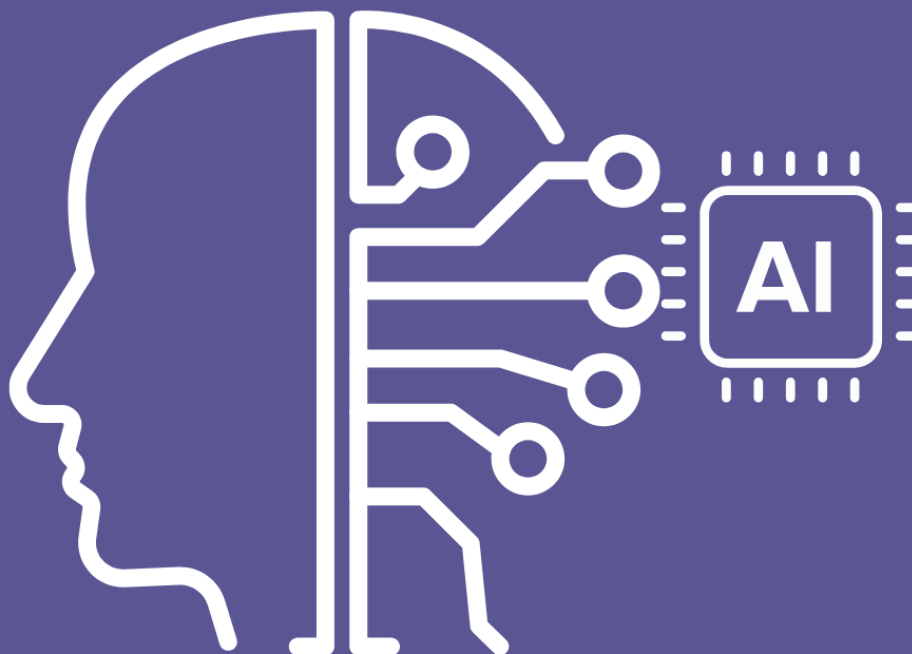


Artificial Intelligence in Human Resource Management: Evidence from Slovak Enterprises

Peter Štetka
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**Organizational Adoption, Application Architecture, and the
Benefit–Risk Calculus**

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Abstract

Artificial intelligence (AI) is diffusing unevenly across the functional architecture of the enterprise, and human resource management (HRM) occupies a distinctive place in that diffusion: it is simultaneously a promising field for automation and augmentation and the function in which algorithmic decision-making touches people most directly. This monograph provides a comprehensive, multi-angle empirical account of AI adoption in HRM among enterprises operating in Slovakia, a Central and Eastern European (CEE) economy that is under-represented in the international evidence base. Drawing on the AI-IMPACT organization-level survey (N = 816 enterprises; 562 current AI users), it concentrates on the 100 enterprises that reported implementing or testing AI in human resources and integrates four analytical perspectives into a single narrative: (1) the positioning of HR among functional domains and the firm-level determinants of HR-AI adoption; (2) the internal application architecture of AI in HR across twelve specific functions and five adoption stages; (3) the perceived benefit-risk calculus through which firms appraise AI in HR; and (4) the employment correlates of HR-AI adoption.

Four findings are central. First, HR is a second-wave functional domain. It ranks fifth of nine areas (17.8% of the 562 AI users; 12.3% of all firms), behind marketing, operations, logistics and R&D, and the firm-level factor most strongly associated with HR-AI adoption is the breadth of a company's wider AI programme (adjusted odds ratio = 1.48 per additional functional area, $p < .001$) rather than its size, ownership or sector. Second, the application picture is broad but shallow. The twelve HR functions behave as one coherent engagement construct (Cronbach's $\alpha = .914$), with a secondary and more tentative split between talent-acquisition and workforce-analytics uses; deployment, however, sits mostly at the pilot or planning stage. Only 29 of the 100 firms use any HR function actively and regularly, and 20 have nothing yet beyond planning. Third, firms read AI in HR with ambivalence rather than as a trade-off. The perceived significance of benefits ($M = 3.59$) and of risks ($M = 3.50$) is statistically indistinguishable; the two are positively correlated ($r = .41$, 95% CI [.20, .61], a correlation that survives adjustment for response style) and form separate factors. The largest single group of firms is the ambivalent one, high on both (39%), and these firms show the deepest adoption. Greater adoption intensity is associated with perceived benefits and organizational maturity, and shows no association with perceived risks. Fourth, on employment, HR-AI adoption is associated with neither higher AI-related layoffs (realized or planned; 9% vs. 11%, n.s.) nor higher manager-perceived employee concern. New-role creation is lower among HR-AI firms, though the gap is only borderline once other factors are held constant (12% vs. 21%; adjusted OR = 0.53, $p = .055$). The employment profile is one of cautious augmentation, not substitution.

The monograph contributes the first organization-level, function-resolved portrait of AI in HRM for Slovakia and, to our knowledge, among the first for the CEE region; an empirically grounded account of how firms hold benefits and risks together rather than trading them off; and a readiness-centred reading in which organizational maturity, dedicated AI budgets and the breadth of the AI programme, far more than demographic firm characteristics, accompany whether and how deeply AI enters the HR function. Implications for managers,

HR professionals and CEE technology policy are developed, and the limitations of cross-sectional, single-informant, screened-sample evidence are discussed at length.

Keywords: artificial intelligence; human resource management; technology adoption; algorithmic HRM; people analytics; organizational maturity; future of work; Slovakia; Central and Eastern Europe; enterprise survey.

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This monograph rests on the work of many hands, and it is a pleasure to acknowledge them. Our first and greatest debt is to the AI-ImpactSK project team, whose collaboration made this study possible: for conceiving and fielding the enterprise survey, for the careful collection, cleaning, and documentation of the data, and for the many conversations that sharpened how we read it. Without their groundwork this book would have had nothing to stand on.

We are equally grateful to the enterprises and their representatives who gave their time to respond. Their willingness to describe, candidly, how they actually use artificial intelligence in their day-to-day work is what gives this study its evidentiary base, and we hope the findings repay that openness.

We thank our colleagues and home institutions for the intellectual environment in which this research took shape, and the reviewers whose questions and corrections improved the manuscript in ways large and small. Any errors that remain are, of course, our own.

Finally, and most personally, we thank our families. Their patience, encouragement, and quiet understanding through the long hours that a project like this demands were a gift we did not take for granted. This book is, in no small part, theirs as well.

Foreword

Artificial intelligence has rapidly become one of the defining technologies of contemporary organizational transformation. Within only a few years, AI has evolved from a specialized analytical capability into a general-purpose technology that increasingly influences virtually every business function, from production and logistics to marketing, finance and strategic decision-making. Among these domains, however, human resource management occupies a particularly distinctive position. HR is simultaneously one of the organizational functions most capable of benefiting from AI-enabled automation and decision support, and one of the functions in which algorithmic decision-making directly affects people, their careers, opportunities and working lives.

Despite the remarkable growth of research on artificial intelligence, surprisingly little empirical evidence exists on how organizations actually implement AI within human resource management. Much of the existing literature remains conceptual, normative or based on case studies of large multinational corporations. Organization-level empirical evidence is comparatively scarce, particularly for Central and Eastern Europe. Consequently, many widely cited assumptions regarding AI adoption, organizational readiness, employee reactions or employment effects continue to rely on evidence generated in a relatively small number of advanced economies whose institutional, economic and organizational environments differ substantially from those found in Slovakia and the wider CEE region.

This monograph emerged from precisely this observation. Rather than asking how AI *could* transform HR in theory, we sought to understand how organizations are actually introducing AI into HR today. The objective was not to advocate AI adoption, nor to warn against it, but to document its current organizational reality through systematic empirical research. The study therefore draws on the AI-ImpactSK project, one of the largest enterprise surveys on artificial intelligence conducted in Slovakia, and examines AI adoption from the perspective of organizations themselves. Throughout the monograph, the emphasis remains on observable organizational behaviour rather than technological speculation.

Another feature distinguishes this work from much of the existing literature. AI adoption is not analysed here as a single organizational decision but as a multidimensional organizational process. Human resource management is examined as one element within a broader organizational AI programme, influenced by organizational readiness, accumulated implementation experience, managerial commitment and enterprise-wide AI maturity. This perspective makes it possible to move beyond simple adoption statistics and explore how AI diffuses across organizational functions, why HR tends to emerge as a second-wave application area, how organizations evaluate both benefits and risks simultaneously, and what early consequences AI appears to have for employment.

Accordingly, the monograph combines several complementary analytical perspectives. It examines the organizational determinants of AI adoption in HR, the internal architecture of AI applications across individual HR activities, the benefit–risk calculus through which

organizations evaluate AI, the relationship between AI adoption and employment outcomes, and the broader organizational readiness that enables AI implementation. Although each chapter addresses a distinct research question, the intention has always been to develop an integrated understanding of AI adoption in HR rather than a collection of independent empirical studies. The integrated conceptual framework presented in the discussion chapter reflects this ambition by synthesizing the principal findings into a coherent organizational model of AI adoption in human resource management.

The empirical picture that emerges is more nuanced than many contemporary public narratives suggest. Rather than confirming either technological optimism or technological pessimism, the evidence consistently portrays organizations as pragmatic adopters. AI in HR appears to spread gradually, alongside broader organizational AI programmes, and remains concentrated primarily in pilot implementations and selected HR activities. Organizations recognize substantial opportunities while simultaneously acknowledging significant ethical, organizational and employment-related risks. Importantly, these two perspectives do not appear to substitute for one another. Instead, many organizations progress precisely because they are capable of recognizing both at the same time and governing the resulting tensions responsibly.

This finding carries an important implication that extends beyond the specific context of human resource management. The successful organizational adoption of AI appears to depend less on technological sophistication alone than on the development of broader organizational capabilities. Throughout the analyses presented in this monograph, organizational readiness, managerial commitment, accumulated implementation experience and governance repeatedly emerge as more informative than traditional organizational characteristics such as firm size or ownership structure. AI therefore appears less as a technological revolution imposed upon organizations than as a gradual organizational transformation requiring new managerial capabilities, new governance mechanisms and continuous organizational learning.

We hope that this monograph will serve several audiences. Researchers may find in it one of the first comprehensive organization-level empirical accounts of AI adoption in HR from the Central and Eastern European region. Managers and HR professionals may use its findings to benchmark their own organizational AI readiness and to better understand how AI typically evolves within enterprises. Policymakers may find empirical evidence supporting the design of technology and innovation policies adapted to the specific needs of organizations operating in the region. Above all, we hope that the book contributes to a more evidence-based discussion of artificial intelligence—one that is grounded less in speculation about future possibilities and more in systematic observation of how organizations are already navigating this technological transformation.

Finally, every empirical study captures only a particular moment within a rapidly evolving technological landscape. Artificial intelligence is developing at an exceptional pace, organizational experience is accumulating continuously, and regulatory frameworks are changing alongside technological capabilities. The evidence presented here should therefore be understood as a carefully documented baseline rather than a definitive

endpoint. We hope that future studies will revisit these questions as AI becomes more deeply embedded within organizations and will build upon the empirical foundation established by the AI-ImpactSK project.

Peter Štetka and Filip Stovíček

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1. Introduction

Artificial intelligence has rapidly evolved from a specialized technological capability into a general-purpose organizational technology with the potential to reshape virtually every business function. Unlike previous waves of digitalization, contemporary AI is no longer confined to isolated analytical applications or process automation. Instead, it increasingly influences strategic decision-making, knowledge work, customer interactions and organizational coordination. Yet despite the widespread public narrative of an inevitable AI revolution, organizational adoption remains highly heterogeneous. Firms differ substantially not only in whether they adopt AI, but also in how broadly they deploy it, how deeply it becomes embedded in organizational processes, and how successfully they translate technological capabilities into organizational value.

Among the various organizational functions affected by this transformation, human resource management occupies a particularly distinctive position. HR is simultaneously one of the functions most capable of benefiting from AI-enabled automation and decision support, and one of the functions where the organizational, ethical and societal implications of AI become most visible. Decisions regarding recruitment, employee evaluation, career development, performance management or workforce planning directly affect individuals and therefore require considerably greater attention to transparency, accountability and human oversight than many operational AI applications.

Understanding AI adoption in HR therefore requires looking beyond the technology itself. It demands an organizational perspective that considers AI implementation as a multidimensional process shaped by organizational readiness, managerial commitment, technological capabilities and the broader maturity of enterprise AI adoption. Rather than treating AI implementation as a single binary decision, this monograph conceptualizes AI adoption in HR as one component of a wider organizational transformation in which different business functions progress at different speeds and through different stages of maturity.

Against this background, the purpose of this introductory chapter is to establish the theoretical and empirical motivation for the study. It first discusses the uneven diffusion of artificial intelligence across organizational functions, then explains why human resource management represents a particularly important domain for investigation, outlines the specific characteristics of the Slovak and Central and Eastern European context, presents the research aims and questions, summarizes the principal contributions of the monograph, and finally introduces its overall structure.

1.1 The uneven enterprise diffusion of artificial intelligence

The contemporary wave of artificial intelligence, built on machine learning, natural-language processing and, most recently, generative models, has moved with unusual speed from research laboratories into the operating fabric of organizations. The popular image of

a uniform “AI transformation” sweeping through firms misrepresents how the technology actually spreads. Adoption is selective and sequential. Enterprises typically begin where data are abundant, returns are legible and organizational resistance is low, and they extend the technology to other functions only as confidence, capability and infrastructure accumulate (Verhoef et al., 2021). The result is an *uneven internal geography* of AI within the firm, in which some functions are early and intensive adopters while others lag.

Human resource management occupies a revealing point in this geography. HR is a data-rich, process-heavy function whose recurring tasks (screening applications, scheduling interviews, routing queries, summarizing performance data) are exactly the kind of work that contemporary AI automates well, and a fast-growing literature documents AI applications across virtually the entire HR value chain, from sourcing and selection through onboarding, development, evaluation and retention (Tambe et al., 2019; Votto et al., 2021; Budhwar et al., 2023). HR is also the function in which algorithmic decisions bear most directly and most visibly on individual human beings, on who is hired, evaluated, developed, promoted or let go, and it is therefore the function in which questions of fairness, transparency, accountability and human dignity are most acute (Mori et al., 2024; Hunkenschroer & Kriebitz, 2022; Tursunbayeva et al., 2021). AI in HR is at once a productivity opportunity and a normative minefield, and how firms navigate that tension is a question of considerable theoretical and practical importance.

This monograph examines how that tension is being resolved in practice by enterprises operating in Slovakia. It asks not only *whether* firms bring AI into HR, but *which* firms do so, *what* they actually deploy and at what depth, *how* they appraise the benefits and risks, and *what* the early workforce consequences appear to be. It treats AI in HR as a layered phenomenon: an adoption decision nested inside a broader AI programme, a portfolio of distinct functional applications at different stages of maturity, a structured set of perceptions, and a set of employment outcomes. Each layer receives a different analytical lens.

1.2 Why human resources, and why now

Three developments make the present moment particularly apt for a focused study of AI in HRM. The first is the maturation of the underlying technologies. Where earlier “e-HRM” and HR information systems largely digitized existing administrative processes, contemporary AI promises to *change the substance* of HR decisions, to predict which candidates will succeed, which employees are at risk of leaving, and which development paths will pay off (Huang et al., 2023; Cho et al., 2023). The arrival of accessible generative AI has accelerated and broadened this shift, putting capable language tools into the hands of HR practitioners and prompting calls to re-examine established HRM frameworks (Budhwar et al., 2023; Chowdhury et al., 2024; Korzyński et al., 2023).

The second development is the growing salience of the *governance* of algorithmic HRM. As AI moves from peripheral administrative support toward consequential decisions about people, regulators, scholars and practitioners have raised pointed concerns about bias, discrimination and the erosion of human judgement (Chen, 2023; Fabris et al., 2024;

Raghavan et al., 2020). The European Union's evolving regulatory posture treats many HR uses of AI as "high-risk", which raises the stakes of adoption decisions for firms operating in the European single market, including those in Slovakia.

The third development is the intensifying public debate about AI and the future of work. Whether AI will displace workers, augment them, or reshape the very tasks that constitute jobs is among the most consequential questions of the decade (Acemoğlu & Restrepo, 2019; Frank et al., 2019; Brougham & Haar, 2017). HR is doubly implicated. It is a *site* of AI application, where the technology may substitute for or augment HR professionals themselves, and it is the *organizational mechanism* through which firms manage the workforce consequences of AI deployed elsewhere. Understanding how AI enters HR is therefore part of understanding how organizations are negotiating the broader transformation of work.

1.3 The Slovak and Central and Eastern European context

Despite the global character of these developments, the empirical evidence base is heavily skewed toward Western Europe, North America and a handful of advanced Asian economies. Central and Eastern Europe, and Slovakia specifically, remains markedly understudied, even though the region's distinctive structural features make it a theoretically valuable case. Slovakia is a small, highly open, manufacturing-intensive economy deeply integrated into European (especially automotive and electronics) value chains, with a substantial presence of foreign-owned subsidiaries alongside domestically owned firms. Its enterprises face the same European regulatory environment as their Western counterparts but operate with different factor endowments, different exposure to multinational management practices, and a different inheritance of digital infrastructure and skills. Studies of digital and Industry 4.0 adoption in the region have repeatedly emphasized that small and medium-sized enterprises (SMEs) confront sharper capability and resource constraints than large or multinational firms (Horváth & Szabó, 2019), and that the determinants of adoption may weight differently than in the settings where dominant theories were developed.

Whether the patterns documented in Western and Asian studies of AI in HRM generalize to a CEE economy such as Slovakia is therefore an open empirical question, and one with practical stakes for regional managers and policymakers. This monograph addresses that gap directly, using a large, recent, organization-level survey designed specifically to capture the multidimensional character of enterprise AI adoption.

1.4 Aims, scope and research questions

The overarching aim of this monograph is to provide a rigorous, multi-angle empirical account of AI adoption in HRM among Slovak enterprises that is at once descriptive (mapping prevalence and patterns), explanatory (identifying determinants and correlates), and interpretive (making sense of the benefit–risk calculus and the employment debate). The unit of analysis is the enterprise; the analytical focus is the subset of firms that have begun implementing or testing AI in HR; and the comparative backdrop is the full

population of surveyed firms, from non-adopters through planners to active users across other functions.

Four research questions organize the work:

RQ1 (Positioning and determinants). How prevalent is enterprise AI-in-HR, where does HR rank among functional domains of AI application, and which firm-level factors are associated with HR-AI adoption among AI-using firms?

RQ2 (Application architecture). Which specific HR functions do firms target with AI, at what stage of adoption, and how do these functions cluster into coherent dimensions?

RQ3 (Benefit-risk calculus). How do firms appraise the positive and negative impacts of AI in HR; are these appraisals empirically distinct; what is the net stance; and what shapes the depth of adoption?

RQ4 (Employment correlates). Is AI-in-HR adoption associated with workforce reductions, new-role creation, or heightened employee apprehension?

A transversal thread running through all four questions concerns *organizational readiness*, the AI maturity, dedicated investment and managerial confidence that condition both whether AI enters HR and how deeply it penetrates.

1.5 Contributions

The monograph makes four contributions. *Empirically*, it offers the first enterprise-level, function-resolved portrait of AI in HRM for Slovakia and, to our knowledge, among the first for the CEE region, documenting not merely that firms adopt AI in HR but precisely which of twelve HR functions they target and at what stage. *Theoretically*, it advances a duality account of the benefit-risk calculus, showing that benefits and risks are perceived as distinct, positively correlated dimensions rather than as opposite ends of a single trade-off, and that the modal organizational stance is one of reflective ambivalence rather than naïve enthusiasm. *Methodologically*, it demonstrates how a richly instrumented adoption survey can be analysed at multiple levels: the functional-area decision, the within-function adoption ladder, the perceptual structure, and the employment outcome, with appropriate attention to effect sizes, confidence intervals and the multiple-comparison problem. *Practically*, it derives readiness-centred implications for managers and HR leaders and evidence-based priorities for CEE technology policy, where the salience of state support as a perceived barrier is a distinctive regional signal.

1.6 Structure of the monograph

The remainder of the monograph proceeds as follows. Chapter 2 develops the conceptual background and reviews the relevant literature across nine thematic streams, deriving an explicit research gap for each analytical angle. Chapter 3 describes the data, instrument, sample, measures and analytical strategy, and is candid about the study's limitations. Chapter 4 maps the landscape of enterprise AI adoption in Slovakia and locates HR within it. Chapters 5 through 8 address the four research questions in turn: the determinants of HR-AI adoption (Chapter 5), the application architecture (Chapter 6), the benefit-risk

calculus (Chapter 7), and the employment question (Chapter 8). Chapter 9 examines organizational readiness and barriers as the substrate that conditions all four. Chapter 10 integrates the findings into a single interpretive synthesis; Chapter 11 develops implications, acknowledges limitations and sets out a future research agenda; and Chapter 12 concludes.

2. Conceptual background and literature review

This chapter situates the study within the international research literature and derives the specific gaps that each of the four analytical angles addresses. It is organized into five substantive streams: the foundations of AI in HRM; the determinants of organizational AI adoption; the application frontier of recruitment, selection and people analytics; fairness, ethics and the human response; and AI, work and employment. A consolidation of research gaps and a statement of how the present monograph contributes follow. The review draws on a structured corpus of peer-reviewed sources identified through systematic queries of the OpenAlex scholarly database; every source cited here is recorded, with a key claim, in the accompanying literature registry. The emphasis throughout falls on what is *known*, what is *contested*, and what remains *unexamined*, particularly at the enterprise level and in the Central and Eastern European context.

