Devi, 2024; Vargas, et al., 2018; Wang, et al., 2024) discuss aspects influencing HRA adoption within this subtheme.

Behavioral intention has a significant positive effect on actual system use (Bonilla-Chaves, et al., 2024). Vargas et al. (2018) and Minbaeva (2018) underline that intrinsic **motivation** plays a key role in this process, as individuals who are intrinsically motivated are more likely to initiate and sustain adoption efforts, often driving adoption in a bottom-up and self-directed manner. Moreover, Wang et al. (2024) introduce the concept of **social enactment**, describing the varying ways individuals engage with HRA in their daily work—for example, using it minimally, collaboratively, or extensively. These day-to-day usage choices ultimately shape HRA adoption, as the system’s effectiveness depends on how users incorporate it into their routines.

Beliefs and Perceived Value

A total of 11 studies (Bonilla-Chaves, et al., 2024; Coolen, et al., 2023; Dahlbom, et al., 2020; Kurikala & Parvathi, 2023; Madhani, 2023; Marler & Boudreau, 2017; Minbaeva, 2018; Moraes & Damian, 2021; Rasmussen & Ulrich, 2015; Shet, et al., 2021; Wang, et al., 2024) highlight factors within this subtheme.

One key factor is **performance expectation**, referring to whether individuals perceive HRA as useful, beneficial, or capable of improving their work and organizational processes. This perceived usefulness influences how employees respond to HRA and can therefore affect the adoption process. Crucial are also **individuals’ convictions or intuitive understandings**, as belief-driven resistance may arise when data insights contradict these. In such cases, people could reject analytics-based conclusions in favor of personal beliefs. Additionally, a **perceived skills gap** among HR professionals can undermine trust in the analytics process. For example,

Dahlbom et al. (2020) note that some employees question whether HR professionals possess the necessary expertise to conduct meaningful analysis, which may further hinder adoption.

Perceived Effort, Complexity, and Confidence

Six studies (Bonilla-Chaves, et al., 2024; Coolen, et al., 2023; Kurikala & Parvathi, 2023; Ratnam & Devi, 2024; Shet, et al., 2021; Vargas, et al., 2018) recognize factors within this subtheme.

One central factor is **self-efficacy**, meaning an individual's belief in their own ability. For HRA adoption this includes confidence in one's quantitative or technological capabilities. Vargas et al. (2018) highlight gendered differences in self-efficacy, noting that women often feel less confident in data-driven contexts traditionally associated with male-dominated domains, potentially influencing their adoption behavior. Closely related is **effort expectancy**, referring to the perceived ease of use or complexity of HRA systems. Coolen et al. (2023) and Shet et al. (2021) highlight this as a relevant factor, explaining that user-friendly solutions are more likely to be adopted, as higher perceived complexity can deter engagement. In contrast, Bonilla-Chaves et al. (2024) found no significant effect of effort expectancy on the behavioral intention to use HRA, opposing to their original hypothesis.

6 Discussion

Insight becomes impact only when findings are critically examined and placed into context. This chapter synthesizes the results, drawing connections to existing theories and research, and answers the research questions. It reflects on gaps, offers practical recommendations, and suggests how future studies can build on the presented framework.

6.1 Interpretation of Main Results

This study specifically focused on organizations in **Western settings**, which typically exhibit advanced technological infrastructures, strong data protection regulations, and institutionalized labor practices. These characteristics form a distinct framework within which HRA adoption is carried out and help contextualize the findings. For instance, the emphasis on data privacy, employee consent, and algorithmic transparency—identified as significant ethical factors—

reflects the influence of regulatory frameworks like the GDPR, which are more prevalent and strictly enforced in Western contexts. Furthermore, the findings related to employee representation and formal stakeholder involvement gain particular relevance in Western labor markets where works councils and unions play a more institutionalized role in shaping workplace technologies. This aligns with observations by Tursunbayeva et al. (2021), who note that attitudes toward personal data protection and participation vary significantly by region, and that aligning practices with local norms is critical—especially in countries with strong traditions of employee participation and privacy protection. Similarly, the importance of a strategic HR function and advanced training approaches align well with the high degree of organizational formalization and cultural emphasis on skills development commonly found in Western firms.