2.1 Foundations: artificial intelligence in human resource management

The first stream of literature establishes what artificial intelligence (AI) is doing to human resource management (HRM) as a field, the applications it enables, and the organizational and ethical tensions it introduces. A foundational contribution is the observation that there remains “a substantial gap between the promise and reality” of AI in HR (Tambe, 2019), attributable to the complexity of HR phenomena, the small data sets characteristic of HR, accountability demands around fairness and legality, and adverse employee reactions to algorithmic decisions. This diagnosis frames much of the subsequent work, which can be read as efforts to specify where AI adds value, how it should be governed, and how it reconfigures HR roles. Contemporary AI-based HRM also has a lineage worth marking. An earlier electronic-HRM (e-HRM) tradition examined how web- and information-technology largely digitized existing HR administration and service delivery (Strohmeier, 2007; Bondarouk & Ruël, 2009). Where e-HRM chiefly moved established administrative processes online, contemporary AI aims at the substance of HR decisions themselves, predicting, recommending and selecting rather than merely recording, which is what makes the present wave both more promising and more fraught.

On the applications side, systematic and scoping reviews document an expanding footprint. Tactical HRM tasks, among them recruitment, performance evaluation, compensation and benefit analysis, discipline management, and training, increasingly incorporate AI within HR information systems (Votto, 2021). Conceptual work extends this by theorizing “personalized HRM,” in which advanced HR analytics and AI deliver individual-level, tailored HR practices argued to constitute a source of sustained competitive advantage (Huang, 2023). At the enterprise level, technical demonstrations such as neural-network-based salary prediction models illustrate how AI digital technology can reshape organizational structures and decision-making (William, 2023). Reviews further synthesize AI’s effects across HR activities and the roles of the “HR triad” of employees, line managers and HR professionals (Dima, 2024), while STARA capability (smart technology, AI, robotics and algorithms) is positioned as a strategic lever linking green HRM to environmental sustainability in emerging economies (Ogbeibu, 2023).

The arrival of generative AI marks a distinct sub-theme. Budhwar and colleagues argue that tools such as ChatGPT have rapidly become focal in debates about HRM, while leaving unresolved whether they displace jobs, create them, or simply shift human labour toward producing new and sometimes trivial information (Budhwar, 2023). Building on this, a strategic HRM framework grounded in institutional entrepreneurship is proposed because existing frameworks fail to capture the novel attributes and impacts of generative AI on workforce dynamics (Chowdhury, 2024). These works signal that AI is more than another HR tool; it is a potential reconfiguration of the HR operating model.

A third concern is the human-AI interface and its ethics. At the team level, close interaction between human workers and AI (primarily robots) generates distinct HRM challenges for which dedicated strategies are required (Arslan, 2021). Ethical decision-making in algorithmic HRM is modelled through a Throughput framework that links individuals' and organizations' ethical positions to strategy selection and post-decision accountability (Rodgers, 2022), reinforcing Tambe's (2019) emphasis on fairness and legitimacy. Empirically, a SmartPLS study of HR professionals reports that AI integration in HR is influential for entrepreneurial success (Wuisan, 2023), and a research synthesis on worker-workplace coexistence maps emerging themes while stressing that scholarship on how workers and AI will co-exist is still evolving (Zirar, 2023).

Across this theme, the literature is rich in conceptual frameworks, systematic reviews and normative models, but comparatively thin in primary, firm-level empirical evidence. Where empirical studies exist, they rely on modest professional samples (Wuisan, 2023) or technical proofs of concept (William, 2023) rather than representative enterprise surveys. The clearest gap that remains is the dominance of reviews and conceptual frameworks largely drawn from Western, Asian and emerging-economy settings, with virtually no enterprise-level survey evidence from Central and Eastern Europe or Slovakia. Little function-level documentation exists of which HR activities firms in this region actually equip with AI, leaving open how strategic and tactical AI-HRM applications materialize in concrete enterprise practice.

2.2 The determinants of organizational AI adoption

A second stream asks what makes some organizations adopt AI while others do not, and supplies the theoretical scaffolding for the determinant analysis in Chapter 5. It is dominated by the Technology–Organization–Environment (TOE) framework, frequently combined with diffusion-of-innovation and technology-acceptance reasoning, and is increasingly attentive to organizational readiness and the distinctive constraints of small and medium-sized enterprises.

The second stream addresses the determinants of AI and digital technology adoption at the organizational level, and is theoretically anchored in the Technology-Organization-Environment (TOE) framework, frequently combined with diffusion-of-innovation (DOI) and technology-acceptance reasoning. Within HRM specifically, Pillai and Sivathanu integrate TOE with Task-Technology-Fit and a survey of 562 HR managers to model AI

adoption for talent acquisition in IT/ITeS firms (Pillai, 2020), providing one of the clearest function-level adoption studies and a template for survey-based work on AI in HR.

A cluster of studies generalizes TOE to firm-level AI and digital adoption across sectors and firm sizes. In SMEs, TOE-plus-DOI models confirm that technological, organizational and environmental factors jointly drive digital and ICT adoption while also surfacing the major barriers SMEs face (Shahadat, 2023; Faiz, 2024), the latter using PLS-SEM and artificial neural networks to rank predictors and explain why SMEs lag larger firms. Extending this to AI explicitly, Badghish and Soomro find the most influential TOE factors for SMEs' AI adoption and show that firm size moderates these effects (Badghish, 2024). Sector-specific applications corroborate the framework's portability: AI acceptance in construction firms is shaped by technological and external factors when TOE is combined with the technology-acceptance model (Na, 2022), and a multiple case study of auditing firms identifies six adoption factors, namely technology affordances and constraints, innovation management, AI readiness, competition and regulation, that vary markedly with firm size (Yang, 2024).

The public sector provides an instructive contrast. A systematic review concludes that the literature lacks a contextual and processual understanding of AI adoption and is pervaded by "AI tensions" of fairness, transparency, privacy and human rights (Madan, 2022). A comparative case study of eight Swiss public organizations refines TOE by showing that the relative weight of technological versus organizational factors depends on the organization's stage in the adoption process, while environmental factors matter less (Neumann, 2022). This stage-contingent and process-sensitive view qualifies the more static, variance-based survey models.

Two further strands situate adoption in its human and economic context. On the human side, employees' digital literacy is theorized, via the Theory of Planned Behavior, as a neglected antecedent of actual technology use, reframing adoption as partly a workforce-capability problem and not a purely organizational decision (Çetindamar et al., 2024); relatedly, dynamic capabilities and digital leadership are shown to drive and moderate digital-workplace performance (Chatterjee, 2023). On the economic side, firm-level evidence from German survey data estimates the productivity effects of AI, treating it as a general-purpose technology that enables new modes of production (Czarnitzki, 2023), while a task-based framework explains how automation simultaneously displaces and reinstates labor (Acemoglu, 2019), grounding adoption decisions in their employment consequences.

This literature offers a robust, repeatedly validated toolkit of adoption determinants, but its empirical base is concentrated in Asian, Middle Eastern, Western European and German or Swiss contexts, and only a minority of studies examine AI in HR functions specifically rather than digital technology in general. Enterprise-level survey evidence on the determinants of AI adoption is largely absent for Central and Eastern Europe and, in particular, Slovakia, where the interplay of technological, organizational and environmental factors may differ from the well-studied Western and emerging-economy settings. Few studies isolate adoption at the level of the HR function or test whether general TOE determinants hold for AI deployed specifically in HRM, leaving the function-level and regional dimensions under-examined.

2.2.1 SMEs, digital transformation and the Central and Eastern European setting

Because the Slovak enterprise population is dominated by SMEs and by manufacturing firms embedded in European value chains, a dedicated body of work on SME and regional digital transformation is directly pertinent.

Research on digital and AI transformation in SMEs and in broader enterprise contexts identifies a recurring paradox: the technologies offer substantial competitive and productivity gains, yet adoption among resource-constrained firms remains hesitant and uneven. Martinez-Pelaez et al. (2023), reviewing 59 studies, show that micro, small, and medium-sized enterprises can secure competitive advantage through sustainable digital transformation, but only when it is mediated by stakeholders, key organizational capabilities, and technology. Iyelolu et al. (2024) similarly argue that AI can markedly improve SME operational efficiency, product development, customer engagement, and competitiveness, provided a set of adoption barriers is overcome through deliberate implementation strategies. The benefits are widely asserted, yet consistently described as contingent on organizational rather than purely technical conditions.

The determinants of adoption form a central theme. AlNuaimi et al. (2022), drawing on new institutional theory, find that digital transformational leadership and organizational agility drive digital transformation, with agility mediating the leadership effect and digital strategy moderating it, which foregrounds leadership and dynamic capability as adoption levers. Peretz-Andersson et al. (2024) deepen this view for manufacturing SMEs through a resource-orchestration lens, showing that successful AI implementation depends on how firms structure, bundle, and leverage scarce resources rather than on simply acquiring technology. Kallmuenzer et al. (2024) provide the demand-side counterpart, demonstrating that pervasive uncertainty about digitalization breeds hesitancy among SME decision-makers and explains why some firms capture benefits while others stall. Kitsios and Kamariotou (2021) generalise this to AI and corporate strategy, finding that firms struggle with practical implementation and lack the expertise to use AI strategically for value creation.

Firm-level empirical evidence reinforces the productivity-through-innovation logic. Liu et al. (2023) show, for listed Chinese firms, that digital transformation significantly raises innovation and, through it, firm value. Gaglio et al. (2022) provide rare evidence from a middle-income economy, finding that digital communication technologies improve innovation and, in turn, productivity among 711 South African manufacturing micro and small enterprises. For regional context, Horvath and Szabo (2019) study Industry 4.0 in Hungary and find that multinationals and SMEs do not enjoy equal opportunities, with SMEs facing greater technological, organizational, and managerial barriers, one of the few CEE-focused contributions in the set. Androniceanu (2023) extends the digital-and-AI transformation question to public administration, arguing that integration reduces bureaucracy and cost while improving service quality, transparency, and efficiency.

The human dimension of enterprise AI adoption surfaces in Mirbabaie et al. (2021), who show that integrating AI into enterprises can threaten employees' work identity through changes to work, loss of status, and fear of replaceability, a workforce-facing consideration

directly relevant to HR. (The fintech/blockchain-focused contribution by LazaroIU et al., 2023, was judged too tangential to enterprise AI-adoption determinants and is excluded from this synthesis.)

Despite growing attention to SME digitalization, robust firm-level evidence remains concentrated in China, Africa, and Western settings, with Central and Eastern Europe, and Slovakia specifically, represented by only isolated, mostly qualitative studies. Little survey-based evidence exists on how CEE enterprises adopt AI across specific business functions, and almost none links the well-documented SME adoption barriers to functional deployment in human resource management.

2.2.2 Organizational AI maturity and readiness

The transversal readiness thread of this monograph connects to a maturing literature on AI maturity, capability and readiness, which conceptualizes adoption as a staged organizational journey rather than a one-off purchase.

The literature on organizational AI maturity and readiness treats adoption as a staged, capability-dependent organizational journey rather than a discrete purchase. Verhoef et al. (2021) provide the foundational maturity framing, distinguishing digitization, digitalization, and full digital transformation and arguing that progression requires specific organizational assets, capabilities, and structures. Nasiri et al. (2022) translate this into measurable antecedents, showing that digital orientation and digital intensity alone do not improve financial success and that digital maturity is the decisive condition, a pivotal finding that separates mere technology intensity from genuine organizational readiness. Guo and Xu (2021) complement this with panel evidence from 2,254 Chinese manufacturers that digital transformation improves operational and financial performance, while underscoring its substantial costs.

A central methodological contribution is the adaptation of readiness frameworks to AI. Johnk et al. (2020), through an interview study, identify organizational AI readiness factors spanning assets, capabilities, and commitment, and argue that an informed, purpose-specific readiness assessment raises the probability of successful adoption and value capture. Uren and Edwards (2022) operationalise this journey using Technology Readiness Levels as a benchmark and propose an AI-adoption model built on an extended People-Process-Technology lens. Lavin et al. (2022) push the readiness logic into engineering practice, proposing Technology Readiness Levels for machine learning systems to impose staged, testable processes that curb technical debt, scope creep, and model failures. These works establish that AI readiness is multidimensional, combining human, process, technical, and commitment factors.

Determinants-of-adoption frameworks broaden the lens beyond the firm's internal capabilities. Malik et al. (2021) extend the Technology-Organization-Environment (TOE) framework in the Australian context, theorising how technological, organizational, and environmental factors jointly shape organizational adoption, a transferable structure for studying enterprise AI decisions. Kulkov et al. (2023), reviewing 57 articles, similarly identify organizational, technical, and processing approaches as the three axes along which AI is deployed toward broader goals, reinforcing the prominence of organizational

readiness alongside technical capacity. Bai et al. (2020) provide complementary tooling, developing a structured, sustainability-oriented assessment of Industry 4.0 technologies to guide organizations in evaluating and prioritising adoption.

Governance and accountability emerge as a maturity dimension in their own right. Asatiani et al. (2021) introduce “envelopment” as a way to deploy inscrutable, non-explainable AI accountably by drawing clear boundaries around how the system interacts with its organizational surroundings, addressing the trust, control, and risk concerns that mature AI deployment must resolve. Across these contributions, readiness is consistently portrayed as the bridge between possessing technology and realising organizational value from it. The maturity-staged perspective of Verhoef et al. (2021) and Nasiri et al. (2022), the readiness-factor inventories of Johnk et al. (2020) and Uren and Edwards (2022), the engineering-grade staging of Lavin et al. (2022), the TOE determinants of Malik et al. (2021), and the governance approach of Asatiani et al. (2021) together describe a layered construct in which human, process, technical, environmental, and accountability dimensions must align before AI delivers value. This convergence implies that measuring an enterprise’s position along these dimensions should help explain observed differences in adoption outcomes.

The readiness and maturity literature is dominated by conceptual models, expert interviews, and evidence from large or Western/Chinese firms, with virtually no enterprise-survey evidence from Slovakia or Central and Eastern Europe. Existing studies tend to stop at general adoption outcomes such as financial performance and transformation success, and do not test how organizational AI readiness or maturity translates into functional AI adoption in specific domains such as human resource management. The readiness-to-HR-deployment link is therefore empirically unexamined in the CEE context.

2.3 The application frontier: recruitment, selection and people analytics

The third and fourth streams concern what AI actually *does* inside HR. Recruitment and selection is the most visible and most studied application domain, while people analytics and algorithmic management describe the broader infrastructure through which data-driven and AI-based tools mediate the management of work.

The third stream concentrates on AI in recruitment and selection (R&S), the HR domain where AI deployment is most visible and most ethically contested. A recurring finding is a dual-edged value proposition. AI-enabled recruitment can enhance hiring quality, increase efficiency and reduce transactional work, yet it reproduces algorithmic bias that yields discriminatory outcomes by gender, race, colour and personality, with bias traced to limited raw data and biased algorithm design (Chen, 2023). Interview-based evidence echoes the efficiency side, showing that AI facilitates effective performance of routine R&S tasks while also carrying risks (Ore, 2021), and descriptive accounts document AI’s use across sourcing, profile analysis, interviewing and candidate selection, with potential to reshape the HR function and firm culture (Meshram, 2023).

Ethics is the organizing concern of the most comprehensive work in this theme. A systematic review of 120 articles reads AI in R&S through utilitarian, justice and rights-based theories, positioning ethics as the central lens and setting a research agenda (Mori,

2024). A complementary normative analysis evaluates AI recruiting from a human rights perspective, noting that despite its now-commonplace use the practice had not previously been assessed normatively (Hunkenschroer, 2022). These contributions move the field beyond cataloguing opportunities and risks toward principled evaluation of when and how algorithmic hiring is defensible.

A second concern is stakeholder acceptance and reactions, which connects R&S to adoption research. Drawing on interviews with recruiters, managers and applicants, personal and contextual factors are shown to shape acceptance of AI-based recruitment tools (Laurim, 2021), and a qualitative study centred on the recruitment phase integrates HRM literature with technology-adoption theory to model the effective use of AI from recruiters' perspectives (Hewage, 2023). This work suggests that the success of AI in hiring depends not only on technical performance but on the legitimacy it holds among those who use and are evaluated by it.

A third, broader strand situates R&S within structural shifts in work. The automation-augmentation paradox holds that, in management tasks, machine substitution and human-machine collaboration are interdependent rather than separable, with consequences for how selection and other HR judgements are organized (Raisch, 2021). The gig-economy literature classifies app-work, crowdwork and capital-platform work and foregrounds algorithmic management as a new mode of organizing labour and employment relations (Duggan, 2019), while employees' "STARA awareness", the perceived likelihood that smart technology, AI, robotics and algorithms could replace their jobs, captures the workforce anxieties that frame reactions to AI in hiring and beyond (Brougham, 2017). These works link selection-level applications to the macro question of how AI redistributes and reframes work.

The theme is thus well developed conceptually and ethically, but its empirical core consists largely of literature reviews, normative analyses and small qualitative samples of recruiters or applicants, often within single multinational or Western and Asian settings. Little representative, enterprise-level survey evidence exists on how firms actually adopt AI within the recruitment and selection function, and almost none from Central and Eastern Europe or Slovakia. The literature rarely connects function-level R&S adoption to firm characteristics and regional context, leaving open how widely, and with what governance of bias and acceptance, enterprises in this region deploy AI specifically for hiring.

2.3.1 People analytics and algorithmic management

Research on people analytics and algorithmic management depicts a field in which data-driven and AI-based tools increasingly mediate the management of work. Cho et al. (2023) frame people analytics as the use of machine-learning and algorithm-based predictive tools for HR decision-making, proposing a five-step analytic process (define, collect, analyze, share, reflect) while cautioning that its application in the public sector remains poorly understood. Meijerink, Boons, et al. (2021) provide a complementary mapping at the disciplinary level, synthesizing fragmented streams (people analytics, HRM algorithms, algorithmic surveillance, algorithmic control, AI and big data) into an emerging field of "algorithmic HRM" that crosses disciplinary boundaries. Jarrahi et al. (2021) sharpen the

conceptual lens further, arguing that algorithmic management is a sociotechnical phenomenon reflecting both technological infrastructures and organizational choices, and that its automation of managerial functions, first observed in platform work, is spreading into standard work settings.

A substantial strand documents the consequences of algorithmic control for workers, predominantly in gig and platform contexts. Wood et al. (2018), drawing on interviews and a cross-regional survey of remote gig workers in six countries, show that algorithmic control is central to online labour platforms and affords flexibility and some autonomy, yet simultaneously generates low pay, social isolation, overwork and irregular hours. Möhlmann et al. (2023), studying Uber drivers, link these tensions to algorithmic opacity: because algorithms exhibit limited transparency, workers struggle to make sense of how they are managed, undermining well-being and productivity. Lu et al. (2024) provide mixed-method evidence from food-delivery platforms that high levels of algorithmic management operate as hindrance demands that erode workers' commitment to service quality and referral behaviors, although high workload as a challenge demand can buffer these negative effects.

Against deterministic accounts of harm, several authors emphasize ambivalence and design choices. Meijerink and Bondarouk (2023) advance a "duality of algorithmic management," arguing that HRM algorithms do not have uniformly negative consequences for job autonomy and worker value but can both constrain and enable them depending on context. Zhang et al. (2022) operationalize this optimism methodologically: through participatory design with gig workers, they show that algorithmic management can be reimaged around workers' own preferences and lived experiences to center well-being, offering worker-led alternatives to detrimental designs. These contributions reframe algorithmic management as contingent and reconfigurable rather than inherently exploitative.

A final strand connects algorithmic management to broader workforce and well-being concerns. Morandini et al. (2023) review how AI automates tasks and reduces cognitive workload, raising productivity but also job-displacement risks, and argue that organizations must implement new working models and deliberate upskilling and reskilling strategies. Tursunbayeva et al. (2021), through a scoping review, synthesize how ethical considerations around people analytics are discussed by researchers and practitioners, identifying its risks and opportunities and offering recommendations for ethical practice. Guest (2017) supplies an underpinning critique, contending that dominant HRM models privilege organizational performance over employee concerns and proposing an alternative framework that prioritizes employee well-being, a corrective directly relevant to evaluating whether analytics-driven HR delivers mutual gains.

Across this literature the empirical center of gravity is the individual worker, overwhelmingly in platform and gig settings (Wood et al., 2018; Möhlmann et al., 2023; Lu et al., 2024; Zhang et al., 2022), with conceptual and review work supplying the organizational framing (Jarrahi et al., 2021; Meijerink, Boons, et al., 2021; Cho et al., 2023). What is largely missing is enterprise-level, survey-based evidence on how conventional (non-platform) organizations adopt and govern people analytics and algorithmic management, and on how the documented duality, productivity and individualized value

creation on one side, opacity, hindrance demands and well-being risks on the other (Meijerink & Bondarouk, 2023; Guest, 2017; Tursunbayeva et al., 2021), actually plays out at the level of the firm. The gap is especially acute outside the public sector and outside Western and global-platform contexts, leaving the determinants and organizational impacts of algorithmic HRM in ordinary enterprises underexplored.

2.4 Fairness, ethics and the human response

If recruitment and people analytics describe what AI does in HR, the next two streams describe the normative and human stakes: the fairness and ethics of algorithmic HR decisions, and the acceptance, trust and apprehension with which employees and managers meet them. Together they motivate the benefit–risk calculus examined in Chapter 7 and the employment analysis in Chapter 8.