A central finding of this study is the **breadth and interdependence of factors** that collectively shape HRA adoption in Western settings. This includes not only technical readiness and data infrastructure, but also factors like leadership behavior, ethical considerations, organizational culture, and user beliefs. Such a wide-ranging set of influences confirms the relevance of combining the TOE framework and the TAM3 as analytical lenses: while TOE captures the broader structural circumstances, TAM3 provides insight into how individual perceptions and experiences influence engagement. Importantly, the results indicate that these various factors are not detached but interwoven, with adoption processes emerging from their mutual reinforcement. This holistic view aligns with earlier studies in IT adoption. For instance, Zhu et al. (2003) and Thiesse et al. (2011) both identified the importance of various technological, organizational, and environmental conditions in shaping innovation uptake, supporting the notion that no single context can sufficiently explain adoption outcomes on its own. In addition, the present findings show that individual-level factors—such as motivation, confidence, and perceived value—interact dynamically with broader organizational and technological structures. Adoption outcomes are therefore shaped both by systemic structures and by the day-to-day behaviors and beliefs of users. This reinforces the need to understand HRA as a sociotechnical phenomenon, as emphasized by Chen et al. (2021), who demonstrate that predictive analytics adoption is shaped by the dynamic interplay between social subsystems—such as culture, skills, and resistance—and technical subsystems like data quality and infrastructure, requiring joint optimization for success. Understanding adoption in this integrated manner enables a more accurate and actionable perspective on how HRA becomes embedded in organizational practice.

The results also show a strong emphasis on **alignment and coherence**—whether between HRA practices and business strategy, between analytics tools and user capabilities, or between data systems and organizational processes. Misalignment in any of these areas is repeatedly associated with weak adoption or limited integration. This view is predominant throughout literature, with for example Ellmer and Reichel’s (2021) concept of epistemic alignment emphasizing the importance of aligning analytical efforts with relevant business issues. This underscores that adoption is not just about introducing new systems but about embedding them in a way that is relevant to the specific circumstances and supported across organizational levels.

Another key insight is the importance of **organizational readiness and maturity**. The availability of financial, temporal, and human resources, leadership commitment, and a data-driven culture shape whether and how HRA becomes institutionalized. This finding aligns with Damanpour and Schneider (2006), who emphasize the role of both external and internal resources—such as organizational size, complexity, and communication structures—across adoption phases. Similarly, Pichlak (2015) views adoption as a dynamic, ongoing process dependent on sustained top management support and the strategic allocation of resources. Together, these studies reinforce the view that HRA adoption is not a fixed milestone, but a continuous process that requires long-term investment and matures over time.

The findings further highlight the significance of **communication and user engagement** in the adoption of HRA, emphasizing that analytical insights must be understandable, trusted, and actionable to have real impact. This is supported by Boldsova (2019) and Bendoly (2016), who emphasize that storytelling and user-centric visualization enhance engagement and comprehension by presenting data in meaningful, behaviorally relevant narratives. In line with this, Oberascher et al. (2023) argue that tailored insight delivery—through combined use of data storytelling and visualization—is critical for bridging the gap between analytical expertise and decision-making. Together, these studies reinforce the conclusion that how insights are communicated plays a significant role for their usefulness and practical impact.

In addition, the review highlights several **underexplored yet potentially impactful aspects**. Power dynamics and the political use of data, for instance, are rarely addressed, despite their significant influence on which narratives gain prominence, how analytics are interpreted, and whose interests are prioritized in decision-making. Similarly, limited attention is given to datafication—the reduction of individuals to quantifiable datapoints—which further reflects a tendency in the literature to view data-based decisions as inherently neutral. Acknowledging

these dynamics challenges the assumption that better data inherently leads to better decisions and calls for a more ethically and politically informed discourse on HRA. This aligns with critiques by Ryan (2019) and Power et al. (2019), who emphasize the need for a critical perspective on the power embedded in data systems and decision-support infrastructures. Their studies highlight that analytics often operate within contested terrains shaped by organizational influence and bias. Furthermore, mechanisms for institutional oversight, such as data governance boards or committees, are seldom examined, despite their potential role in ensuring ethical and strategic use of HRA. This reveals a practical blind spot and suggests that even where organizations adopt analytics, they may lack systems to manage risks, biases, or misuse—limiting the strategic and responsible potential of HRA. Additionally, while stakeholder involvement is commonly discussed, few studies within the scoping review explicitly consider the role of employee representatives, whose formal inclusion may be critical in contexts with strong labor institutions. Finally, the social enactment of analytics—how individuals use and integrate analytics into their daily routines—remains insufficiently examined, though it has clear implications for sustained adoption. The neglect of social enactment and employee representation implies that long-term, widespread use of HRA may falter without broader cultural and participatory foundations. Adoption must be not only authorized but also lived and accepted across levels of the organization, aligning with De Jaegher and Di Paolo’s (2007) view of sense-making as a participatory and interactive process.

Interestingly, the results showed a **contradiction** regarding the relevance of effort expectancy for HRA adoption. While Coolen et al. (2023) and Shet et al. (2021) emphasize the importance of system ease of use, Bonilla-Chaves et al. (2024) found no notable impact of effort expectancy on behavioral intention. This divergence may stem from contextual and methodological differences. Bonilla-Chaves et al. surveyed predominantly IT and telecom professionals in mid-sized US firms, a population likely more technologically literate and less sensitive to system complexity. In contrast, the other studies included broader samples of HR professionals, for whom ease of use may be a more significant barrier. The contradiction suggests that the influence of effort expectancy may be context-dependent, influenced by users’ digital fluency, organizational support structures, and perceived relevance of the technology to their roles.

6.2 Linking Findings to the Research Questions

Appendix 2 presents the complete overview of the identified subthemes influencing HRA adoption in Western settings, integrating all four contexts into a single mapped framework.

Within the **environmental** context, the study identified factors such as social influence, availability and awareness of technologies, and the role of external actors. Industry-specific conditions—including digital maturity, competitive pressure, and the availability of analytics talent—also influence readiness for adoption. Regulatory requirements, sectoral characteristics, and the formal involvement of employee representatives add further complexity. In addition, ethical considerations play a significant role, encompassing data privacy, security, and employee consent; algorithmic transparency and bias; and overall trust in data use. Underlying all of these is the broader issue of datafication, which remains an underexplored but critical area in understanding the broader social and ethical implications of HRA.

In the **technological** context, the study discovered key factors such as availability, quality, storage, and consistency of data, supported by standardization and clear ownership structures. Tool trialability fosters familiarity and confidence, while broad accessibility ensures that data can be effectively leveraged across functions. System integration and interoperability are also critical, particularly in overcoming data silos and enabling seamless information flow between platforms. Moreover, the capability and compatibility of technological solutions with organizational goals, their user-friendliness, and the availability of technical support strongly influence both initial acceptance and long-term integration of HRA systems.

Within the **organizational** context, a range of factors have been identified to influence HRA adoption. Strategic alignment with broader business objectives, clear problem framing, and the targeted delivery of actionable insights are essential for ensuring its relevance and impact. Stakeholder involvement enhances buy-in and promotes follow-through on analytics-driven actions, while the structural positioning of the HRA function, whether centralized or not, affects its integration and visibility. A supportive organizational culture—characterized by openness to change, commitment to learning, and cross-functional collaboration—further facilitates adoption, especially when combined with leadership that actively champions analytics and integrates it into strategic decision-making. However, leadership styles marked by risk aversion or political use of data can act as barriers. In addition, organizational readiness and size play a critical role, as financial and temporal resources must be allocated not only for system setup but also for ongoing operations and development. Layered training strategies—addressing needs from basic data literacy to advanced analytics skills—further strengthen capabilities across levels and help cultivate a culture of data-driven decision-making.