The literature on fairness, bias and ethics in algorithmic hiring is animated by a tension between the promise of objective, bias-reducing automation and evidence that such systems can entrench discrimination. Fabris et al. (2024), in a multidisciplinary survey, articulate this as two competing narratives, one optimistic about replacing biased recruiter decisions, one pessimistic about automating discrimination, and conclude that whether, and which types of, algorithmic hiring can be less biased and more beneficial than low-tech alternatives remains an open question. The tension also carries legal and regulatory weight. Because algorithmic systems can reproduce bias against protected groups, their use in hiring raises fairness-compliance and liability concerns that adopting firms increasingly cannot ignore (Rigotti & Fosch-Villaronga, 2024; Fabris et al., 2024).

A central theme is that bias originates in data and propagates through deployment. Agbasiere and Nze-Igwe (2025) warn that tools trained on historical performance data can institutionalize discrimination against minorities and women, invoking Amazon’s biased resume-screening system as a cautionary case, even though such tools aim to improve efficiency and reduce human bias. Yarger et al. (2019) locate bias in talent-acquisition software affecting underrepresented IT candidates (women, African-American and Latinx professionals) and propose feminist design thinking as a lens for building more equitable tools. Debiasing the technology alone may be insufficient: Hofeditz et al. (2022) show experimentally that AI recommendations influence human hiring decisions, and that because the final decision typically remains with a human, prevalent human biases can still produce discrimination even when the system itself is controlled for bias.

The contested meaning of “fairness” and the limits of technical fixes form a further strand. Rigotti and Fosch-Villaronga (2024) argue that fairness has become crucial in AI-recruitment debates precisely because algorithms can reproduce bias against vulnerable groups, yet show that fairness itself is a contested concept signifying different things to different actors. Sánchez-Monedero et al. (2020) extend this critique by interrogating what it means to “solve” discrimination in automated hiring systems, contending that hiring discrimination is embedded in broader social and economic inequality and therefore not reducible to a technical adjustment. These works caution against treating fairness as a property that can be straightforwardly engineered into a system.

Questions of transparency, accountability and inclusivity round out the field. Raghavan et al. (2020) document the claims and practices of vendors of algorithmic pre-employment assessments and find that little is publicly known about how such tools are built, validated and examined for bias, a transparency deficit at the point of procurement. Iftikhar et al. (2024) broaden the fairness lens to disability and accessibility, evaluating the inclusivity of AI recruitment tools for applicants with disabilities in the UAE and foregrounding bias and accessibility concerns for applicants with diverse needs. Collectively, this body of work establishes that algorithmic hiring occupies a high-stakes intersection of efficiency gains and structural inequality.

This literature is rich in conceptual, legal, critical and vendor-facing analysis (Fabris et al., 2024; Rigotti & Fosch-Villaronga, 2024; Sánchez-Monedero et al., 2020; Raghavan et al., 2020) and in applicant- or system-level studies (Hofeditz et al., 2022; Iftikhar et al., 2024), but it offers little enterprise-level survey evidence on how organizations actually perceive, govern and weigh fairness risks when adopting AI hiring tools. The benefit–risk duality, efficiency and potential debiasing on one side, reproduction of discrimination and legal liability on the other (Fabris et al., 2024; Agbasiere & Nze-Igwe, 2025), is rarely examined from the standpoint of the adopting firm, and almost never in Central/Eastern European enterprise settings, leaving open how organizations themselves reconcile fairness ambitions with operational pressures.

2.4.1 Employee acceptance, trust and apprehension

Research on employee acceptance and trust treats the value of organizational AI as contingent on whether the people who must use it actually accept it. Dabbous et al. (2021) state this premise directly, arguing that organizational AI innovations create little value unless employees adopt them, and modeling the individual-level factors that drive employees' intentions to use AI at work. Beneath such organization-level acceptance lies an individual-level mechanism that shapes how people respond to algorithmic advice. Dietvorst et al. (2015) document algorithm aversion: people lose confidence in an algorithm and avoid relying on it more readily after seeing it err, even when it outperforms human judgement. Logg et al. (2019), by contrast, report algorithm appreciation: under other conditions people weight algorithmic advice more heavily than identical advice from a person. Reactions to algorithmic HR decisions are therefore context-dependent rather than uniformly hostile or trusting, which helps explain why the same tool can meet acceptance in one setting and resistance in another. Tanantong and Wongras (2024) operationalize the organizational view through a UTAUT-based framework for intention to adopt AI in HR recruitment in Thailand, framing AI as a means to automate time-consuming manual recruitment stages while noting that adoption there remains limited. Cao et al. (2021) extend the acceptance lens to decision-makers, developing and testing an integrated AI acceptance-avoidance model on 269 UK managers and showing that managerial attitudes and behavioral intentions toward AI for organizational decision-making are shaped jointly by positive factors and “dark side” negative factors.

Trust, transparency and psychological appraisal recur as core mechanisms. Yu et al. (2023) find that employees' challenge appraisals, threat appraisals and trust differ between transparent and opaque AI decision agents, with transparency shaping trust through these

appraisals and employees' domain knowledge moderating the relationship. Chang et al. (2024), drawing on Affective Events Theory and the Challenge-Hindrance Stressor Framework, show that AI-driven technostress can both promote and hinder adoption intention via affective reactions, with technical self-efficacy as a boundary condition. Park et al. (2021) probe the resistance side directly, using interviews to identify why employees resist AI performance evaluation, what they like and dislike about algorithmic management, and how the burdens fuelling antipathy might be mitigated. These studies converge on the view that acceptance is mediated by perceived transparency, stress and a sense of fairness rather than automatic.

A further strand examines perceptions of impact on jobs and the employee experience. Bhargava et al. (2020) find through interviews across diverse industries that working adults perceive robotics, AI and automation as affecting their job security, job satisfaction and employability, surfacing both opportunities and anxieties. Abdullah and Fakieh (2020) survey healthcare employees in Saudi Arabia and show that perceptions of AI implementation vary with employee knowledge and job title, underscoring that acceptance is socially stratified within organizations. Prentice et al. (2019) integrate emotional and artificial intelligence among hotel service employees, examining how AI as a workplace capability influences employee retention and performance.

Evidence on AI-enabled HR delivery and new generative contexts points to concrete organizational benefits and shifting theory. Malik et al. (2020), in an in-depth MNE case study in India, show that HRM-focused, AI-enabled applications improved HR cost-effectiveness and delivered hyper-personalized, individualized employee experiences, theorized through individualization of HRM and AI-mediated social exchange. Korzyński et al. (2023) argue that generative AI such as ChatGPT constitutes a new context for management theories across decision-making, knowledge management, customer service, HRM and administrative tasks, implying that established acceptance and management theories require re-examination.

Acceptance models, trust mechanisms and perceptions are well studied at the level of individual employees and managers (Dabbous et al., 2021; Yu et al., 2023; Chang et al., 2024; Cao et al., 2021), yet the evidence is dispersed across specific national and sectoral settings, among them Thailand, the UK, Saudi healthcare, hospitality and a single Indian MNE (Tanantong & Wongras, 2024; Abdullah & Fakieh, 2020; Prentice et al., 2019; Malik et al., 2020). Little organization-level survey evidence aggregates how enterprises experience the duality of AI benefits (cost-effectiveness, personalization, efficiency) against employee technostress, resistance and job-security concerns (Bhargava et al., 2020; Park et al., 2021). Enterprise-level acceptance evidence is particularly scarce in Central/Eastern European contexts, as are integrative accounts spanning both worker and managerial perspectives within the same organizations, especially as generative AI reshapes the terrain (Korzyński et al., 2023).

2.5 Artificial intelligence, work and employment

The fifth stream addresses the macro question that frames the employment analysis: whether AI and automation displace workers, augment them, or reshape the tasks that constitute jobs.

The literature on artificial intelligence and the future of work converges on a task-based interpretation of technological change, while diverging sharply on the magnitude and direction of net employment effects. Acemoglu and Restrepo (2019) provide the central conceptual frame: AI is a technology platform that can either automate tasks previously performed by labour or create new tasks in which workers are productively employed. They argue that recent innovation has been excessively biased toward automation, “the wrong kind of AI,” producing stagnating labour demand, a declining labour share, rising inequality, and disappointing productivity growth. This task-displacement-versus-task-creation tension organises the entire theme and reframes the policy question from whether machines destroy jobs to which kind of AI firms choose to develop.

Establishment-level evidence sharpens this picture. Acemoglu et al. (2022), studying the near-universe of US online vacancies, show that AI-related hiring grew rapidly and concentrated in establishments whose workers perform tasks compatible with current AI capabilities; as these AI-exposed establishments adopt AI, they cut hiring in non-AI roles and rewrite the skill requirements of remaining postings, even though aggregate labour-market effects remained difficult to detect. Dauth et al. (2021) reach a more reassuring conclusion for Germany: robot exposure displaces manufacturing jobs, but these losses are fully offset by new service-sector employment, with incumbents often shielded as they take over new and higher-quality tasks within their firms, though the incidence falls disproportionately on young labour-market entrants. Damioli et al. (2021) add a productivity dimension, showing across 5,257 AI-patenting firms worldwide that AI patenting generates an extra positive effect on labour productivity concentrated among SMEs and services, which connects AI directly to firm-level performance rather than to displacement alone.

A second strand emphasises heterogeneity and distributional consequences. Filippi et al. (2023), reviewing 102 studies, stress that automation’s employment effects vary enormously across levels of analysis (from global to task level) and methods, cautioning against any single uniform conclusion. Frank et al. (2019) likewise argue that AI will augment some workers, replace others, and transform nearly all occupations to some degree, while highlighting data and methodological barriers to measuring these effects. Gallego and Kurer (2022) document that routine workers are the consistent losers of automation, digitalization, and AI, and extend the consequences into political behaviour. Autor et al. (2020) connect technological and globalisation-driven reallocation toward highly productive “superstar firms” to the falling labour share, locating AI within a broader structural shift in industry concentration.

A distinct, more behavioural line examines workers’ subjective responses. Schwabe and Castellacci (2020) show that the mere fear of future replacement by robots reduces workers’ current job satisfaction, even absent direct displacement, with effects differing by

skill level. Tiwari (2023) synthesises the displacement-versus-creation debate at a conceptual level and emphasises the mitigating role of government and organizational interventions. These studies indicate that the labour-market impact of AI is mediated by firm-level adoption choices, task composition, skill structures, and perception, precisely the variables an enterprise survey can capture.

This body of work is overwhelmingly anchored in the United States and Western Europe and in macro, regional, or patent-based data, with almost no enterprise-level evidence from Slovakia or the wider Central and Eastern European region. The future-of-work literature also rarely connects firm-level AI adoption to specific organizational functions such as human resource management, leaving open how CEE enterprises actually deploy AI in workforce-facing processes and how perceived employment effects shape that adoption.

2.6 Synthesis of research gaps and the present contribution

Read together, the five streams reveal a consistent structure of strengths and silences. The literature is rich in conceptual frameworks, systematic reviews and normative analysis; it is comparatively poor in representative, enterprise-level, *function-resolved* primary evidence, and it is geographically concentrated in Western, advanced-Asian and a handful of emerging-economy settings. Five gaps follow directly and map onto the four analytical angles of this monograph.

First, the determinants literature has validated a robust TOE-based toolkit, but it rarely isolates adoption *at the level of the HR function*, and almost never in a Central and Eastern European economy; whether general firm-level determinants such as size, sector and maturity govern specifically whether AI enters HR, as opposed to whether a firm uses AI at all, is largely untested (addressed in Chapter 5). Second, although reviews catalogue an expanding range of HR-AI applications, there is little quantitative evidence on *which* HR functions enterprises actually equip with AI and at *what stage* of adoption, leaving the internal architecture of AI in HR undocumented (Chapter 6). Third, the fairness/ethics and acceptance literatures establish that AI in HR carries both substantial benefits and serious risks, yet they rarely examine how the *adopting organization itself* weighs the two; whether firms treat benefits and risks as a trade-off or as a co-occurring duality is an open question (Chapter 7). Fourth, the employment literature is overwhelmingly macroeconomic or worker-level; the association between *function-specific* AI adoption in HR and firm-level employment outcomes, layoffs, new roles and employee fear, has not been examined directly (Chapter 8). Fifth, across all streams, enterprise-level evidence from Slovakia and the wider CEE region is essentially absent, so the external validity of the dominant findings in this setting is unknown.

The present monograph addresses these gaps with a single, richly instrumented dataset and a multi-angle analytical design. It does not merely transplant existing questions to a new country. It reframes AI-in-HR adoption as a layered phenomenon and brings function-level resolution, a duality model of perception, and an employment lens to bear on it simultaneously.

3. Data and methods

The credibility of empirical conclusions depends not only on the quality of the underlying data but also on the transparency with which the analytical process is documented. Because this monograph examines AI adoption in human resource management from multiple complementary perspectives, ranging from organizational determinants and application patterns to managerial perceptions and employment outcomes, no single analytical technique is sufficient to address all research questions. Instead, the methodological design follows the logic of the research objectives and combines descriptive, comparative and multivariate approaches into a coherent analytical framework.

The study adopts the enterprise as the primary unit of analysis and conceptualizes AI adoption in HR as one manifestation of broader organizational AI transformation. Consequently, the analytical strategy proceeds from the general to the specific. It first characterizes the surveyed enterprises and their overall AI adoption landscape before focusing on the subset of organizations that have implemented or tested AI in human resource management. This layered design makes it possible to distinguish factors associated with the decision to adopt AI in HR from factors associated with the depth, breadth and consequences of that adoption.

Throughout the monograph, particular emphasis is placed on methodological transparency and proportional interpretation of empirical evidence. Given that some analyses rely on a relatively specialized subsample of HR adopters, the interpretation consistently prioritizes effect sizes, confidence intervals and the practical importance of observed relationships rather than relying solely on statistical significance. Likewise, each analytical method is selected according to the nature of the underlying variables and the specific research question being addressed, ensuring that methodological choices remain aligned with the substantive objectives of the study. The remainder of this chapter describes the AI-ImpactSK dataset and its ethical foundations, presents the survey instrument and sampling procedure, defines the analytical samples and derived measures, explains the statistical techniques employed throughout the monograph, and concludes by discussing the principal methodological limitations that should be considered when interpreting the findings.

3.1 The AI-IMPACT project and research ethics

The empirical basis of this monograph is the AI-IMPACT organization-level survey, collected in 2025 within the research project *Empirical Examination of Artificial Intelligence Adoption and its Consequential Impact on Enterprise Performance, Market Dynamics, and Policy Formulation in the Slovak Economy (AI-ImpactSK)* at the Bratislava University of Economics and Business. The research received a Certificate of Ethical Conduct from the institution's Ethics Committee (reference EKEUBA 5/2025, 27 April 2025), which confirmed that the study complied with the institutional Code of Ethical Conduct and the European Code of Conduct for Research Integrity, that it involved no identifiable human participants in its analytical form, and that the data were anonymized. The publicly released analytical dataset is distributed under a Creative Commons Attribution 4.0 International

licence, with direct identifiers and potentially identifying free-text responses removed. The present monograph is a secondary analysis of that dataset, focused specifically on the human-resources dimension of AI adoption.

3.2 Survey instrument and measurement

The survey instrument is a structured questionnaire organized into thematic blocks that mirror the logic of enterprise AI adoption: company and respondent characteristics; organizational AI maturity; AI adoption status and intensity; functional areas of AI application and their evaluation; barriers to implementation; and corporate sentiment toward AI. The instrument was administered in Slovak. An English version is provided in the dataset documentation, and English item wording is used throughout this monograph. Several distinct response formats are combined. Single-choice categorical items capture firm demographics (sector, size, sales, ownership, age) and adoption status. Multiple-choice items capture the functional areas in which AI has been implemented or tested. Ordinal “stage” items, on a five-point ladder, capture the depth of adoption within each function. Five-point Likert items capture perceived impacts, sentiment and barriers. Single-item ordinal scales capture self-assessed maturity across seven dimensions.

A small number of documentation and data issues were identified and resolved transparently. The corporate-sentiment block is described in one help text as a six-point scale, yet the answer options and the realized data are five-point. The five-point coding (1 = strongly disagree to 5 = strongly agree) is used here. One negative-impact column carried a transcription artefact in its variable name (HRMnegativeI_2); it was renamed to its intended position so that the full twelve-item negative-impact scale could be analysed. These and other data-handling decisions are recorded in the project’s analytical documentation.

3.3 Sampling, screening and the realized sample

The survey targeted enterprises operating in the Slovak Republic and applied explicit inclusion criteria at screening. Firms with fewer than ten employees, with annual net sales below €200,000, with fewer than five years of operation in Slovakia, or under public (state) ownership were screened out. These criteria define the target population to which the findings generalize: established (five years or older), non-micro (ten or more employees), commercially substantial, privately or foreign- or mixed-owned enterprises. The criteria are clearly reflected in the realized data, which contain no firms in the smallest size, lowest turnover, youngest age, or state-ownership categories.

From an initial invitation pool, complete responses were obtained and, after removal of duplicate company representations, an analytical file of **816 unique enterprises** was retained; this deduplicated file is used throughout. The realized sample is broadly distributed across firm sizes (222 firms, 27.2%, with 10–49 employees, 246, 30.1%, with 50–249, and 348, 42.6%, with 250 or more) and across ownership types (391, 47.9%, privately owned Slovak firms, 326, 39.9%, foreign-owned firms registered in Slovakia, and 99, 12.1%, of mixed ownership). The large majority (568; 69.6%) have operated for eleven

years or more. Manufacturing is the single largest sector (201 firms; 24.6%), consistent with the structure of the Slovak economy, followed by information and communication, financial and insurance activities, transport, and construction. Respondents span managerial levels, from top management (126) through middle (203) and lower (197) management to non-managerial specialists (203), with managerial level missing for 87 respondents.

The realized sample is a large, screened, non-probability sample of the target population, not a strict probability sample. This has implications for inference that are discussed in Section 3.7 and Chapter 11.

3.4 Defining the HR analytic sample and comparison groups

The master adoption variable distinguishes seven states, from active use across multiple areas to no use and no plans. Following the survey's skip logic, the block on functional areas of AI application was presented only to firms reporting current AI use (the 562 firms, 68.9% of the sample, that use AI in multiple areas, in specific processes, or on a testing/piloting basis). Among these AI users, the survey asked in which functional areas AI had been implemented or tested; **100 firms selected "Human Resources"**, and these constitute the primary HR analytic sample. These 100 firms were then routed to a dedicated HR module that assessed, for twelve specific HR functions, the stage of AI adoption, and that elicited perceived positive and negative impacts of AI in HR.

The analysis uses three comparison frames. For questions about *who* adopts AI in HR (Chapter 5) and about employment correlates (Chapter 8), the natural comparison is between the 100 HR-AI adopters and the 462 firms that use AI in other functions but not (yet) in HR, holding constant the fact that all are AI users. For questions about the *landscape* (Chapter 4) and *readiness* (Chapter 9), the full four-way contrast is informative: non-adopters (123 firms; 15.1%), planners who intend to adopt within three or more years (131; 16.1%), AI users not applying AI in HR (462), and HR-AI adopters (100). For questions about the *internal architecture* and *appraisal* of AI in HR (Chapters 6 and 7), the analysis is conducted within the 100 HR adopters, who alone answered the HR module.

3.5 Derived measures and indices

Several composite measures were constructed and validated. **AI maturity** is indexed as the mean of seven self-assessed maturity dimensions (culture and mindset, strategy, organization, technology, data, ethics, privacy), each on a five-point stage scale; the index is highly reliable (Cronbach's $\alpha = .908$). **HR-AI penetration** within the HR module is captured in three ways: the mean adoption stage across the twelve HR functions (the *intensity* index; $\alpha = .914$), the *count of functions in use* (those rated at the pilot or active-use stage), and the *count of functions in active, regular use*. **Perceived benefits** and **perceived risks** are the means of twelve positive-impact and twelve negative-impact items respectively ($\alpha = .897$ and $.907$), and their difference defines a *net stance*. A *positive-sentiment* scale aggregates five corporate-sentiment items ($\alpha = .701$). The breadth of a firm's AI programme is measured as the number of functional areas in which it applies AI; in adoption models this

is computed *excluding* HR itself to avoid tautology. Firm size is treated both as an ordinal variable and as a large-firm indicator (250+ employees), and knowledge-intensive services are flagged as a sector grouping.

3.6 Analytical strategy

Analysis proceeds from description to confirmation. Descriptive statistics (frequencies, means, standard deviations, medians and full response distributions) characterize the sample, the adoption landscape and the HR module. Proportions are reported with Wilson 95% confidence intervals, and means with bias-corrected bootstrap (4,000–5,000 resample) confidence intervals, to convey precision honestly given the moderate size of the HR subsample.

Confirmatory analyses are matched to each research question. Group comparisons on ordinal or non-normal measures use the Mann–Whitney U test (two groups) or the Kruskal–Wallis test (more than two), with Cliff’s delta or the rank-biserial correlation as distribution-free effect sizes and bootstrap confidence intervals where informative. Associations between categorical variables use the chi-square or Fisher exact test with Cramér’s V or the odds ratio as the effect size. The determinants of HR-AI adoption are modelled with hierarchical binary logistic regression, entered in blocks (firm characteristics; readiness; AI breadth), with results reported as odds ratios with 95% confidence intervals, model fit as McFadden’s pseudo- R^2 and the area under the ROC curve, and multicollinearity checked through variance inflation factors. The depth of HR-AI adoption is modelled with ordinary least squares regression. The dimensional structure of the HR functions and of the perceived impacts is examined with reliability analysis and exploratory factor analysis (principal-axis extraction with promax rotation), with the number of factors guided by parallel analysis against the 95th percentile of random eigenvalues, and corroborated by hierarchical cluster analysis of the inter-item correlations.