In terms of the **individual** context, HRA adoption is found to depend on a combination of user motivation, beliefs, and capabilities. Employees' intention to use HRA, their intrinsic

motivation, and the way they enact analytics in their daily work routines are essential for sustained engagement. These behaviors are influenced by perceived usefulness and trustworthiness of HRA, as well as confidence in their own analytical and technological abilities. Effort expectancy, including perceptions of complexity and ease of use, further influences adoption decisions, particularly when users feel overwhelmed or underprepared. Personal convictions can lead to resistance when data-driven insights conflict with existing beliefs. Moreover, a broad skillset is essential, including business and domain understanding, stakeholder management, technical and analytical proficiency, communication, and visualization skills, as well as competencies in change and knowledge management. The ability to interpret, translate, and act on data is as important as conducting analysis itself. Rather than concentrating all skills in one individual, building HR analytics teams with a balanced blend of complementary strengths can enhance overall effectiveness.

6.3 Theoretical Contributions

This study contributes to the theoretical understanding of HRA adoption by synthesizing a previously fragmented body of research into a unified and structured framework. Drawing on the TOE and TAM3 models, the findings offer a comprehensive mapping of critical factors across environmental, technological, organizational, and individual contexts. This integrative perspective helps clarify how diverse elements interrelate and provides a theoretical frame that future research can build upon or use to position empirical investigations.

Another central contribution lies in emphasizing adoption as a dynamic and staged process, rather than an isolated moment. By incorporating factors relevant to initiation, adoption decision, and implementation, the study encourages a shift away from static adoption models toward a more process-oriented understanding. This perspective better reflects the evolving and iterative nature of HRA adoption in organizations.

The review also highlights several underexplored yet theoretically significant areas—such as datafication, ethical governance, trust, and power dynamics—that are rarely accounted for in existing adoption models. These findings indicate that prevailing theories may insufficiently capture the ethical and socio-political complexities inherent in data-driven practices like HRA. We therefore propose extending the TOE framework into a more comprehensive TOEEH framework, which explicitly incorporates Ethics and Human contexts to better reflect the roles of individual agency, values, and power in technology adoption processes. Additionally, the

study affirms the relevance of sociotechnical perspectives, as both technological infrastructure and social dynamics emerged as essential. This underscores the importance of balanced, multidisciplinary approaches when theorizing about analytics adoption in complex organizational settings. Taken together, the insights presented in this study offer a theoretically grounded map for future research, particularly in Western settings, and contributes to advancing more holistic, ethically conscious models of digital innovation adoption.

6.4 Recommendations for Practice

The findings of this study provide organizations with a clear understanding of the diverse factors that shape the adoption of HRA. Building on this foundation, several specific and actionable recommendations can help organizations improve their adoption strategies and better embed analytics into their structures and routines. First, organizations are encouraged to create **internal communities of practice** for analytics. By bringing together HRA professionals with peers from business intelligence, finance, and other data-related departments, these communities foster cross-functional learning, peer mentoring, and alignment. Such networks can act as forums for knowledge diffusion, peer review of projects, and the coordination of analytics efforts across domains. This collaborative structure reduces silos, accelerates capability development, and ensures that analytics initiatives are both technically sound and strategically aligned.

Second, HRA capability-building efforts should be structured through a **layered and role-specific training model**. A foundational level of data literacy training should be offered to all employees to promote a shared understanding and general trust in analytics. Those in strategic or managerial positions require training that emphasizes how to interpret and apply insights into decision-making and long-term planning. Technical experts in analytics should receive in-depth education tailored to advanced tools and methods. We further recommend specified **team-level facilitators**—employees who are not analysts themselves, but who receive intermediate training to understand analytics, translate results to their team, and support evidence-based decisions. These facilitators can act as catalysts for culture change by helping their colleagues engage with analytics more confidently. Connecting these facilitators through regular meetings also enables shared problem-solving and peer support, which can drive consistency and foster an organization-wide, data-informed mindset.

To further promote transparency and trust, organizations should develop an **internal dashboard** accessible to all employees. This dashboard could communicate the key findings of

completed HRA projects and the resulting organizational actions. Complementing this, regular communication formats such as monthly “**show-and-tell**” sessions—either as part of town halls or standalone events—can highlight current analytics work and introduce upcoming initiatives. These efforts make the often invisible analytics work more tangible and relevant to the wider workforce, encouraging engagement and alignment.

Lastly, the ethical dimension of analytics adoption should not be left to ad hoc consideration. To ensure responsible practice, organizations should establish **formal oversight mechanisms**, such as internal ethics review boards or data governance committees. These bodies would review proposed HRA projects before adoption, assessing their relevance, intrusiveness, and ethical implications—particularly regarding employee privacy. Requiring teams to submit a formal project outline for approval encourages reflection, prevents misuse, and builds trust among employees that analytics initiatives are conducted with integrity and care. Together, these recommendations offer concrete steps to not only enhance the effectiveness of HRA adoption, but also to ensure that it becomes an integrated, participatory, and ethically grounded part of the organization.

6.5 Implications for Future Research

This scoping review reveals a notable lack of empirical research on HRA adoption. Of the 24 articles analyzed, only four presented original data-based findings, while the majority were literature reviews—highlighting the need for more empirical studies in this area. Nevertheless, our review adds value by synthesizing and thematically organizing a wide array of factors from existing work, offering a structured foundation for future inquiry. To build on these insights, we encourage follow-up studies using diverse methodological approaches, including qualitative, quantitative, and mixed-method research. Longitudinal studies would be instrumental in capturing the evolving and iterative nature of adoption over time. Researchers should also seek to incorporate grey literature and lesser-cited sources to broaden the scope of perspectives typically filtered out by traditional peer-review preferences.

Future research could further enhance practical relevance by mapping the identified factors to specific stages of the adoption process. This would enable more targeted support for HR professionals and organizational leaders, aligned with their current position on the adoption journey. Moreover, empirical investigations should examine both the strength and interrelation of separate influencing factors. Such analyses, however, need to be situated within specific

organizational, regional, or sectoral contexts, as the relative importance of factors is likely to vary across different settings.

In addition, translating theoretical insights into actionable tools should be a priority. Given the diverse set of skills and competencies identified in this review—ranging from data visualization and storytelling to data governance and ethical awareness—there is an opportunity to update and extend Ulrich’s HR competency model to better reflect the demands of a data-driven HR function. Building on this framework, future research could develop diagnostic tools, such as self-assessment questionnaires, to help HR professionals evaluate their capabilities, identify development needs, and guide targeted upskilling initiatives.

Complementing this, we see strong potential in the development of a multidimensional maturity model for HRA adoption. Such a model would define progressive maturity levels across key themes—such as leadership engagement, data infrastructure, and organizational culture—allowing organizations to assess their current state, identify lagging areas, and prioritize targeted improvements. This structured approach would provide HR leaders with a roadmap for advancing adoption in a coherent and sustainable manner.

Furthermore, future research should examine how adoption patterns differ across industries, sectors, organization sizes, and geographical regions. Cross-contextual studies would enrich our understanding and support more tailored strategies. Lastly, several underexplored yet theoretically important themes—such as power dynamics, the political use of data, datafication, mechanisms for institutional oversight, and the role of employee representatives—deserve closer attention. Addressing these gaps will be crucial to capturing the full ethical, political, and organizational complexity of HRA adoption.

7 Conclusion

The growing interest in HRA reflects a broader shift toward data-driven decision-making within HR functions. However, despite increased investment, many organizations continue to struggle with transitioning from experimentation to institutionalized, value-adding use of HRA. Without a comprehensive understanding of the diverse factors influencing HRA adoption, such efforts often remain fragmented, under-resourced, or misaligned with strategic priorities. To address this gap, this scoping review identified a wide range of factors influencing HRA adoption in Western settings. Guided by the combined use of the TOE framework and TAM3, the factors were organized across environmental, technological, organizational, and individual contexts.

Within these contexts, 11 themes and 30 associated subthemes emerged, capturing the complex landscape in which HRA adoption occurs.

The study contributed with both theoretical and practical insights, advancing the academic literature and the development of HRA practices in Western settings. It emphasized that adoption is not a single event but an ongoing process—beginning with initial awareness and extending through implementation, institutionalization, and long-term cultural integration—requiring alignment across systems, people, and values. In Western settings, where legal obligations, digital infrastructures, and institutionalized employee rights shape expectations around data use, these dynamics become particularly important. Overlooked factors such as power dynamics, ethical governance, and the formal role of employee representatives must be addressed to ensure responsible and sustainable use of HRA. While HRA holds the potential to reposition HR as a more strategic and evidence-informed function, realizing this potential requires more than the employment of analytics tools. It depends on the complex interplay of factors across environmental, technological, organizational, and individual contexts, which must be considered holistically rather than in isolation.