Multiplicity is handled within pre-specified families of tests. Benjamini–Hochberg false-discovery-rate control is applied separately within each such family, for example the bivariate determinant comparisons and the seven maturity-dimension comparisons, with q-values reported alongside unadjusted p-values (and Holm-adjusted p-values where conservatism is warranted) so that readers can judge robustness directly. Regression coefficients are not folded into a single multiplicity family; they are interpreted through their effect sizes and confidence intervals. Single-item ordinal measures, such as the individual maturity dimensions and individual sentiment items including the employee-concern item, are compared on a rank basis and are not over-interpreted at the single-item level. Common-method variance was probed using a Harman single-factor test and partial correlations controlling for response-style markers, with results reported in Chapter 7.

Two principles govern interpretation throughout. First, given a primary subsample of 100 firms, the analysis privileges *effect sizes with confidence intervals* over isolated p-values, and is explicit about statistical power: small or borderline effects are reported as such, and are not dichotomized into “significant” or “not”. Second, Likert items are treated as interval

scales for the computation of means, a standard and defensible practice for multi-item scales of high reliability, while distributions and medians are reported alongside means so that no conclusion rests on the interval assumption alone. All analyses were conducted in Python (pandas, SciPy, statsmodels, pingouin, factor-analyzer, scikit-learn); every numerical result reported in this monograph is recorded in an accompanying master results registry, and every figure is reproduced at publication resolution.

3.7 Limitations of the design

Four design features bound the conclusions and are revisited in Chapter 11. The study is *cross-sectional*, so associations cannot be read as causal and the direction of relationships, for example between maturity and HR-AI adoption, cannot be established. It relies on *self-report* from a single organizational informant, which introduces the possibility of common-method variance and social-desirability effects, particularly for sentiment and impact perceptions. The sample is *screened and non-probabilistic*, so the findings generalize to the defined target population of established, non-micro, private/foreign/mixed-owned Slovak enterprises rather than to all firms. And the primary HR analytic sample, at 100 firms, while ample for descriptive characterization and moderate confirmatory testing, *limits statistical power* for complex multivariable models and fine-grained subgroup analysis; this is the reason for the consistent emphasis on effect sizes, confidence intervals and multiplicity control. None of these limitations is fatal, since the dataset is unusually large and richly instrumented for this topic and region, but each shapes how strongly particular claims can be advanced.

4. The landscape of enterprise AI adoption in Slovakia

Before turning to human resources specifically, this chapter maps the broader terrain of AI adoption among Slovak enterprises and locates HR within it. The purpose is twofold: to provide the descriptive overview that frames every subsequent analysis, and to establish the central positional fact of the monograph, that HR is a *second-wave* functional domain whose adoption is embedded in, and follows, a firm's broader AI engagement.

4.1 The adoption gradient: users, planners and non-adopters

Slovak enterprises in the target population are, in the main, already engaged with AI. Of the 816 firms, 562 (68.9%, 95% CI [65.6, 72.0]) report current use: 135 (16.5%) across multiple areas, 216 (26.5%) in specific processes, and 211 (25.9%) on a testing or piloting basis. A further 131 firms (16.1%) are planners who intend to adopt AI within timeframes ranging from one to three-plus years, and 123 (15.1%) neither use AI nor plan to (Figure 1). That roughly seven in ten firms already use AI in some form indicates how far diffusion has progressed in this manufacturing-intensive, export-oriented economy. The distribution within “use”, with piloting and process-specific use together outnumbering broad, multi-area deployment by more than three to one, signals that much of this engagement remains early-stage and exploratory rather than pervasive.

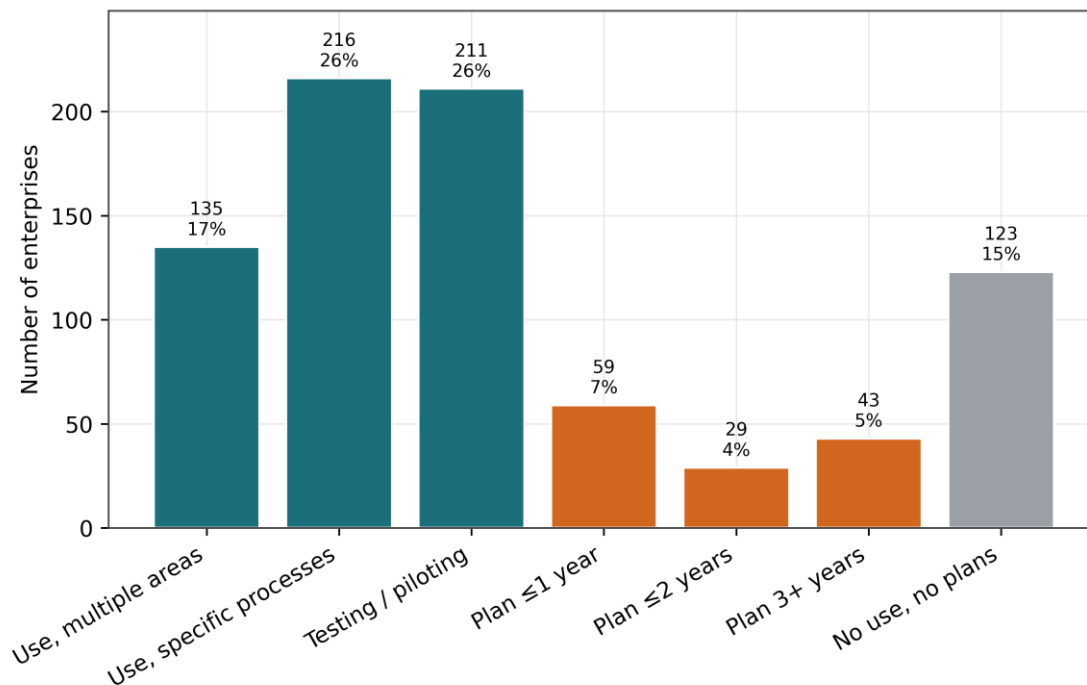


Figure 1. Distribution of AI adoption status across the 816 surveyed enterprises.

Bars are coloured to distinguish current users (teal), planners (orange) and non-adopters (grey).

This adoption gradient reflects more than stated intent; it is mirrored in organizational substance, as the maturity analysis below shows. It also defines the funnel through which the HR question must be read: only current users were asked about functional areas, so the HR analytic sample is properly understood as a subset of an already-engaged population.

4.2 The functional geography of AI: where HR sits

Among the 562 current users, AI is most prevalent in customer- and operations-facing functions. Marketing and sales leads the field, reported by 209 firms (37.2% of users, 95% CI [33.3, 41.3]), followed by production and operational processes (157; 27.9%), logistics (142; 25.3%) and research, development and innovation (121; 21.5%). Human resources is reported by 100 firms, 17.8% of users (95% CI [14.9, 21.2]) and 12.3% of the full sample, placing it fifth of the nine functional areas, ahead of company management (91; 16.2%), information and cybersecurity (78; 13.9%) and finance (75; 13.3%), but well behind the front-running commercial and operational functions (Figure 2).

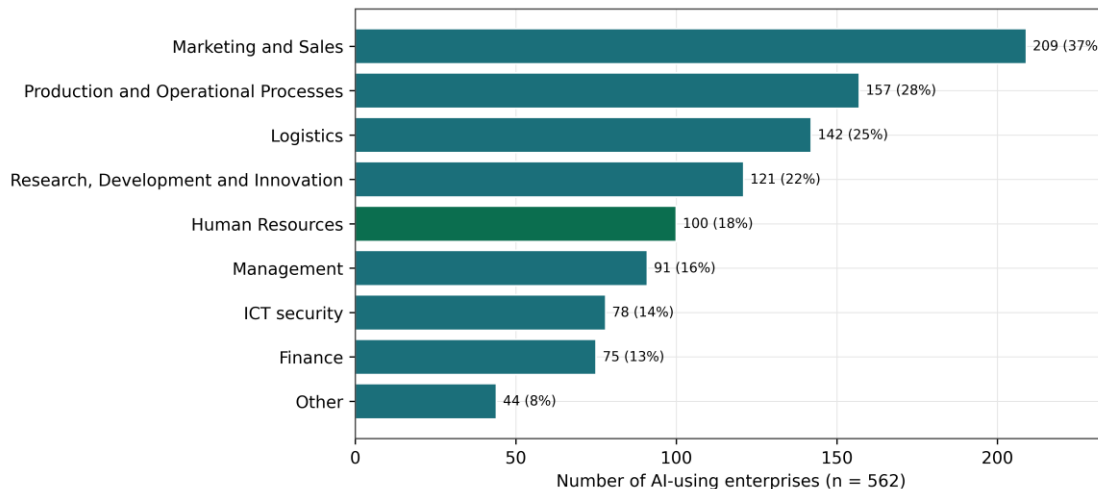


Figure 2. Functional areas of AI adoption among the 562 AI-using enterprises.

Human resources (highlighted) ranks fifth of nine areas.

This ordering is itself a finding. The leading functions, marketing, production and logistics, are those in which AI's value proposition is most legible (revenue uplift, throughput, routing efficiency) and in which decisions bear on processes and products rather than directly on people. HR is a *people-facing* function in which the same technologies raise sharper questions of fairness and acceptability, and in which the returns are more diffuse and harder to quantify. That HR occupies the middle of the distribution, neither a frontier nor a laggard, is consistent with a sequential diffusion in which firms extend AI to the HR function only after establishing it in commercially proximate domains. Chapter 5 confirms this interpretation directly: the strongest predictor of HR-AI adoption is the breadth of a firm's AI programme across other areas.

4.3 Organizational AI maturity and the adoption gradient

Self-assessed AI maturity tracks the adoption gradient closely and steeply. On the seven-dimension maturity index (1–5), non-adopters average 1.27 (95% CI [1.17, 1.38]), planners 2.14 [2.02, 2.26], AI users not applying AI in HR 2.85 [2.77, 2.93], and HR-AI adopters 3.03 [2.88, 3.18] (Figure 3). A Kruskal–Wallis test across these four mutually exclusive groups is highly significant ($H = 312.2$, $p \approx 2.3 \times 10^{-67}$), and the monotonic ordering is clear: organizational readiness rises at every step from non-adoption through planning and broad use to HR application. HR-AI adopters are, on average, the most mature firms in the sample, a pattern whose interpretation (maturity as enabler versus maturity as correlate of breadth) is examined carefully in Chapters 5 and 9.

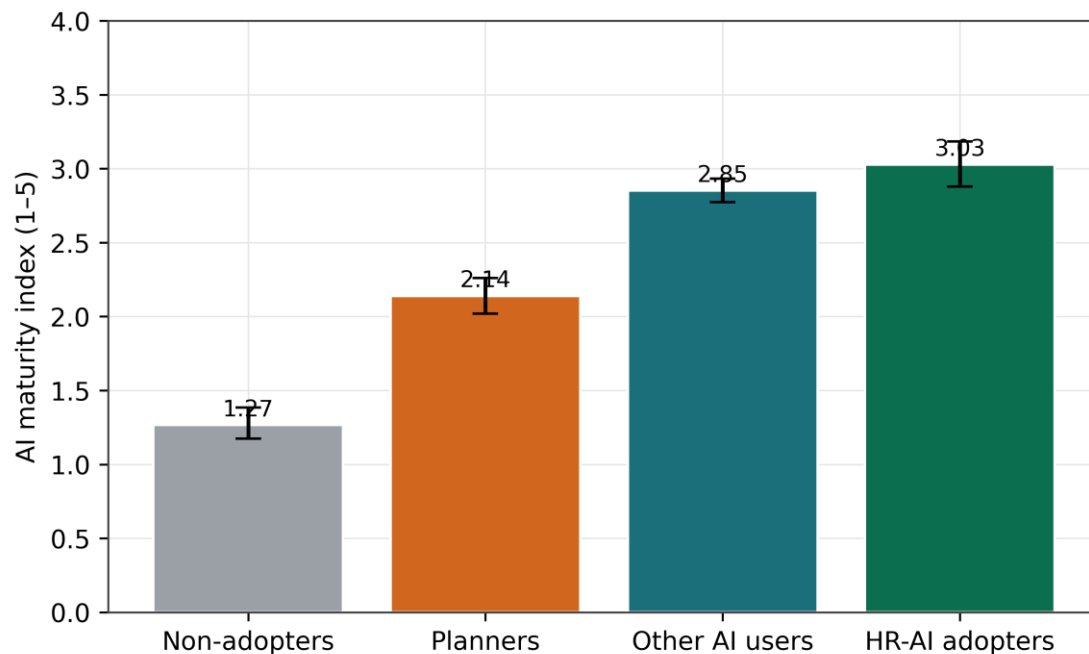


Figure 3. AI maturity index.

Mean of seven dimensions, 1–5, by adoption group, with bootstrap 95% confidence intervals.

Across the full sample, maturity is highest on the “softer” dimension of culture and mindset (2.76) and on technology (2.63), and lowest on the more demanding dimensions of organizational embedding (2.37), strategy (2.42) and ethics (2.42), with data (2.52) and privacy (2.54) in between. The pattern is telling. Slovak enterprises are, on average, more *culturally* and *technologically* open to AI than they are *organizationally* and *strategically* prepared for it, an “enthusiasm-ahead-of-embedding” profile that recurs in the HR-specific findings. Comparing HR-AI adopters with other AI users dimension by dimension (Figure 4), adopters score modestly higher on every dimension, with the largest raw gaps on privacy, ethics and technology. None of these single-dimension differences survives correction for multiple comparisons, however, indicating that it is *general* maturity rather than any particular dimension that distinguishes HR adopters.

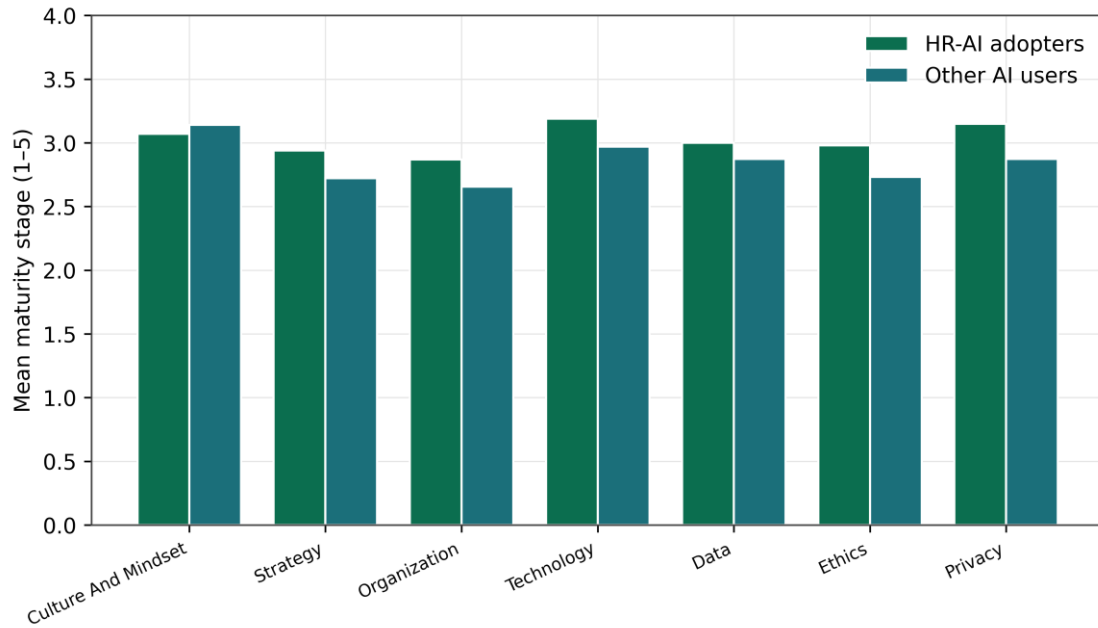


Figure 4. AI maturity dimensions compared between HR-AI adopters and other AI users.

4.4 Recency, governance and the structure of the sample

Two further contextual facts frame the analysis. First, enterprise AI in Slovakia is *recent*: among firms that reported the year of their first AI project, the clear majority date their first initiative to 2022 or later, with comparatively few histories extending before 2020. The HR applications examined in this monograph are therefore, in most cases, very young, a consideration that bears directly on the pilot-dominated picture documented in Chapter 6. Second, the decision to adopt AI is, in most firms, a *departmental* matter rather than an individual or whole-of-leadership one: a specific department (most often IT or innovation) drove the decision in the plurality of cases, with top management and cross-departmental collaborative processes next, and decisions by a single individual least common. The governance of AI adoption does not differ significantly between HR adopters and other users, suggesting that HR-AI is folded into the same organizational decision machinery as AI elsewhere rather than being governed by a distinct, HR-specific process.

The composition of the sample itself, predominantly established firms, with large enterprises somewhat over-represented and manufacturing the leading sector (Figure 5), should be borne in mind when interpreting what follows. The patterns documented here describe a population of serious, established, commercially substantial Slovak enterprises that are, for the most part, already on an AI trajectory; they do not describe micro-firms, start-ups or the public sector, which the survey design deliberately excluded.

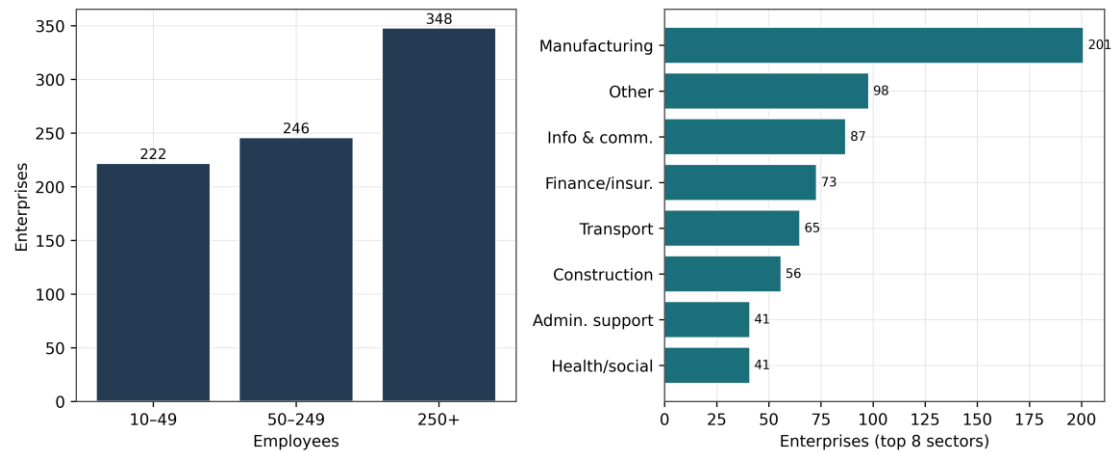


Figure 5. Composition of the sample by firm size (left) and leading sectors (right).

Against this backdrop, the central questions of the monograph come into focus. If HR is a second-wave function reached by the more mature, broader AI adopters, then *which* firms cross the threshold into HR-AI, and why? That is the subject of Chapter 5.

5. Determinants of AI-in-HR adoption

The preceding chapter demonstrated that human resource management occupies a distinctive position within the organizational diffusion of artificial intelligence. Although AI has already become established in many Slovak enterprises, its adoption is uneven across business functions, with HR emerging as a relatively later destination in the broader organizational AI journey. Describing this pattern, however, answers only part of the research problem. An equally important question concerns why some enterprises extend AI into human resource management while others, despite already using AI elsewhere, do not.

This distinction is analytically important. Much of the existing literature examines the determinants of organizational AI adoption in general, comparing adopters with non-adopters. Such an approach is valuable for explaining whether organizations begin using AI, but it cannot distinguish the factors that influence the subsequent diffusion of AI across individual organizational functions. The present analysis therefore shifts the analytical focus from enterprise-level AI adoption to function-specific AI adoption, asking what differentiates organizations that incorporate AI into HR from organizations that have already embraced AI but continue to use it exclusively in other business areas.

This perspective also reflects the conceptual view developed throughout the monograph, namely that AI implementation is not a single organizational decision but a cumulative process of organizational expansion. As enterprises accumulate technological capabilities, managerial experience and organizational confidence, AI gradually spreads from early operational applications toward functions that involve greater organizational complexity, higher regulatory sensitivity and more direct consequences for employees. Human resource management represents one such function. Consequently, the determinants examined in this chapter should be interpreted not simply as predictors of technology adoption, but as factors associated with the organizational extension of AI into one of the enterprise's most strategically and socially sensitive domains.

The analyses that follow therefore combine bivariate and multivariable approaches to evaluate the relative contribution of organizational characteristics, AI readiness and programme breadth while deliberately conditioning the comparison on current AI users. This design isolates the HR-specific adoption decision from the broader decision to adopt AI itself and provides a more precise understanding of how artificial intelligence diffuses across organizational functions.

5.1 Question and hypotheses

Chapter 4 established that human resources is a second-wave functional domain reached disproportionately by mature, broadly engaged AI adopters. This chapter asks *which* firm-level factors distinguish the enterprises that bring AI into HR from those that use AI elsewhere but not in HR (RQ1). The analysis is deliberately conditioned on current AI use, comparing the 100 HR-AI adopters with the 462 other AI users, so that it isolates the decision to extend AI to the HR function from the prior and quite different decision to use AI

at all. This conditioning matters. Many apparent “determinants” of HR-AI in the full population would simply reflect determinants of AI use in general, and holding AI use constant lets the analysis target the genuinely HR-specific adoption question.