The findings further underscored that a more socio-politically sensitive, ethically grounded, and system-aware approach is needed—not just in future studies, but also in how HRA is adopted and governed today. From a practical standpoint, strategies such as layered training, cross-functional collaboration, and the creation of internal networks of practice can serve as powerful enablers of successful adoption and long-term engagement.

Although this scoping review has certain methodological limitations—such as reliance on secondary sources, potential bias in source selection and interpretation, as well as the constraints associated with the theoretical frameworks employed—these do not diminish the study’s contribution. Rather, they underscore the need for future empirical research to validate and build upon the presented findings, and to develop more dynamic, context-sensitive models of HRA adoption.

Ultimately, this thesis provided a structured foundation that HR professionals, organizational leaders, analytical teams, and other key stakeholders—including employee representatives, IT and data governance professionals, or personnel and organizational development specialists—can use to assess readiness, identify barriers, and design targeted interventions in Western settings. In doing so, it helps bridge the gap between strategic vision and operational capability—moving HRA from aspiration to action.

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Appendix

Appendix 1: Themes, Subthemes and Example Quotes from the Scoping Review

Environmental Context	
External Influences	
Social Influence, Technological Trends, and Collaborative Expertise	Wang et al. (2024, p. 8): “External involvement refers to accelerating progress with analytics implementation through partnerships with HR vendors and researchers [...] HR vendors bring extensive professional experience in analytics projects, and partnering with them enhances analytical knowledge and skills (Lawler et al., 2004; Tursunbayeva et al., 2018).”
Industry-Specific Readiness, Competitive Pressure, and Talent Availability	Shet et al. (2021, pp. 317-318): “Thus, if a competitor can improve their ability to manage people by being better at hiring, developing, rewarding, and retaining talent using analytics, it becomes imperative for the HR team to leverage analytics to manage their people like their competitors do. Thus, to remain competitive, HR managers might be forced to keep abreast of technological developments and follow the dominant trends.”
Regulations, Sectoral Context, and Employee Representation	Cho et al. (2023, p. 18): “In the public sector, special attention should be paid to privacy/security issues, ethics of algorithms, power imbalance and the publicness of government organizations.”
Ethics	
Data Privacy, Security, and Employee Consent	Madhani (2023, p. 44): “Due to the sensitive nature of HR data, organizations need to become more concerned about data confidentiality, local regulations regarding the use of employee data, and the risk of public disclosure.”
Algorithmic Transparency, Bias, and Fair Decision-Making	Dahlbom et al. (2020, p. 135): “Therefore, the future HR professionals should be well aware of the issues like fairness in decision making, and understand the black box of algorithms, which, if utilized without due caution and necessary understanding of the inner workings of HRA systems, may lead to biased decisions, or even violating the legal rights of the personnel analyzed and managed based on the results.”
Employee Trust, Involvement, and Autonomy	Green (2017, p. 141): “Employee trust [...] is one of the most important aspects of doing great people analytics. If your employees do not trust what you will do with their data they will not give it to you, or will not provide relevant, truthful data.”
Datafication	Gal et al. (2020, p. 6): “In datafied organizations, members are not treated as fully-fleshed, subjective beings. Instead, they are reconstituted and known as collections of objective digital data that