Drawing on the TOE and readiness literatures reviewed in Chapter 2, three hypotheses were specified in advance:

H1a. HR-AI adoption increases with the breadth of a firm’s AI portfolio, the number of other functional areas in which it already applies AI.

H1b. HR-AI adoption is positively associated with organizational AI maturity and with dedicated investment in AI (budget and training).

H1c. Firm size and ownership are *not* decisive determinants of HR-AI adoption among AI-using firms.

5.2 Bivariate associations

Table-level comparisons of the 100 HR adopters with the 462 other AI users yield a clear and somewhat counter-intuitive pattern (see the master registry for the full set). The variables that distinguish HR adopters relate to the scope and seriousness of the firm’s AI engagement, while its demographic profile does little to separate the two groups. HR adopters apply AI in markedly more other functional areas than non-HR users (mean breadth excluding HR 2.22 vs. 1.50; Cliff’s $\delta = +0.17$, 95% CI [+0.02, +0.33], $p = .002$), they report higher organizational AI maturity (3.03 vs. 2.85; $\delta = +0.13$, $p = .040$), and they more strongly endorse having a dedicated AI budget and training plan (3.41 vs. 3.18 on the corresponding sentiment item; $\delta = +0.15$, $p = .010$). Positive AI sentiment is marginally higher among adopters (3.42 vs. 3.29; $p = .069$).

By contrast, the classic demographic determinants are inert. HR adopters are no more likely to be large firms (50% vs. 45% with 250+ employees; Cramér’s $V = 0.04$, $p = .33$), no more likely to be foreign-owned (44% vs. 44%; $p = .99$), and no more likely to belong to knowledge-intensive services (28% vs. 35%; $p = .15$) or to manufacturing (28% vs. 23%; $p = .24$). Firm age, if anything, trends in the opposite direction, with adopters slightly less likely to be long-established (58% vs. 66% aged eleven years or more; $p = .11$). The distribution across the three use stages (multi-area, process-specific and piloting) is statistically identical between HR adopters and other users ($p = .99$). HR adoption thus marks a broader scope of use rather than a more advanced stage of it.

When the family of bivariate tests is subjected to Benjamini–Hochberg false-discovery-rate control, three associations remain significant at $q < .05$: AI breadth including HR ($q < .001$), AI breadth excluding HR ($q = .012$) and dedicated AI budget/training ($q = .041$). The maturity and sentiment differences, significant or marginal in unadjusted tests, do not survive correction ($q = .12$ and $.17$ respectively). The robust bivariate signals are programme breadth and dedicated investment, with maturity and sentiment as weaker, correlated accompaniments.

5.3 Multivariable model

To assess the joint and independent contributions of these factors, HR-AI adoption was modelled with hierarchical binary logistic regression on the 562 AI users, entering predictors in three theoretically ordered blocks (Table in the master registry; coefficients visualized in Figure 6). Block 1 contained firm characteristics (size, ownership, age, knowledge-intensive-services sector); Block 2 added readiness (maturity, dedicated budget, positive sentiment); Block 3 added AI breadth (number of other functional areas).

The blocks tell a consistent story. Firm characteristics alone explain almost nothing (McFadden pseudo- $R^2 = .011$; ROC AUC = .577), so the demographic profile of a firm is essentially uninformative about whether it brings AI into HR. Adding readiness improves fit only modestly (pseudo- $R^2 = .026$; AUC = .617). The largest increment comes from AI breadth (pseudo- $R^2 = .064$; AUC = .648), which more than doubles the variance explained relative to the readiness model. In the full model, the only predictor that reaches significance is AI breadth. Among AI users, firms applying AI in more functional areas are correspondingly more likely to include HR, with each additional area associated with roughly half-again the odds of HR-AI adoption (adjusted odds ratio = 1.48, 95% CI [1.24, 1.75], $p < .001$). Size (OR = 1.00), foreign ownership (OR = 0.98), maturity (OR = 1.10), dedicated budget (OR = 1.23) and positive sentiment (OR = 0.95) are all non-significant once breadth is controlled, and age and the knowledge-services sector trend negative but do not reach significance (OR = 0.65, $p = .07$; OR = 0.67, $p = .12$). Variance inflation factors are uniformly low (all < 2.4), so the null results are not artefacts of collinearity; rather, the bivariate maturity and budget signals are substantially absorbed by AI breadth, with which they are positively correlated.

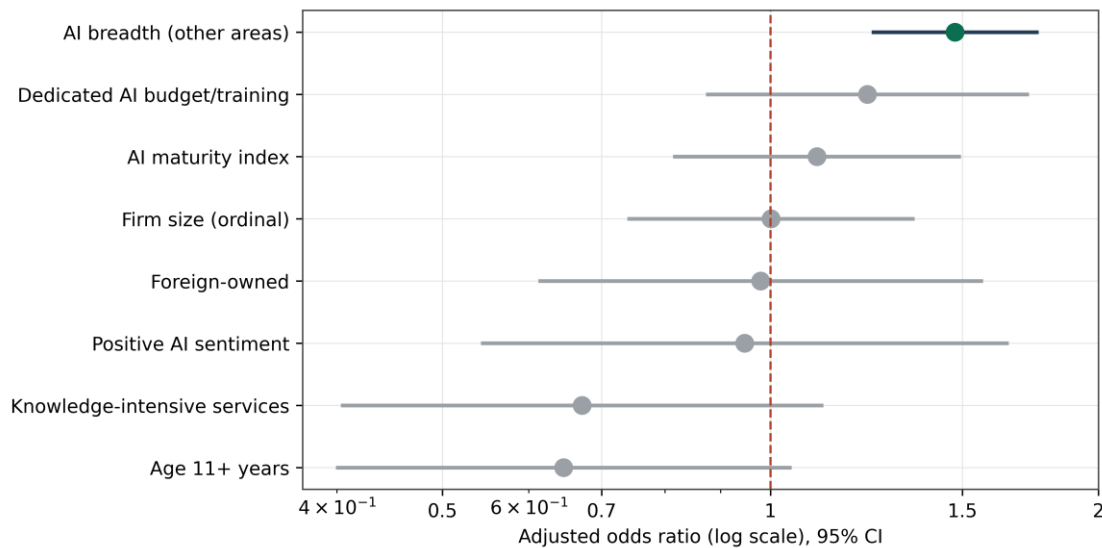


Figure 6. Adjusted odds ratios (95% CI, log scale) for predictors of HR-AI adoption among AI-using firms, from the full hierarchical logistic model.

Only AI portfolio breadth is significant.

The overall fit deserves an honest reading. With an AUC of .648, the model discriminates HR adopters from other users only modestly. This is a substantive result in its own right: HR-AI adoption is weakly stratified by observable firm characteristics. Whether a firm extends AI to HR is largely unpredictable from its size, sector, ownership, age or even its general maturity. The best available predictor is simply how broadly the firm has already deployed AI elsewhere.

5.4 Interpretation: HR-AI and the breadth of the AI portfolio

These results support H1a strongly, H1c clearly, and H1b only partially. The central finding is that HR-AI adoption is associated with the breadth of a firm's AI portfolio more than with its demographic profile. The pattern is consistent with HR being incorporated into a widening AI footprint as firms accumulate applications across functions, though the cross-sectional data cannot confirm such a process. Firms applying AI in more areas are correspondingly more likely to include HR, and once breadth is accounted for, the demographic and even readiness characteristics of the firm add little. One caution should be entered before any of this is read causally. AI breadth is a count of the other functional areas in which a firm uses AI, and the HR flag records whether HR is one such area; both measures register the same underlying AI-deployment behaviour. Part of the breadth-HR association may therefore be mechanical, or may reflect selection on firms that are already heavy AI users. A corroborating but tempering observation points the same way. Among the 100 HR adopters, AI breadth does not significantly predict the depth of HR-AI adoption (Spearman $\rho = .16$, $p = .11$), which cautions against a strong causal reading of the breadth effect.

This framing has several implications that later chapters develop. It is consistent with the second-wave positioning of HR documented in Chapter 4: if HR adoption tracks breadth, and breadth accumulates over time, HR tends to be reached after commercially proximate functions. It also qualifies the maturity story. HR adopters are more mature (Chapter 4), but in these data maturity is associated with HR-AI adoption largely via its association with breadth rather than as an independent gatekeeper, an ordering the cross-sectional data cannot establish; the reading is consistent with treating maturity as the staged capacity that allows a firm to widen its AI programme in the first place (Jöhnk et al., 2020; Uren & Edwards, 2022). The findings also nuance the contrast with the determinants literature, much of which is conducted at the level of "AI adoption" in general, often in single-function or SME-wide framings, and finds size and sector effects (Badghish & Soomro, 2024; Shahadat et al., 2023; Pillai & Sivathanu, 2020). At the level of the specific functional decision, conditioned on prior AI use, those demographic effects largely dissolve and a programme-level variable takes their place. This is a contribution of the function-resolved, use-conditioned design. What is associated with the spread of AI into a particular function differs from what is associated with whether a firm uses AI at all, a relationship rarely tested directly. The practical reading is equally clear. For managers and HR leaders, HR-AI is unlikely to arrive through a stand-alone HR initiative in a firm that is otherwise narrow in its AI use; in this sample it tends to accompany a broader organizational AI programme. For analysts and policymakers seeking to identify likely HR-AI adopters, firm demographics are poor predictors, whereas the breadth of existing AI deployment is a strong one.

6. The application architecture of AI in human resources

Knowing that an enterprise has adopted artificial intelligence in human resource management reveals remarkably little about how AI is actually used. HR encompasses a diverse portfolio of organizational activities that differ substantially in their objectives, data requirements, regulatory sensitivity and degree of managerial discretion. Consequently, two organizations that both report using AI in HR may, in practice, have implemented entirely different technological solutions. One may employ AI solely for CV screening during recruitment, while another may apply it across learning and development, employee evaluation, workforce planning and retention analytics. Treating HR-AI adoption as a single binary phenomenon therefore conceals potentially important differences in the internal architecture of implementation.

This chapter moves beyond the question of whether enterprises adopt AI in HR and examines how that adoption is distributed across individual HR functions. Rather than viewing AI implementation as a homogeneous organizational capability, the analysis considers the HR function as a collection of interconnected yet distinct processes, each of which may occupy a different stage of technological maturity. This perspective makes it possible to distinguish broad organizational engagement from genuinely deep implementation and to assess whether enterprises develop AI capabilities evenly across the HR value chain or concentrate them in a limited number of activities.

The chapter also addresses a broader methodological question. If AI applications across recruitment, onboarding, learning, performance management and workforce analytics consistently co-occur, they may represent manifestations of a single underlying organizational capability rather than independent implementation decisions. Conversely, systematic clustering of functions would suggest that organizations follow recognizable pathways of HR digitalization. Examining the internal structure of AI deployment therefore contributes not only to understanding current implementation patterns but also to clarifying whether AI adoption in HR should be conceptualized as a unified organizational construct or as a collection of function-specific trajectories.

The analyses presented in this chapter therefore combine descriptive profiling with multivariate structural techniques to map the internal architecture of AI adoption in HR. Together, they provide a function-level perspective that complements the organization-level analyses presented in the previous chapters and forms the empirical foundation for the subsequent examination of perceived benefits, risks and organizational consequences.

6.1 Question and hypotheses

Chapters 4 and 5 treated HR-AI adoption as a single threshold, namely whether a firm has begun applying AI in HR at all. Yet “AI in HR” covers many activities: recruitment and selection, workforce planning, learning and development, onboarding, performance evaluation, retention analytics, compensation. A firm may be deep in some and absent from others. This chapter opens the black box, asking which specific HR functions the 100

adopters target, at what stage of adoption, and how the functions cluster (RQ2). Three hypotheses guide the analysis:

H2a. AI in HR is concentrated in talent-acquisition functions (recruitment, screening, candidate matching) relative to developmental and analytical functions.

H2b. HR-AI applications are predominantly at the pilot or early stage rather than in active, regular use.

H2c. The HR functions form coherent dimensions rather than being adopted independently.

The HR module assessed each of twelve functions on a five-point adoption ladder: (1) no use and no plans; (2) considering for the more distant future; (3) planning within two years; (4) already using on a pilot or occasional basis; and (5) using actively and regularly. Throughout this chapter, “in use (≥ 4)” denotes pilot/occasional or active use, and the term “intensity” refers to an engagement-stage index (1–5) that blends intention and use rather than a measure of usage volume. The ladder is more informative than a binary “use/not” because it captures the depth of adoption function by function.

6.2 The adoption ladder, function by function

Two features dominate the function-level picture (Figures 7 and 8). The first is compression. The twelve functions occupy a narrow band of mean adoption stages, from 2.82 to 3.20 on the five-point ladder, with considerable overlap in their confidence intervals. The second is a slight talent-acquisition lead. The highest-ranked functions are recruitment (mean 3.20; 40% of adopters at pilot or active use; 12% in active regular use), personalized learning and development (3.12; 30% in use), screening of CVs and personnel documents (3.09; 40% in use), candidate matching (3.06; 36%) and personalized onboarding (3.06; 36%). The lowest-ranked are employee compensation (2.82), turnover prediction (2.86), e-HRM (2.86) and prediction of candidate success and career planning (2.86). A Friedman test detects statistically significant but negligible differences across the twelve functions ($\chi^2 = 30.1$, $p = .002$; Kendall’s $W = .027$), confirming the visual impression that recruitment-adjacent functions lead while the differences between functions remain small in magnitude.

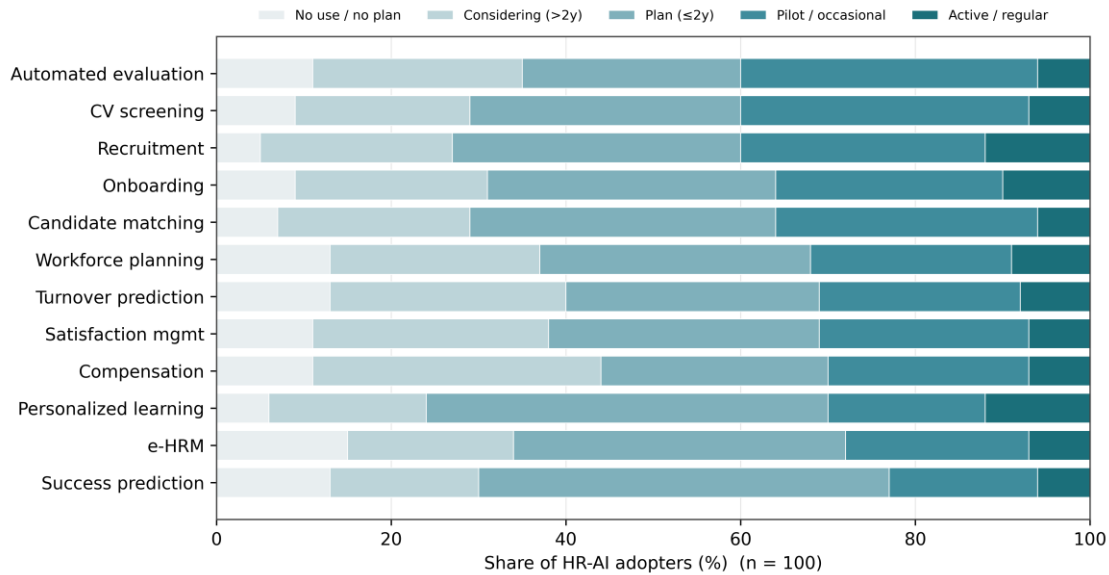


Figure 7. Adoption-ladder profile of twelve HR functions among the 100 HR-AI adopters. Each bar shows the share of firms at each of the five adoption stages, sorted by the share in pilot or active use.

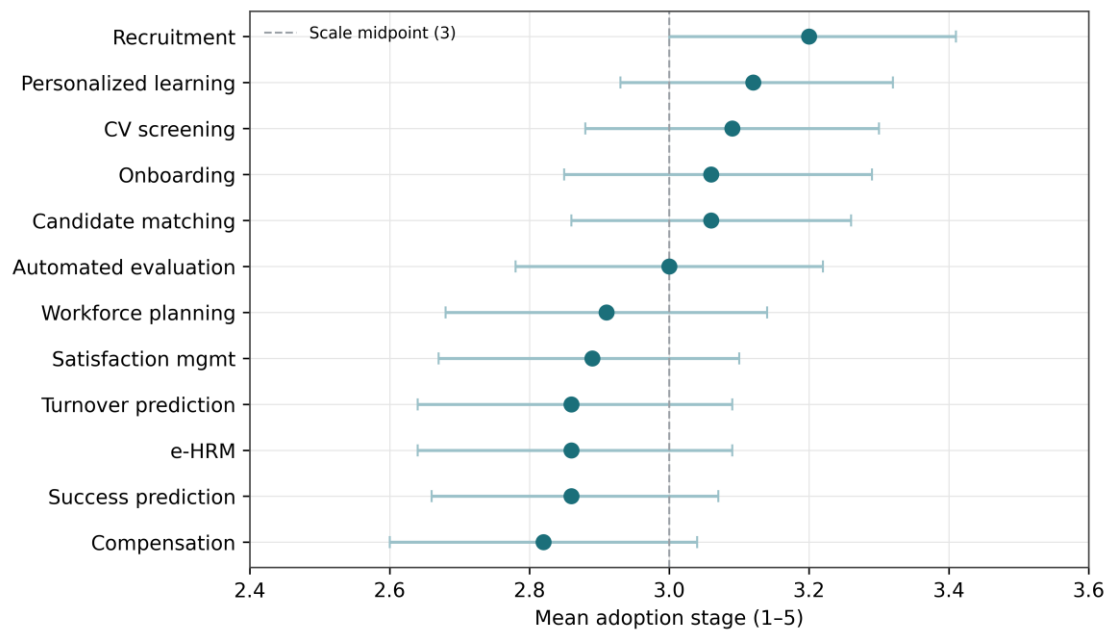


Figure 8. Mean adoption stage (1–5) for each HR function with bootstrap 95% confidence intervals.

All functions cluster near the scale midpoint, indicating broad but shallow adoption.

The picture that emerges is of broad but shallow engagement. The mean adoption intensity across the twelve functions, on the 1–5 engagement-stage index, is 2.98 (SD 0.79), almost exactly the scale midpoint and corresponding to “planning within two years”. The

deployment-only figures are the clearer guide to depth. Only 29 of the 100 adopters actively and regularly use any HR function, and 20 report no function yet even at the pilot-or-active stage, having flagged HR in response to the broad question of where they have “implemented or tested” AI on the basis of plans and intentions rather than live deployments (Figure 9). Firms have, on average, 3.97 of the twelve functions at pilot or active use but only 0.97 in active, regular use. The distribution of the in-use count is heavily right-skewed, with a minority of firms deep across many functions while the majority test one or two.

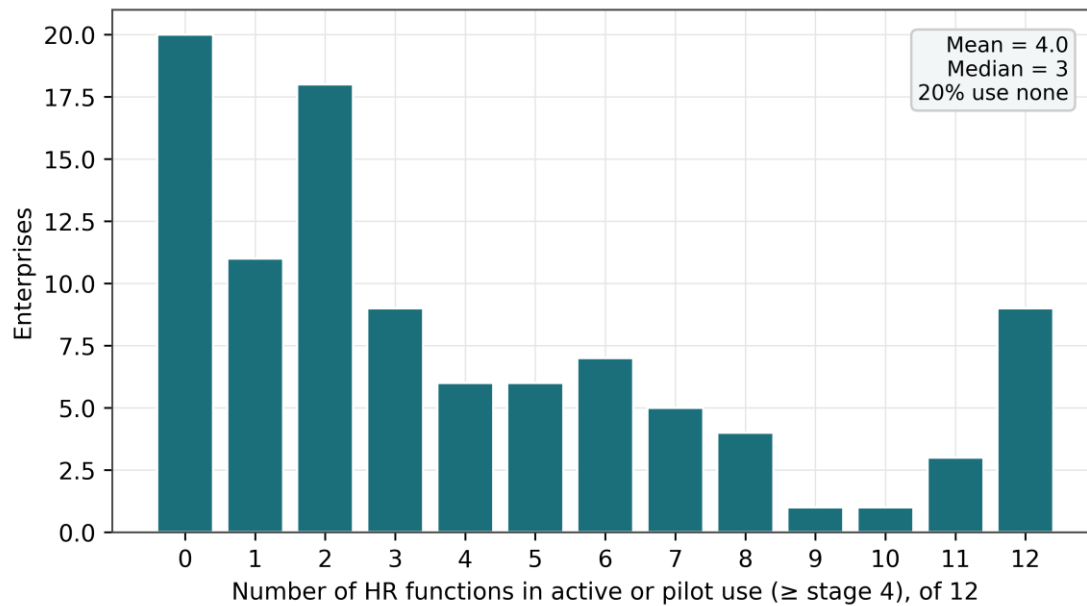


Figure 9. Distribution of the number of HR functions in active or pilot use (stage ≥ 4) per adopter.

Twenty firms have none yet in use; the mean is four of twelve.

These results provide strong support for H2b (pilot dominance) and only partial support for H2a. Talent-acquisition functions do lead the ranking, consistent with the international evidence that recruitment and selection is the most mature application domain for AI in HR (Mori et al., 2024; Chen, 2023; Pillai & Sivathanu, 2020). The lead is narrow, and, as Section 6.4 shows, the broader acquisition-versus-development distinction does not translate into a statistically significant intensity gap. Recruitment, CV screening and candidate matching are the entry points and the modal applications, yet Slovak adopters are extending AI fairly evenly across the HR value chain instead of concentrating it in hiring.

6.3 The dimensional structure of HR-AI

Are the twelve functions adopted as a coherent whole, or do they form distinct bundles? The reliability evidence points firmly to coherence. The twelve-function intensity scale has a Cronbach’s α of .914, and the mean inter-function Spearman correlation is .46 (ranging from .21 to .66), which indicates that firms adopting AI more deeply in one HR function

tend to do so across the others. The sampling adequacy is excellent for factor analysis (Kaiser–Meyer–Olkin = .874; Bartlett’s test $p \approx 10^{-103}$).

When the dimensionality is examined formally, the primary result is unidimensionality. By the conservative criterion of parallel analysis, which compares observed eigenvalues against the 95th percentile of eigenvalues from random data, only a single factor is retained. The first eigenvalue (6.24) exceeds the parallel-analysis threshold (1.77), while the second (1.30) falls just below its threshold (1.54). On this reading the HR-function scale is essentially unidimensional: one underlying “depth of AI in HR” runs across all functions, which justifies the use of the single intensity index throughout the monograph.

A tentative secondary structure can nonetheless be discerned, and it is offered as a refinement rather than as a strong second dimension. A two-factor solution (promax rotation; 53% of variance explained) separates a talent-acquisition factor (workforce planning, recruitment, CV screening and candidate matching) from a workforce-analytics and development factor comprising personalized learning, onboarding, automated evaluation and feedback, e-HRM, satisfaction management, turnover prediction and compensation. The same split appears in a hierarchical cluster analysis of the inter-function correlations (Figures 10 and 11), where the two-cluster solution reproduces the acquisition bundle and the three-cluster solution further isolates evaluation and satisfaction management as a small “performance-monitoring” sub-bundle. Because the clustering operates on the same correlation matrix as the factor analysis, it corroborates the partition rather than confirming it independently. The two subscales, moreover, do not differ in adoption depth (Wilcoxon $p = .30$; Section 6.4), so the distinction is best treated as a secondary refinement of a dominant general factor.

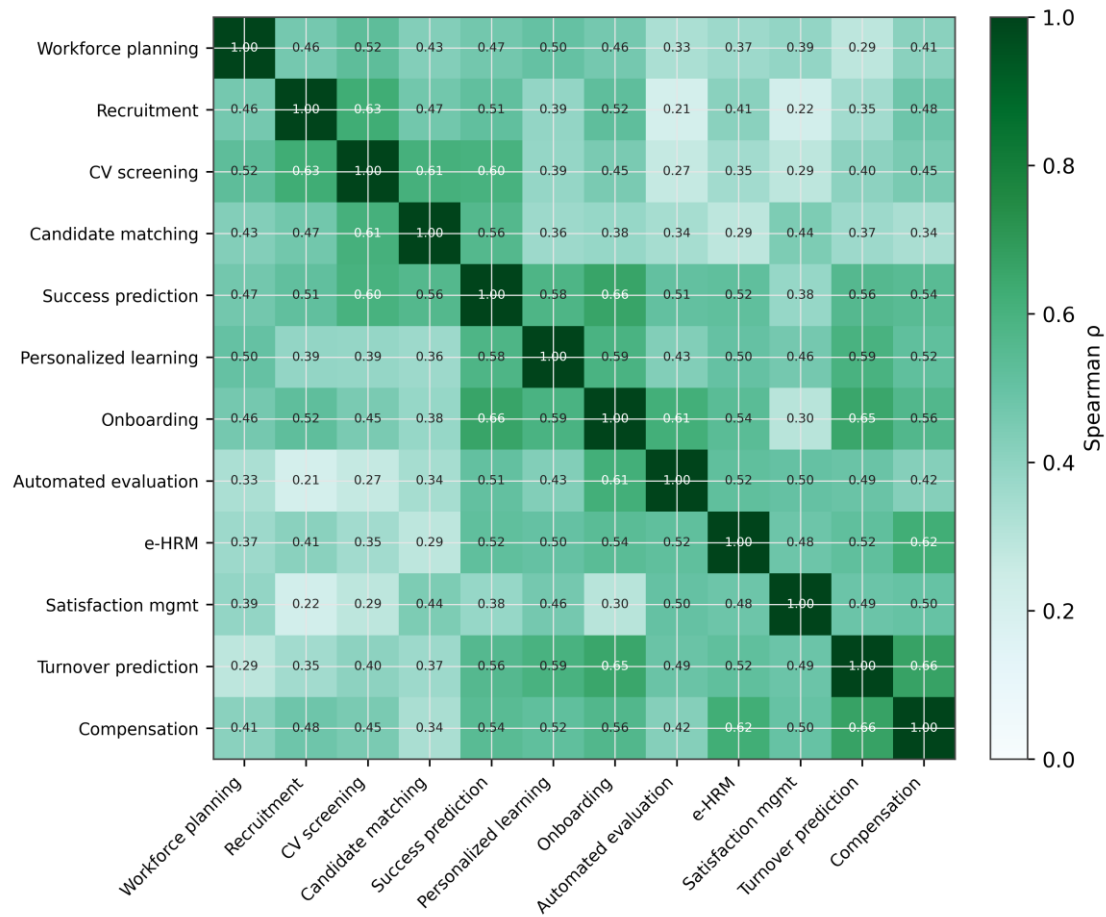


Figure 10. Spearman correlation matrix of the twelve HR-AI functions among adopters. Uniformly positive, moderate-to-strong correlations underpin the high scale reliability.

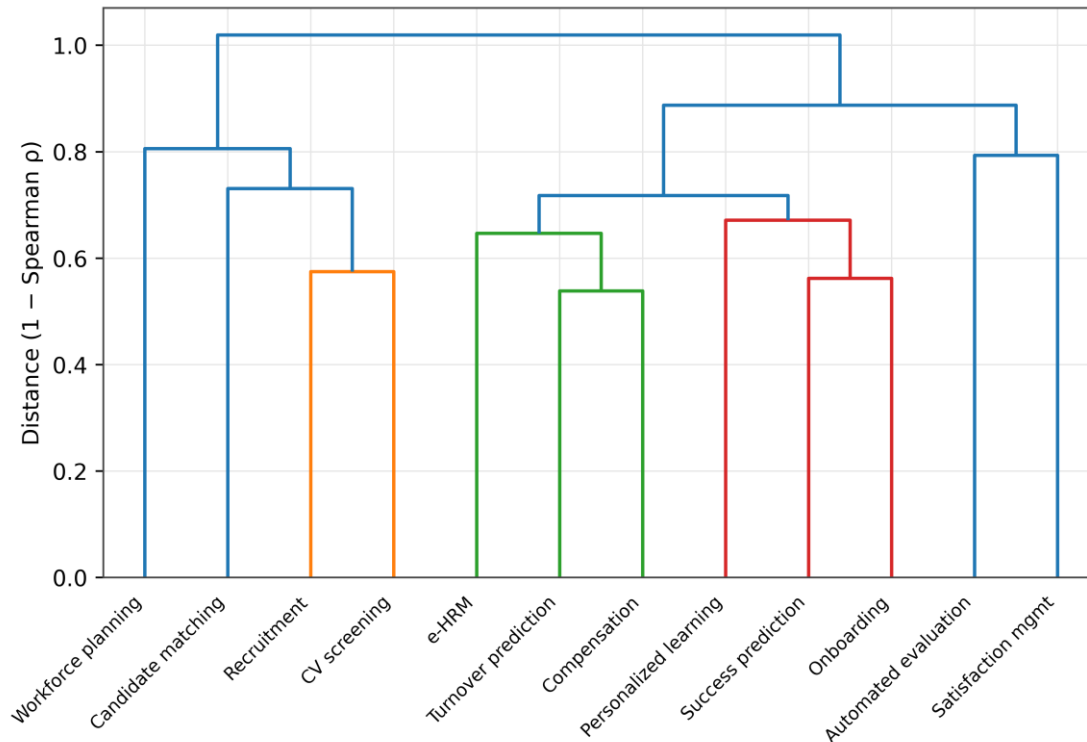


Figure 11. Hierarchical clustering of HR functions (average linkage on $1 - \text{Spearman } \rho$).

The first split separates the talent-acquisition bundle (workforce planning, recruitment, CV screening, candidate matching) from the development/analytics functions.

H2c is therefore supported in a qualified form. The functions form a coherent structure dominated by a single general penetration factor, with a tentative, theory-consistent acquisition/development refinement layered on top. The co-occurrence patterns add texture. The most frequently co-deployed function pairs are e-HRM with compensation, recruitment with CV screening, and onboarding with automated evaluation, which suggests that firms tend to add AI in tightly related task clusters instead of scattering it across unrelated functions.

6.4 Acquisition versus development: a distinction without a gap

Given the tentative two-factor structure, one might expect the talent-acquisition bundle to be adopted more intensively than the development/analytics bundle, the natural reading of H2a. The data do not bear this out. The acquisition subscale (mean 3.02) and the development subscale (mean 2.94) are statistically indistinguishable (Wilcoxon signed-rank $p = .30$). Individual acquisition functions occupy the top of the ranking, yet the acquisition bundle as a whole is adopted no more deeply than the development bundle. This qualification matters: the popular narrative that “AI in HR means AI in hiring” overstates the case for Slovak adopters, who are extending AI into learning, onboarding, evaluation and retention analytics at broadly comparable depth. The talent-acquisition lead is real but marginal, and the developmental and analytical applications follow close behind.

6.5 Depth and the broader AI programme

Finally, does deeper HR-AI penetration go with a more advanced overall AI posture? The relationship is weak and not significant at the level of use stage. HR-AI intensity is slightly higher among firms that use AI across multiple areas (3.28) than among those still piloting AI generally (2.82), but the difference across the three use stages does not reach significance (Kruskal–Wallis $p = .17$). Depth of HR-AI is not simply a function of how advanced the firm's general AI use is. As Chapter 7 shows, it is more closely tied to how the firm appraises AI in HR, in particular to its perception of benefits, and to its organizational maturity. The architecture of AI in HR is broad, coherent, shallow and only loosely coupled to the firm's general AI stage, a function in early, exploratory expansion across its whole value chain rather than deep specialization in any one corner of it.

7. The benefit–risk calculus of AI in human resources

Previous chapters have examined AI in HR primarily as an organizational phenomenon, identifying which enterprises adopt AI, how broadly they deploy it across HR functions, and how deeply those applications become embedded in organizational practice. Adoption decisions, however, are not driven solely by technological capability or organizational readiness. They are also shaped by how managers perceive the opportunities and challenges associated with AI implementation. Every organizational decision to expand AI into human resource management implicitly reflects an evaluation of expected organizational benefits alongside perceived ethical, managerial and operational risks.

This evaluative dimension is particularly important in HR because AI simultaneously promises considerable organizational gains and raises concerns that extend beyond technological performance. Improvements in efficiency, consistency and decision support coexist with questions regarding fairness, transparency, employee trust and the preservation of human judgement. Unlike many other organizational technologies, AI in HR directly affects decisions concerning people, making managerial perceptions an integral component of the adoption process rather than a secondary consequence of implementation.

Rather than assuming that organizations simply balance expected benefits against perceived risks, this chapter investigates whether these evaluations constitute a more complex cognitive structure. Enterprises may simultaneously recognize substantial opportunities and substantial risks, resulting in organizational ambivalence rather than straightforward optimism or resistance. Understanding this evaluative landscape is essential because managerial perceptions influence not only whether AI is accepted but also how extensively organizations are willing to integrate it into sensitive HR processes. Accordingly, this chapter examines the internal structure of benefit and risk perceptions, their relationship to one another, and their association with organizational maturity and the depth of AI adoption in HR. Together, these analyses move beyond technological implementation to explain how organizations interpret AI as a managerial innovation and provide an important conceptual bridge between the application architecture examined in the previous chapter and the employment outcomes analysed in Chapter 8.

7.1 Question and hypotheses

If Chapter 6 described what firms *do* with AI in HR, this chapter examines how they *evaluate* it. AI in HR is unusual among enterprise technologies in that its benefits and its risks are both salient and both serious. It promises faster, more consistent and more personalised people management, yet it also raises the spectre of discrimination, of dehumanised decisions, and of eroded trust between staff and managers (Tambe et al., 2019; Fabris et al., 2024; Tursunbayeva et al., 2021). How firms reconcile these competing considerations is both theoretically interesting and practically consequential: do they treat them as a trade-off, in which more perceived benefit accompanies less perceived risk, or as a duality, in which the two coexist? The HR module asked the 100 adopters to rate the

significance of twelve positive and twelve negative potential impacts of AI in HR, each on a five-point significance scale. Three hypotheses structure the analysis:

H3a. Perceived positive and negative impacts are empirically distinct dimensions rather than opposite poles of one evaluation.

H3b. Perceived benefits and risks are *positively* correlated across firms (a duality, not a trade-off).

H3c. The depth of HR-AI adoption is associated with perceived benefits and organizational maturity, and is *not* dampened by perceived risks.

7.2 What firms see as the benefits — and the risks

The perceived benefits of AI in HR are, in the eyes of adopters, primarily about *efficiency and consistency*. The highest-rated positive impacts are the reduction of administrative burden and more efficient management of personnel data (mean 3.72), increased objectivity and regularity of employee evaluation (3.67), acceleration of recruitment (3.66), faster adaptation of new employees through personalized onboarding (3.65), early identification of workplace problems (3.64) and improved internal communication (3.64) (Figure 12). The lowest-rated benefits, though still above the scale midpoint, are fairer, benchmark-based compensation (3.45) and job optimization (3.41). The benefit profile is dominated by operational efficiency and process consistency, with transformative or strategic gains rated lower.

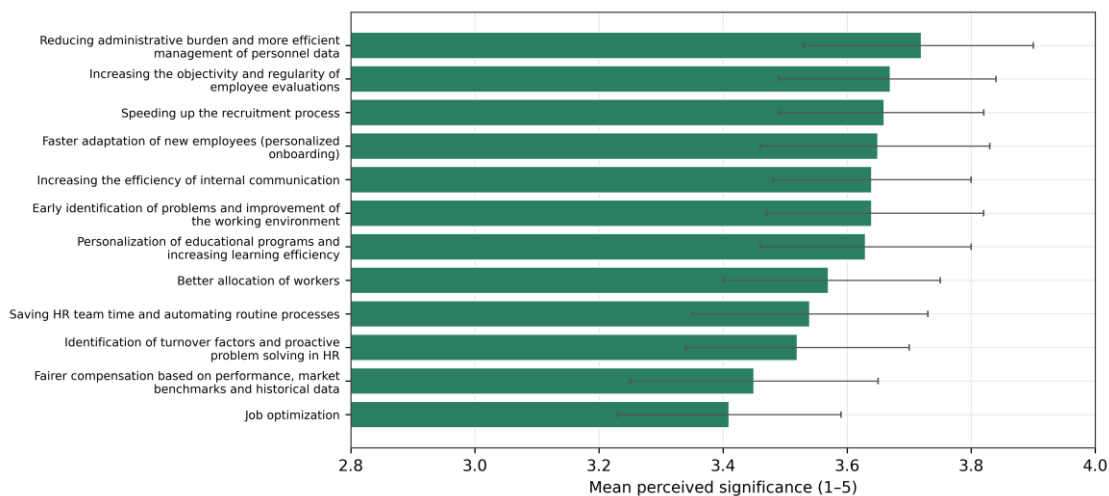


Figure 11. Perceived positive impacts of AI in HR, mean significance (1–5) with bootstrap 95% confidence intervals.

The perceived risks are, revealingly, predominantly *human and relational* in character (Figure 13). The most significant negative impacts are the overlooking of unconventional candidates and the narrowing of diversity (mean 3.68), decreased social interaction and weakened teamwork (3.65), the weakening of relations between employees and management (3.56), the risk of discrimination and unfairness in recruitment and evaluation (3.53) and the loss of employee trust due to constant monitoring (3.52). The least

significant risk is the most technical one, namely problems with IT-infrastructure outages and dependence on AI systems (3.36). When the twelve risks are grouped thematically, the *relational and social* cluster (mean 3.55) and the *fairness and bias* cluster (3.53) rank above the *dehumanization and quality* cluster (3.45) and well above the *technical and dependence* cluster (3.36) (Figure 17). Slovak adopters worry less about AI breaking down and more about it eroding the human and equitable fabric of the workplace, a concern profile that resonates with the fairness and human-centred critiques in the international literature (Chen, 2023; Sánchez-Monedero et al., 2020; Yarger et al., 2019).

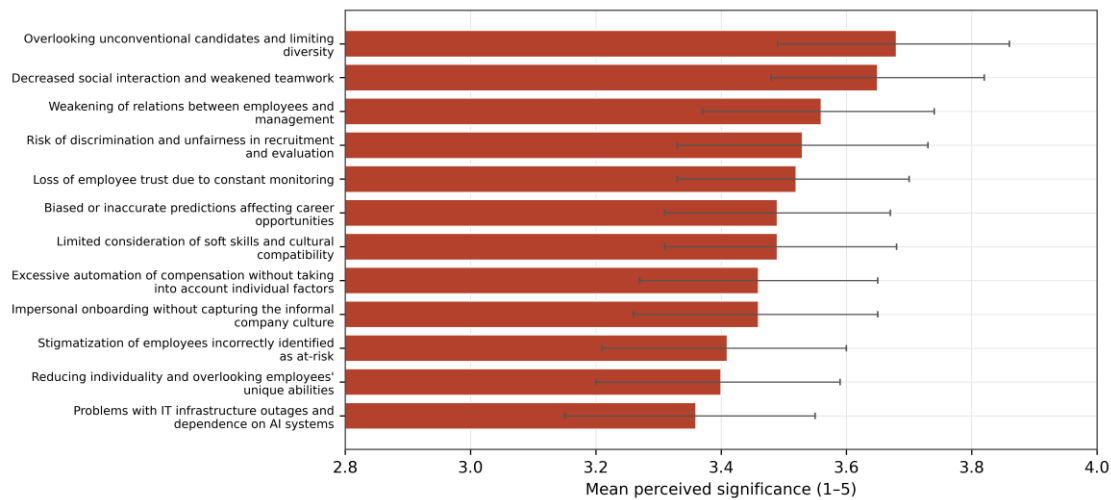


Figure 12. Perceived negative impacts of AI in HR, mean significance (1–5) with bootstrap 95% confidence intervals.

The leading concerns are relational and fairness-related, not technical.

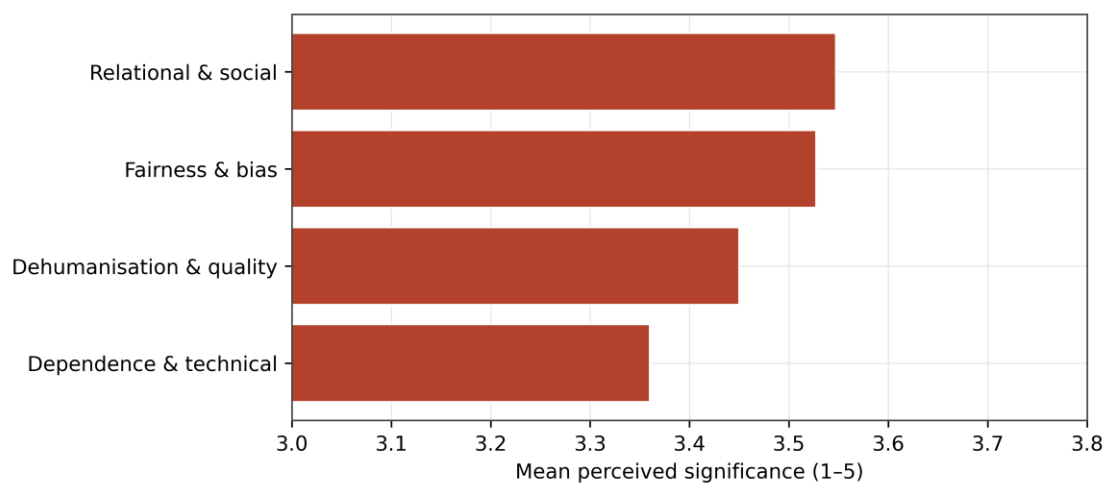


Figure 13. Negative-impact theme clusters.

Relational/social and fairness/bias concerns outweigh dehumanization and technical/dependence concerns.

7.3 Benefits and risks: a duality, not a trade-off

The central perceptual finding is that adopters weigh benefits and risks as *roughly equal in significance*. The *net stance* is defined throughout as the difference between the perceived-significance ratings (1–5) of positive and negative impacts; it is a comparison of salience, not a utility or cost–benefit balance. The mean perceived-benefit score (3.59, 95% CI [3.47, 3.72]) is only marginally and non-significantly higher than the mean perceived-risk score (3.50, [3.36, 3.63]); a within-firm Wilcoxon signed-rank test finds no significant difference ($p = .27$, rank-biserial = .14). Decomposing the net stance firm by firm, 44 adopters are benefit-dominant, 33 are risk-dominant, and 23 are balanced, a near-symmetric distribution with only a slight lean toward benefits (Figure 15). There is no general optimism that the benefits of AI in HR clearly outweigh the risks. The population of adopters is split, with substantial minorities on each side and a large balanced centre.