	they produce actively and passively as they go about their work (Constantiou & Kallinikos, 2015).”
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Technological Context	
Data Governance	
Data Availability, Quality, Storage, and Standardization	Fernandez and Gallardo-Gallardo (2021, p. 173): “Regardless of the type of data used, its quality is crucial. All authors agree on the fact that HR analytics results depend on the quality of the raw material. Therefore, data quality is one of the most crucial requirements to succeed in the use of HR analytics (Harris et al., 2011, Russell and Bennett, 2015; N’Cho, 2017)”
Tool Trialability	Vargas et al. (2018, pp. 3059-3060): “Moreover, respondents reported low levels of quantitative self-efficacy and trialability (fear of math/statistics, lack of quantitative training, low analytics awareness, lack of resources and organizational support promoting analytics and its tools), implying that these determinants act as a barrier rather than a driver of the analytics adoption proces”
Data Accessibility and Ownership	Wang et al. (2024, p. 8): “Organizational silos may hinder effective HR analytics as HR may not have access to all the necessary data for crafting an analytics program (Gobble, 2017).”
Technology & Digital Infrastructure	
System Integration, Interoperability, and Technological Capabilities	Ratnam and Devi (2024, p. 145): “Not having advanced analytical software that is built based on the HR demands but built by developers who do not understand the concept of ‘people’ is one of the major impediments (Angrave et al. 2016) and other barriers include having technological silos, as quoted ‘systems don’t talk to each other’ (Davenport and Anderson 2019).”
Compatibility, User-friendliness, and Support	Kurikala and Parvathi (2023, p. 72): “Compatibility is how well an invention fits potential adopters' ideas, experiences, and needs (Rogers, 2003, p. 240). HRA solutions and metrics help transform processes and should align with an organization's fundamental values and aims.”

Organizational Context	
Strategic Focus & Insights	
Strategic Alignment with Organizational Context	Coolen et al. (2023, p. 13): “According to various authors, the focus of workforce analytics should be on those areas that deliver the most value for the organization and its stakeholders (Miles & Snow, 1978; Minbaeva, 2018; Paauwe & Farndale, 2017). For this, HR

	<p>must have an in-depth understanding of the business strategy (Ben-Gal, 2019; Levenson, 2018; Margherita, 2021). Alignment with the strategy of the organization, its stakeholders, and its business processes was also found to be a significant driver for business analytics institutionalization (Daradkeh, 2019; Gong & Janssen, 2021; Mishra et al., 2019). Understanding the business model increases the ability to align analytical projects to business strategy and business processes, which drives adoption and, ultimately, institutionalization.”</p>
Stakeholder Involvement and Follow-Up Actions	<p>Wang et al. (2024, p. 8): “HR analytics functions as an open system, characterized by electronic connections among participants, various functions, and integration with external service providers (Ellmer & Reichel, 2021; Hamilton & Sodeman, 2020). Its effectiveness hinges on the actions of both internal and external stakeholders (Wang et al., 2022; Zhou et al., 2021). To foster consensus on the optimal utilization of HR analytics, it is imperative to consider a broad spectrum of stakeholders. Thus, this study posits that the involvement of both internal and external stakeholders constitutes a pivotal facilitator for the effective implementation of HR analytics.”</p>
Targeted, Actionable, and Graspable Insight Delivery	<p>Shet et al. (2021, p. 320): “Thus, for business users to understand the underlying assumptions and the basis of the (analytics) outcomes, the process needs to be explained in an easy-to-grasp manner. [...] Analysts who can make complex data easily understandable can influence the final decision-making. Often, this technical ability is also aligned with the ability to create visualizations that help the audience to focus on and understand the important aspects of the analysis.”</p>
Organizational Structure	
Centralization and Structural Positioning of the HRA Function	<p>Peeters et al. (2020, pp. 212-213): “With regard to the organizational structure, two prevalent views are presented in the literature (Guenole et al., 2017). According to the first view, people analytics should be placed inside the HR function as a center of excellence (CoE). [...] The second view argues that a people analytics team would benefit more from being placed outside of HR and together with other analytical teams (e.g. Rasmussen and Ulrich, 2015).”</p>
Organizational Culture	
Attitude Towards Change and Data, Learning, Collaboration, and Dynamic Capabilities	<p>Peeters et al. (2020, p. 208): “After all, once the use of data and analytics becomes more common practice, stakeholders will likely value their outputs more, which also further increases the power</p>