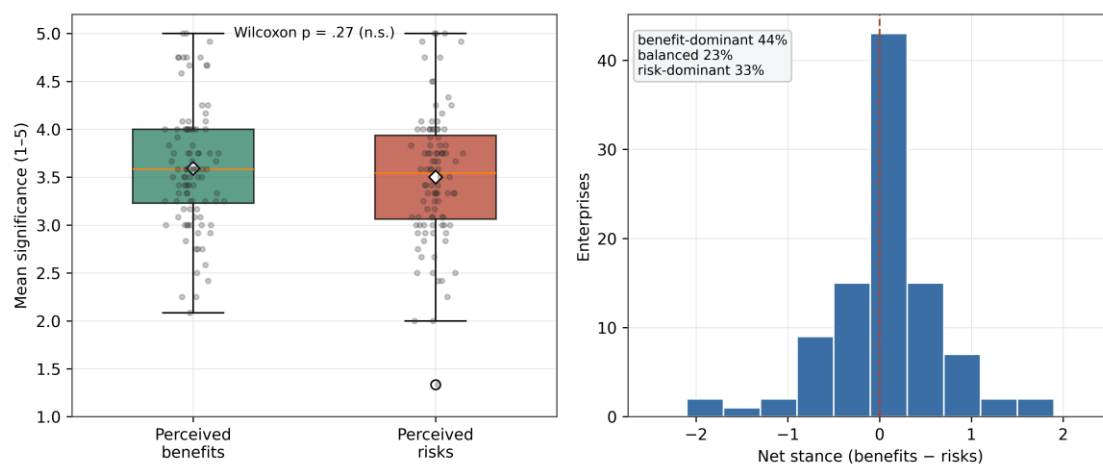


Figure 14. Perceived benefits versus risks.

Left: the two distributions are statistically indistinguishable (Wilcoxon $p = .27$). Right: the firm-level net stance is near-symmetric, with a slight benefit lean.

The more arresting result is the *positive* association between perceived benefits and perceived risks. A naïve model in which enthusiasts downplay risks and skeptics discount benefits would predict a trade-off; instead, benefits and risks are positively correlated across firms (Pearson $r = .41$, 95% CI [.20, .61], $p < .001$; Spearman $\rho = .51$). Firms that see more to gain from AI in HR also see more to fear. This is the signature of *engaged ambivalence*: the firms thinking hardest about AI in HR perceive its potential on both sides of the ledger more acutely, while the firms that see little benefit also see little risk, presumably because they have engaged less deeply with the technology’s implications.

Because both rating sets come from a single respondent on a single instrument, this correlation invites a common-method-variance objection: a general acquiescent or extreme response style could inflate benefit and risk ratings together. Two checks make response style an unlikely *sole* explanation. A Harman single-factor test attributes 34.6% of the variance to the first unrotated factor, below the conventional 50% rule-of-thumb, so no single dominant method factor emerges. The positive benefit–risk correlation also survives

partialling out response-style markers (partial $r = .36$ to $.43$, both $p < .001$). These results are consistent with a substantive duality rather than proof of one; they show that acquiescence alone cannot account for the co-occurrence of perceived benefits and perceived risks.

That benefits and risks are not merely correlated but *distinct constructs* is confirmed by the dimensional analysis. Both scales are highly reliable (positive $\alpha = .897$; negative $\alpha = .907$). An exploratory factor analysis of all twenty-four impact items ($KMO = .82$) yields a clean two-factor solution in which the twelve positive items load on one factor and the twelve negative items on the other; the two factor scores correlate at $r = .47$. A parallel analysis on the same 24 impact items supports retaining two factors, with the first two empirical eigenvalues (8.29 and 3.53) each exceeding their respective parallel-analysis thresholds. Benefits and risks are separate dimensions that nonetheless move together, the structure that H3a and H3b predicted and that distinguishes a duality from a one-dimensional trade-off.

7.4 An empirical typology of evaluative stances

Crossing the benefit and risk dimensions at their medians yields a fourfold typology of evaluative stances whose distribution is itself instructive (Figure 16). The single largest group is the *ambivalent* (39 firms), high on both perceived benefits and perceived risks. The *indifferent* (37 firms), low on both, form the second-largest group. *Enthusiasts* (high benefit, low risk; 13 firms) and *skeptics* (low benefit, high risk; 11 firms) are comparatively rare. The modal organizational stance toward AI in HR is *reflective ambivalence*, a simultaneous appreciation of substantial promise and substantial peril, in preference to either uncritical enthusiasm or reflexive skepticism.

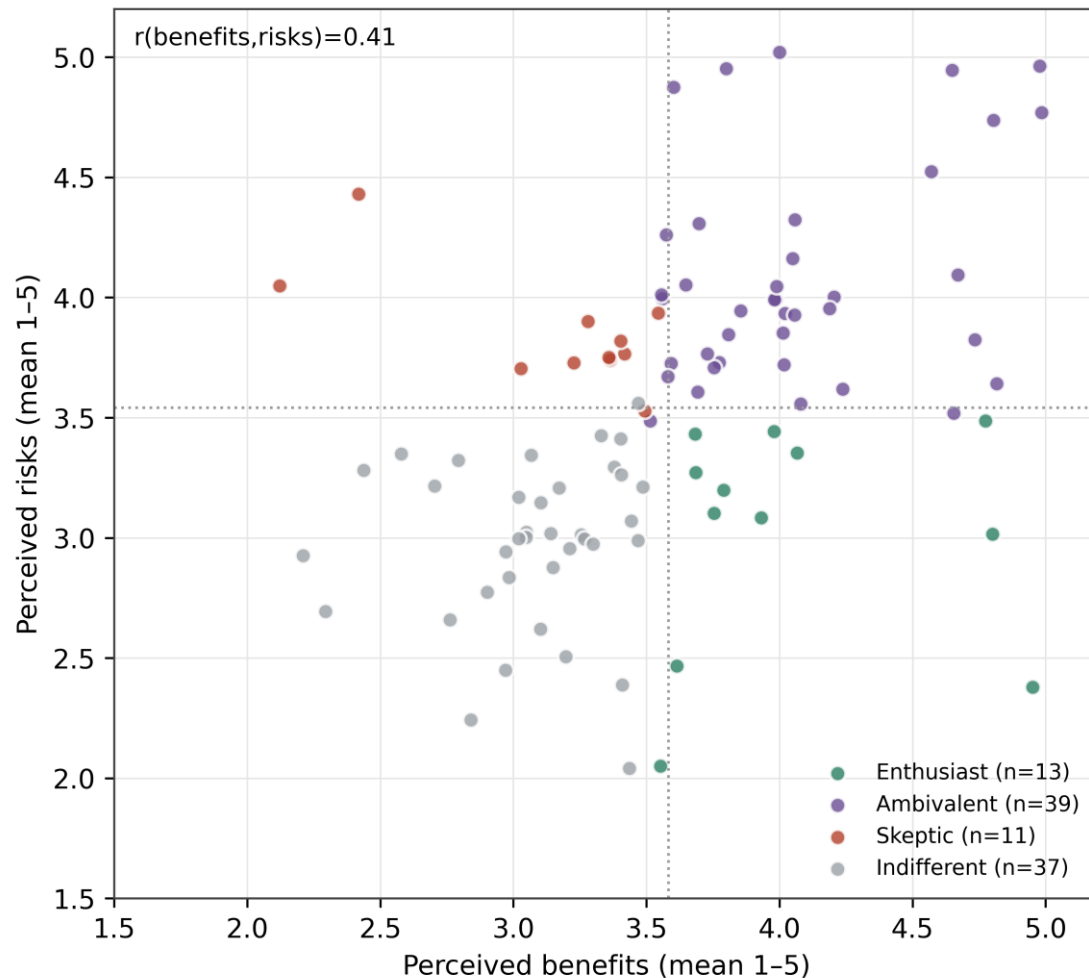


Figure 15. The benefit-risk typology.

Each point is a firm, positioned by its mean perceived benefits and risks; quadrants are defined by the medians. The “ambivalent” quadrant (high-high) is the most populated.

The typology gains practical importance from its relationship to behaviour. Ambivalent firms are not paralysed by their dual awareness. They exhibit the *deepest* HR-AI adoption (mean intensity 3.24) and the highest organizational maturity (3.25). Indifferent firms show the shallowest adoption (2.70) and the lowest maturity (2.72), with enthusiasts and skeptics in between. The pattern suggests that engagement with AI in HR brings *both* benefits and risks into sharper focus, and that the firms going deepest are precisely those that hold the two in tension, a hopeful finding for the prospect of responsible adoption, since it implies that depth of use is associated with heightened, not diminished, risk awareness.

7.5 What is associated with the depth of adoption

The final question is which appraisals accompany deeper adoption. An ordinary least squares regression of HR-AI intensity on perceived benefits, perceived risks, maturity and

firm size (Figure 17) tells a consistent story. Perceived benefits are the strongest correlate of adoption depth (standardized-scale coefficient $b = 0.51$, 95% CI $[0.27, 0.74]$, $p < .001$), with organizational maturity close behind ($b = 0.35$, $[0.17, 0.52]$, $p < .001$). Perceived risks show no association with adoption intensity ($b = -0.03$, $p = .79$), and neither does firm size. The model accounts for 36% of the variance in adoption intensity in-sample (adjusted $R^2 = .33$); a cross-validated estimate is more modest ($R^2 \approx .24$), so the fit is appreciable rather than overwhelming.

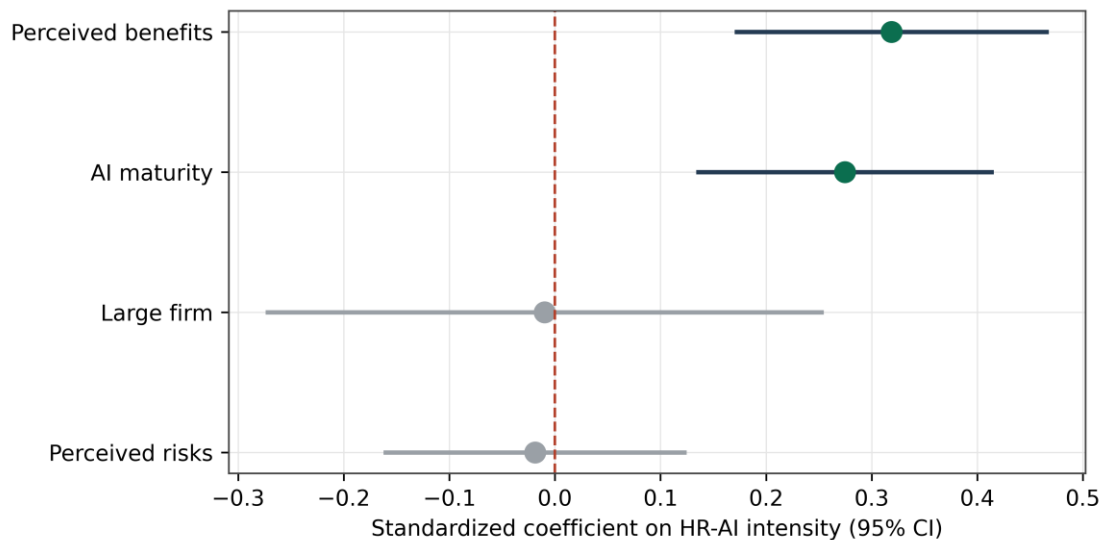


Figure 16. Standardized predictors of HR-AI adoption intensity.

Perceived benefits and organizational maturity are the strongest correlates of adoption depth; perceived risks show no association.

This evidence bears on H3c and completes the duality picture. Firms deepen their use of AI in HR in proportion to the benefits they perceive and the maturity they possess, while the risks they perceive, substantial though they are and rising in lockstep with the benefits, show no association with adoption depth. Risk awareness, in this population, accompanies adoption rather than restraining it. The design is cross-sectional, so the direction of influence is not settled: deeper adopters may come to rationalize higher perceived benefits as readily as higher perceived benefits may encourage deeper adoption. Whether the configuration represents healthy, eyes-open adoption or a worrying tendency to proceed despite recognized hazards is a question of interpretation that Chapter 10 takes up. What the data show is that, behaviourally, perceived benefits and readiness are the correlates of depth, while perceived risks are not.

7.6 Synthesis

The benefit–risk calculus of AI in HR among Slovak adopters is, on this evidence, a *duality resolved in favour of action*. Benefits and risks are distinct dimensions that co-occur and are judged roughly equal in salience. Most firms are reflectively ambivalent. The risks that weigh heaviest are human and relational, not technical; and depth of adoption follows

perceived benefits and organizational maturity while remaining unmoved by perceived risks. This benefit–risk duality concerns *perceptions* and should be distinguished from Meijerink and Bondarouk’s (2023) “duality of algorithmic management”, which concerns the simultaneous consequences of algorithmic control for worker autonomy and value. The configuration of high risk awareness coexisting with risk-undeterred adoption is the central interpretive puzzle of the monograph, and it sets up the employment question of Chapter 8: if firms are proceeding with eyes open to the relational and fairness risks, what are the early consequences for the workforce?

8. Artificial intelligence in HR and the employment question

Few aspects of artificial intelligence have generated more public attention than its anticipated consequences for employment. While organizational research has increasingly shifted from asking whether AI will be adopted to examining how it is implemented, public and managerial debate continues to revolve around a more immediate question: what happens to jobs once AI enters the workplace? Human resource management occupies a particularly distinctive position within this discussion because it simultaneously represents a function that may itself be transformed by AI and the organizational mechanism through which broader workforce changes are planned, communicated and implemented.

The relationship between AI adoption and employment, however, is unlikely to be straightforward. Workforce outcomes emerge only after organizations move beyond experimentation and integrate AI into routine organizational practice. Consequently, the employment implications of AI cannot be inferred directly from adoption itself. Organizations may implement AI primarily to support existing employees, to automate selected administrative tasks, to improve managerial decision-making or to redesign work processes without necessarily altering overall employment levels. Likewise, the creation of new AI-related roles and the displacement of existing jobs need not occur simultaneously, nor should they be assumed to represent opposite ends of a single process.

This perspective is particularly relevant for interpreting the AI-ImpactSK data. Previous chapters have shown that AI adoption in HR remains relatively broad but shallow, with most organizations still operating at planning or pilot stages rather than full-scale deployment. Under such conditions, immediate employment effects should not necessarily be expected. Instead, the present analysis focuses on identifying whether measurable differences already exist between organizations that have extended AI into HR and those that continue to apply AI exclusively in other business functions, while recognizing that longer-term workforce consequences may emerge only as organizational adoption matures. This chapter examines three complementary dimensions of employment: workforce reductions associated with AI, the creation of new AI-related positions, and managers' perceptions of employee concern regarding AI-driven job displacement. Together, these analyses complete the empirical picture developed throughout the monograph by linking organizational AI adoption not only to implementation patterns and managerial perceptions but also to its earliest observable implications for the workforce.

8.1 Question and hypotheses

No discussion of AI in human resources can avoid the question that animates the broader public debate: what does it mean for jobs? The concern is doubly pointed for HR-AI, because the HR function is both a potential *target* of automation, in that AI may substitute for recruiters, administrators and analysts, and the *instrument* through which firms execute whatever workforce changes AI elsewhere implies. This chapter brings the survey's

employment items to bear on the question, asking whether HR-AI adoption is associated with workforce reductions, with the creation of new roles, or with heightened employee apprehension (RQ4). Three hypotheses are tested, each framed against the alarmist “AI destroys jobs” narrative:

H4a. HR-AI adoption is *not* associated with higher AI-related layoffs than other uses of AI.

H4b. HR-AI adopters differ from other AI users in their creation of new AI-related roles.

H4c. Manager-reported employee concern about AI-driven job loss is *not* elevated among HR-AI adopters relative to other AI users.

The comparison is again between the 100 HR-AI adopters and the 462 other AI users, so that any differences are attributable to the HR application of AI rather than to AI use in general.

8.2 Layoffs: no substitution shock

The data offer no support for an alarmist reading. Among HR-AI adopters, 9.0% (95% CI [4.8, 16.2]) report that AI has led, or is planned to lead, to employee layoffs (realized or planned), a rate that is, if anything, slightly *lower* than the 10.8% [8.3, 14.0] reported by other AI users. The difference is not significant (Fisher exact odds ratio = 0.81, $p = .72$), and it remains non-significant after adjustment for firm size, maturity and AI breadth (adjusted OR = 0.91, $p = .82$). HR-AI adoption, in this population, is not associated with elevated workforce reductions (Figure 18). This supports H4a and is consistent with the broader pattern in which AI-related layoffs are reported by a minority of AI users across all functions (around one in ten), with no concentration in firms that have brought AI specifically into the people-management function.

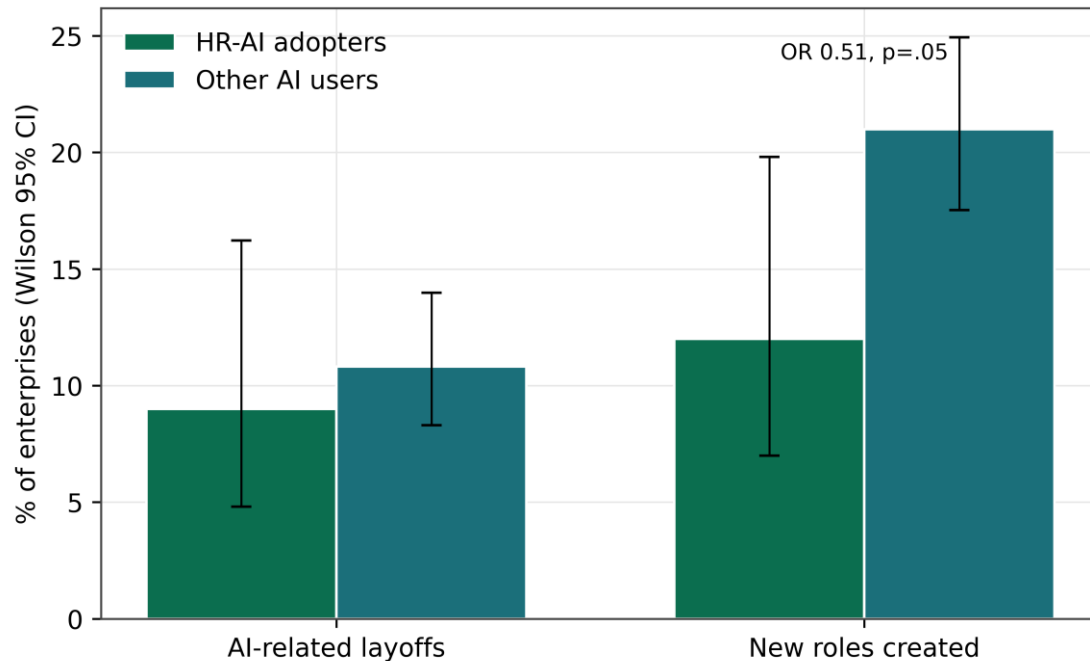


Figure 17. Employment outcomes of HR-AI adopters versus other AI users.

Shares reporting AI-related layoffs and AI-related new roles, with Wilson 95% confidence intervals.

8.3 Employee apprehension: present but not HR-specific

Does bringing AI into the people-management function heighten employees' fear of being displaced? The survey's corporate-sentiment block includes an item that captures the respondent's perception that employees are concerned AI threatens jobs; it records manager-reported perceived concern rather than a direct measurement of employee fear. Across the four adoption groups, manager-reported perception of employee concern is lowest among non-adopters (2.74), and similar and somewhat higher among planners (3.08), other AI users (3.00) and HR-AI adopters (3.08) (Figure 19). A Kruskal-Wallis test is significant across the four groups ($H = 8.89$, $p = .031$), but the effect is driven by the low perceived concern among non-adopters. The direct comparison that matters for H4c, HR-AI adopters versus other AI users, is non-significant and negligible in size (Mann-Whitney $p = .47$; Cliff's $\delta = +0.05$). Perceived employee apprehension is associated with AI engagement *in general*, since firms that use or plan AI report more employee concern than firms that do not, but it is *not* specifically elevated by the application of AI to HR. H4c is supported.

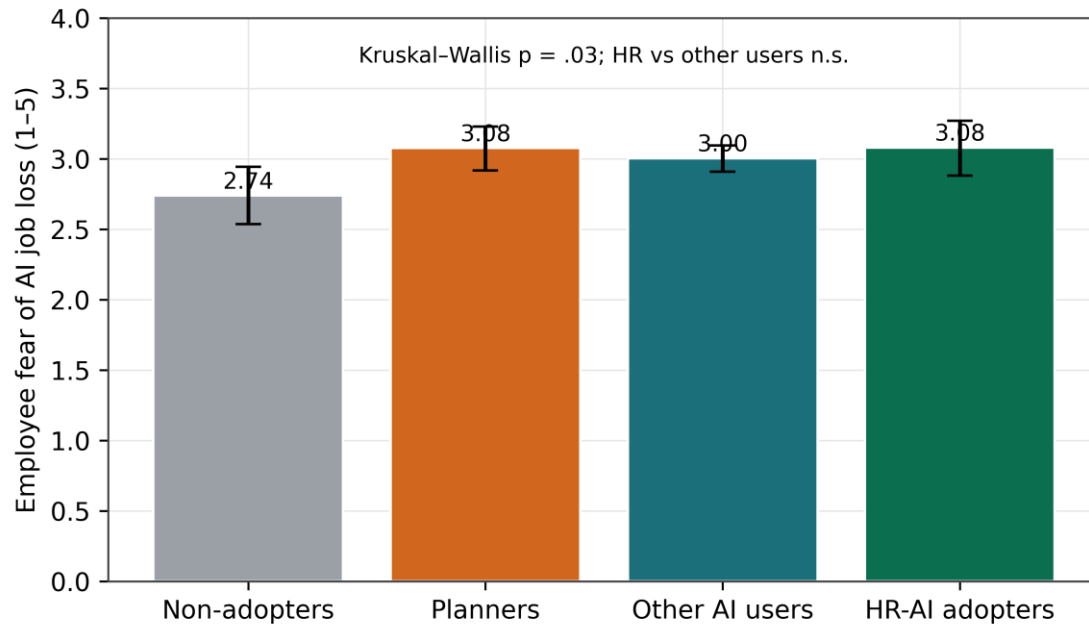


Figure 18. Manager-reported perception of employee concern about AI displacing jobs (1–5), by adoption group.