	and reputation of the team. As such, the establishment of an evidence-based culture will likely directly influence the effectiveness and added value of people analytics teams.”
Leadership	
Leadership Commitment and Strategic Sponsorship	Opatha and Dayarathna (2024, p. 95): “Senior management’s strong support is acknowledged as a fundamental factor in ensuring the effectiveness of a people analytics team (Peeters, Paauwe and Voorde, 2020). Senior leaders play a significant role in underscoring the value of HR analytics not only to internal stakeholders but also to customers.”
Business Focus, Risk Aversion, and Political Use in Leadership Decision-Making	Dahlbom et al. (2020, p. 135): “It is also essential to find the means to overcome the hesitation of decision makers to rely on HR data and analysis, rather than intuition and past experience, when it comes to decision making regarding “soft” people-related business decisions.”
Organizational Resources & Readiness	
Financial Resources and Organization Size	Coolen et al. (2023, p. 9): “Financial support, driving investments in technology, software, and talent, is a fundamental resource to adopt and institutionalize (workforce) analytics, as identified by several authors (Gupta & George, 2016; Gurusinghe et al., 2021; Lautenbach et al., 2017; Mikalef & Krogstie, 2020; Min, 2021).”
Temporal Resources	Vargas et al. (2018, p. 3061): “Also the availability of tools with which to experiment with analytics and the slack time to do so should be provided.”
Training	Ratnam and Devi (2024, p. 148): “The successful implementation of HR Analytics lies in the training and development of employees vertically from top leaders to entry-level HR executives and horizontally in terms of the employees from different functions. In this context, HRD teams can play a critical role in upskilling and reskilling the employees as per the requirements of adopting an innovation. Apart from introducing training on new software tools, it is also necessary to train and develop employees on other aspects like proper data management and security.”

Individual Context	
Skills, Capabilities & Expertise	
Business and Domain Understanding	Andersen (2017, p. 136): “Understand the business: a final skill, which is most often not present as much as it should be, is the simple but powerful skill of understanding the business. This requires you to fully understand what is the customer value

	proposition is, what the strategy is, key differentiating factors, financial situation and more.”
Communication, Storytelling, and Visualization Skills	Green (2017, p. 140): “You can create the best insights in the world, but if you do not tell the story in a compelling way that resonates with your audience then it is highly likely that no action will be taken. [...] Successful people analytics teams are adept at understanding what their audience needs to know, how they want them to feel and what they want them to do.”
Knowledge, Stakeholder, and Change Management Capabilities	Coolen et al. (2023, p. 11): “Furthermore, change management skills (7), ensuring a smooth transition from the start of an analytical project to action-taking, are driving the institutionalization of workforce analytics (Daradkeh, 2019; Huselid, 2015; Minbaeva, 2017). Consequently, also stakeholder management skills (8) are vital in the acceptance of workforce analytics, dealing with aligning with senior management, functional stakeholders such as legal, compliance, and IT experts, or employees or their representatives such as works councils (Peeters et al., 2020; Tabesh et al., 2019).”
Technical and Analytical Competencies	Opatha and Dayarathna (2024, p. 93): “A profound understanding of statistics and proficiency with statistical tools is paramount for data analysis and interpretation. HR professionals should grasp the intricacies of data collection, survey design, and experiment formulation (Bhattacharyya, 2017).”
Balanced Blend of Competencies within HR Analytics Teams	Fernandez and Gallardo-Gallardo (2021, p. 182): “Rather than talking about the ideal profile of the employees who should be involved in HR analytics, the right questions would be: What different profiles are needed in the development team of HR?”
Individual Motivation & Beliefs	
Intention, Motivation, and Social Enactment	Wang et al. (2010, p. 9): “A critical dynamic aspect of the HR analytics implementation model lies in social action, which refers to the choices made by users regarding how they utilize the structures and resources of a new technology in their day-to-day work (DeSanctis & Poole, 1994). Users possess the freedom to employ HR analytics technology in various ways, such as minimal usage, individual or collaborative invocation, and selective use of available structural features, which significantly influence the effectiveness of HR analytics implementation (Hamilton & Sodeman, 2020).”
Beliefs and Perceived Value	Rasmussen and Ulrich (2015, p. 239): “These findings highlight that for most people, given the choice between existing beliefs and

	new data showing your beliefs are misguided, people will choose their belief system and reject the data.”
Perceived Effort, Complexity, and Confidence	Vargas et al. (2018, p. 3060): “The variables with the greatest total impact on HR Analytics adoption appear to be related to the individual’s perception that he/she is capable of doing analytics (attitude and self-efficacies). Quantitative self-efficacy was also a significant predictor of the positive attitude towards analytics.”

Appendix 2: Mapping the Influences on HRA Adoption