Apprehension rises with AI engagement generally but is not elevated among HR-AI adopters relative to other AI users.

Two accompanying sentiment gradients sharpen the picture. Dedicated AI budget and training rise monotonically across the groups, from 2.09 among non-adopters through 2.96 (planners) and 3.18 (other users) to 3.41 among HR-AI adopters, as does top-management confidence in AI (2.37, 3.16, 3.51, 3.69). HR-AI adopters thus combine the highest organizational investment in AI capability and the highest leadership confidence with manager-reported employee concern no greater than that of other AI users. This configuration is consistent with the engaged-ambivalence theme of Chapter 7: the firms going furthest with AI in HR are also those investing most in capability and most confident at the top, while their workforces are reported as no more apprehensive than those of other AI-using firms.

8.4 New roles: a suggestive but not reliable difference

The new-role finding is the one place where HR-AI adopters look distinctive, though the difference does not survive statistical scrutiny. Only 12.0% of HR-AI adopters (95% CI [7.0, 19.8]) report introducing or planning new job positions because of AI (realized or planned), compared with 21.0% [17.5, 24.9] of other AI users, roughly half the rate. The bivariate association is borderline (Fisher OR = 0.51, $p = .050$), and after adjustment for size, maturity and breadth it falls just short of significance (adjusted OR = 0.53, 95% CI includes 1, $p = .055$), resting on only 12 cases in the HR cell. The data are therefore *suggestive* that HR-AI adopters are less likely than other AI users to create new AI-related roles, but the estimate is not statistically reliable once covariates are included. H4b is best read as

partially supported on a suggestive basis, with the indicated direction the less job-generative one.

This apparent asymmetry, comparable and low layoff rates alongside a lower point estimate for new-role creation, is itself worth noting. It is consistent with AI in HR being, at this early stage, a *quietly augmenting* technology: used to do existing HR work more efficiently rather than to shed HR headcount or to spawn new specialist positions. Other AI applications are roughly twice as likely to be accompanied by new roles, which fits the view that customer- and operations-facing AI (the leading functional domains of Chapter 4) is more likely to generate new technical and analytical positions, whereas HR-AI is absorbed into the existing function. New-role creation also declines across the general use stages, from 29% among multi-area users to 13% among firms still piloting AI, which suggests that role creation tracks the breadth and ambition of the overall AI programme more than the HR application specifically.

8.5 Within the HR adopters: intensity and employment

Finally, within the 100 adopters, does *deeper* HR-AI penetration correlate with employment consequences? The associations are weak and not significant. HR-AI intensity is essentially uncorrelated with manager-reported employee concern (Spearman $\rho = -0.03$, $p = .75$), and firms reporting layoffs or new roles have, if anything, marginally *lower* HR-AI intensity than those that do not, counter to any simple “more AI in HR means more workforce disruption” story. The depth of AI penetration in the HR function, at least at this early stage, does not translate into measurable employment effects within adopters.

8.6 Synthesis

The employment evidence sits at odds with both the alarmist and the techno-optimist narratives, and it is the null results that carry it. AI in HR among Slovak enterprises is not associated with elevated layoffs, nor with elevated employee concern relative to other AI uses; the lower rate of new-role creation is suggestive but not statistically reliable once covariates enter. In employment terms it behaves as a quiet technology, absorbed into the existing HR function as an efficiency and consistency tool rather than precipitating either large-scale substitution or a wave of new specialist hiring. This early-stage neutrality must be read against the pilot-dominated adoption profile of Chapter 6: with most applications still in testing and only one HR function in active regular use on average, the employment consequences, for good or ill, may simply not have materialized yet. The chapter therefore closes with a forward-looking caution that recurs in Chapter 11: the present employment calm is that of a technology still in its enterprise infancy, and the trajectory as pilots scale into routine use remains to be seen.

9. Organizational readiness and barriers

The preceding chapters repeatedly pointed to organizational readiness as the substrate on which AI-in-HR adoption rests. Maturity rises monotonically across the adoption gradient (Chapter 4), it accompanies the depth of HR-AI penetration (Chapter 7), and much of its association with that depth runs through the breadth of the AI programme (Chapter 5). This chapter draws those threads together. It also turns to the obverse question of what holds firms back, examining the barrier profile of Slovak enterprises and how that profile varies with adoption.

9.1 Readiness as the enabling substrate

The maturity evidence is among the most robust in the monograph. The seven-dimension index is highly reliable ($\alpha = .908$), and it discriminates sharply across the adoption gradient, from 1.27 among non-adopters to 3.03 among HR-AI adopters, with a decisive Kruskal-Wallis result ($p \approx 10^{-67}$; Chapter 4). At the dimension level, HR-AI adopters score modestly higher than other AI users on every maturity dimension, with the largest raw gaps on privacy (3.15 vs. 2.87), ethics (2.98 vs. 2.73) and technology (3.19 vs. 2.97). It is tempting to read the privacy and ethics edge as evidence that firms bringing AI into the sensitive HR domain are distinctively attentive to governance, an attractive interpretation. The data counsel caution. Although privacy and ethics show the largest raw differences ($p = .028$ and $p = .039$), neither survives Benjamini-Hochberg correction for multiple comparisons (minimum $q = .098$), and no single dimension reaches significance once the seven tests are corrected jointly. The safer conclusion is that HR-AI adopters are distinguished by *generally* higher maturity, not by any one governance-specific orientation. This fits the Chapter 5 finding that it is overall AI breadth and maturity, and not a narrowly governance-related capability, that accompanies HR-AI adoption.

The broader maturity profile of the sample is relatively strong on culture and technology and weaker on organizational embedding, strategy and ethics. It reinforces a theme that runs through the international readiness literature: firms' cultural and technological enthusiasm for AI tends to run ahead of their organizational and strategic preparation for it (Jöhnk et al., 2020; Uren & Edwards, 2022; Asatiani et al., 2021). For AI in HR specifically, where the organizational and ethical dimensions are precisely the ones that govern responsible use, this enthusiasm-ahead-of-embedding profile is a latent vulnerability that Chapter 11 develops into a practical recommendation.

9.2 The barrier landscape

The survey's twenty-item barrier battery ($\alpha = .947$) was answered by all firms, allowing a comparison of perceived barriers across the adoption gradient. The most salient barriers overall are a recognizable mix of cost, complexity and regulation, alongside a more unusual emphasis on *state support* (Figure 20). The single highest-rated barrier is the high cost of maintaining and further developing AI systems (mean 3.32), followed closely by uncertainty regarding the legal and regulatory aspects of AI use (3.28) and the complexity

of integrating AI into existing business systems (3.26). A cluster of *public-policy* barriers sits just behind: the level of financial support (grants) from the state for AI implementation (3.24), the level of technical support from the state (3.23), and the level of state support for workforce training (3.23). High initial investment costs (3.24) and insufficient quality or availability of AI data (3.23) round out the leading barriers.

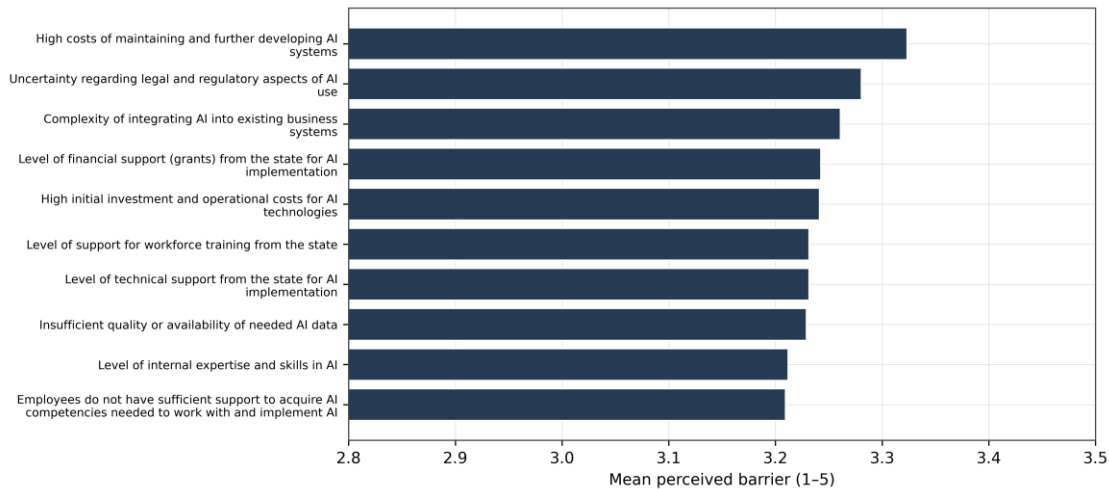


Figure 19. The ten most salient perceived barriers to AI implementation across all surveyed firms (mean, 1–5).

Cost, regulatory uncertainty, integration complexity and — distinctively — state support feature prominently.

The prominence of state-support items is worth dwelling on. In the international SME and adoption literature, internal barriers such as cost, skills, data and integration typically dominate (Horváth & Szabó, 2019; Shahadat et al., 2023; Faiz et al., 2024). Slovak enterprises in this survey rate the adequacy of state financial, technical and training support on par with internal cost and integration barriers. That emphasis is notable in this sample, and more prominent than the internal-barrier emphasis typical of Western SME studies; it suggests that, here at least, firms look substantially to public institutions to lower the cost and risk of AI adoption. We read it as an observation bounded by these respondents rather than a benchmarked cross-country fact, but it has direct implications for technology policy, developed in Chapter 11.

9.3 Barriers decline as adoption advances

Perceived barriers fall systematically as firms move along the adoption gradient (Figure 21). The mean barrier index is highest among non-adopters (3.50), lower among planners (3.35), lower still among HR-AI adopters (3.20), and lowest among other AI users (3.09), with a decisive Kruskal–Wallis result across the four groups ($p < .001$). The cross-sectional design cannot disentangle the direction of this relationship. Perceiving fewer barriers may enable adoption, adoption experience may dissolve perceived barriers, or both may operate at once. Either way, the monotonic pattern is consistent with a cycle in which engagement and the erosion of perceived obstacles reinforce one another. One detail cuts against the

trend: HR-AI adopters perceive *slightly higher* barriers than other AI users despite their greater maturity, which may reflect the additional legal, ethical and data-quality hurdles specific to deploying AI in the sensitive HR domain.

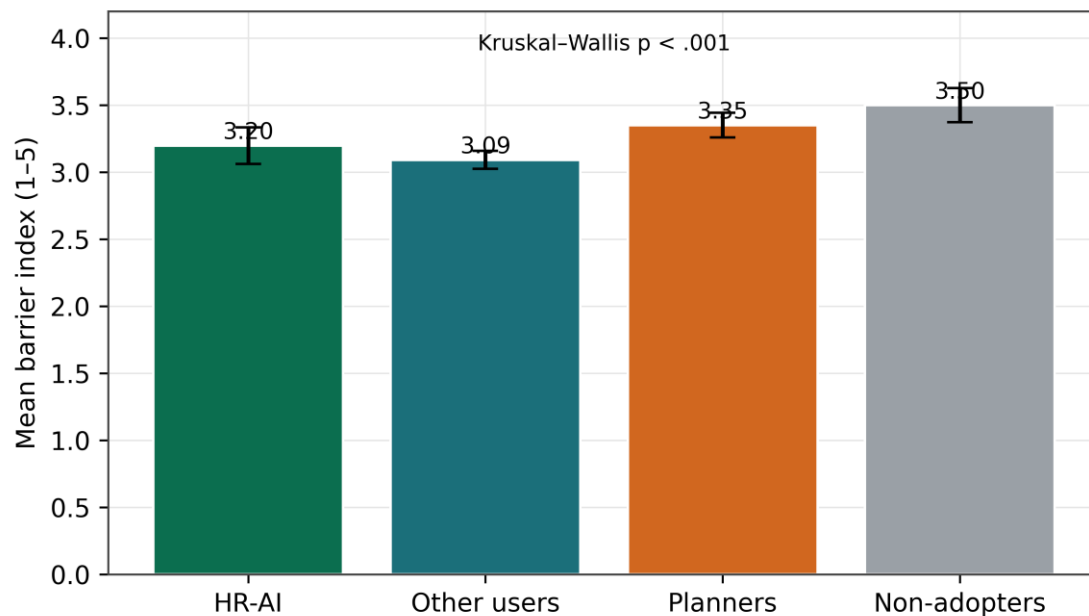


Figure 20. Mean perceived-barrier index (1–5) by adoption group.

Perceived barriers decline monotonically from non-adopters through planners to active users.

9.4 What drives adoption: the efficiency imperative

If barriers describe the brakes, the survey's adoption-driver battery describes the accelerator. Among AI users, the factors rated most important in convincing management to adopt AI are squarely about efficiency and automation: the desire to increase efficiency (mean 3.67), to automate business processes (3.66), to reduce costs (3.59), to speed up innovation (3.57) and to react faster to demand and market trends (3.56) (Figure 22). Data-related motives, namely handling growing data volumes and analysing large volumes of data in real time, follow closely. The driver profile is operational in character more than strategic or transformational, mirroring the benefit profile of Chapter 7, where the leading perceived benefits of AI in HR were administrative efficiency and process consistency. Across the firm's AI programme and within its HR application alike, the dominant logic is the rationalization of existing work, not the pursuit of novel strategic capability. The coherence between general motivation and HR-specific appraisal lends credibility to both.

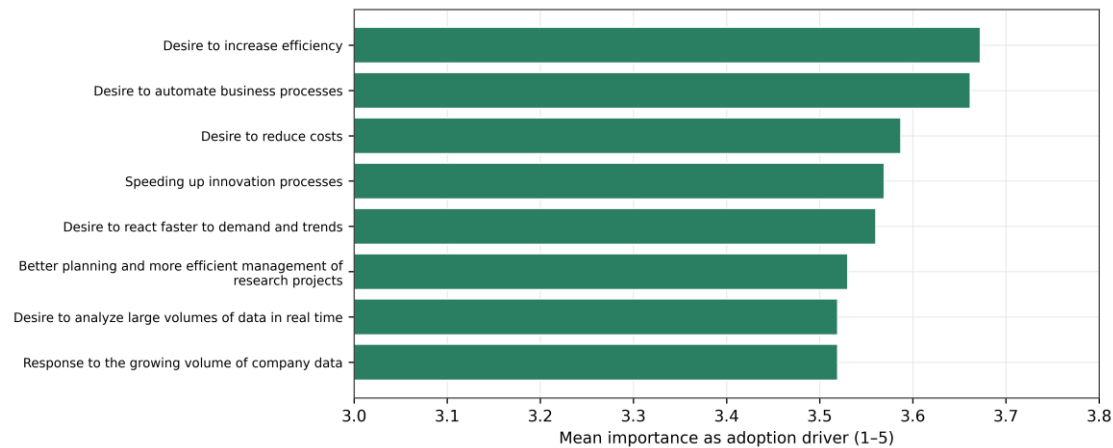


Figure 21. The most important drivers of AI adoption as rated by AI-using firms (mean importance, 1–5).

Efficiency, automation and cost reduction dominate.

9.5 Synthesis

Readiness and barriers together frame the adoption decision as a balance of enabling capacity against perceived obstacles, tilted by an efficiency imperative. The enabling capacity, organizational AI maturity, is the strongest and most consistent correlate of HR-AI adoption and depth in the entire study, though much of its association with depth runs through the breadth of the AI programme. The obstacles are a familiar mix of cost, regulation, integration and data, distinguished in the Slovak case by an unusually prominent role for state support. And the motivation is overwhelmingly the pursuit of efficiency. This readiness-centred account helps explain why HR-AI is a second-wave phenomenon concentrated among the most mature, broadly engaged firms, and it sets the stage for the integrated interpretation of Chapter 10.

10. Integrated discussion

The four analytical angles of this monograph were pursued separately, but they describe a single phenomenon. This chapter draws them together into an integrated interpretation of AI in HR among Slovak enterprises, situates that interpretation against the international literature, and articulates the study's theoretical contributions.

10.1 An integrated portrait of AI in Slovak HR

Five propositions summarize the findings and together constitute the monograph's central account.

The first concerns where adoption comes from. AI-in-HR adoption is portfolio-embedded: it accompanies the wider spread of AI across the firm and does not simply track firm characteristics. HR is a second-wave functional domain, reached after the commercially proximate functions of marketing, operations, logistics and R&D, and the single best predictor of whether a firm brings AI into HR is the breadth of its AI deployment elsewhere (adjusted OR = 1.48 per additional area) rather than its size, sector, ownership or age. Bringing AI into HR looks less like a discrete strategic choice about people management and more like a by-product of a widening organizational AI programme. This reframes the determinants question. At the level of the specific functional decision, conditioned on prior AI use, the demographic determinants that dominate the general adoption literature largely dissolve, and a programme-level variable takes their place. Two cautions temper how strongly the breadth result should be read. Breadth and the HR flag both register the same underlying AI-deployment behaviour, so part of the association may be mechanical, or may reflect selection on firms that are already heavy AI users. And among adopters, AI breadth does not predict the depth of HR-AI penetration (Spearman $\rho = .16$, not significant), so breadth bears on whether AI reaches HR, not on how far it goes once there.

The application architecture, second, is broad but shallow. Adopters extend AI across the whole HR value chain, with recruitment, screening and matching leading at the margin but learning, onboarding, evaluation, retention analytics and compensation following at comparable depth, and they do so overwhelmingly at the pilot and planning stages. The twelve functions form a coherent, highly reliable penetration construct with a secondary, method-robust acquisition/development structure, yet only 29 of 100 adopters actively and regularly use any function, and the average firm has just one function in routine use. AI in HR in Slovakia is a wide frontier of shallow pilots, not a beachhead of deep specialization.

Third, the appraisal is one of engaged ambivalence. Firms perceive the benefits and risks of AI in HR as roughly equal in significance and as distinct but positively correlated dimensions, and the modal stance, held by the largest cluster of firms (Figure 23), is "ambivalent": high on both. The ambivalent firms are the deepest adopters and the most mature, while indifferent firms are the shallowest and least mature. Depth of adoption is associated with perceived benefits and organizational maturity and is undeterred by perceived risks, which are rated most acute in their human and relational forms, less so in their technical ones. Risk awareness accompanies adoption rather than braking it. The

association between perceived benefits and depth should be read with reverse causation in mind: deeper adopters may rationalize higher perceived benefits as much as benefit perceptions drive deeper adoption.

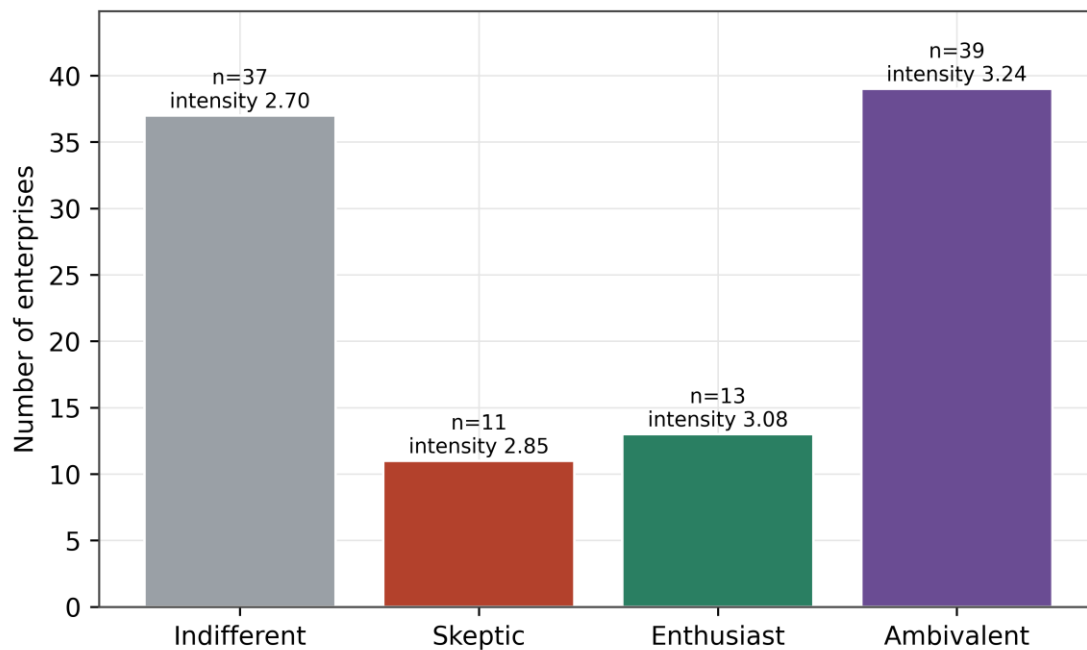


Figure 22. Sizes and mean adoption intensity of the four evaluative stances.

The “ambivalent” group is both the largest and the deepest-adopting.

Fourth, the employment footprint is quiet. HR-AI adoption is associated with neither elevated layoffs nor elevated employee fear relative to other AI uses, and with somewhat less new-role creation, though the new-role difference is borderline rather than firmly established. The pattern is consistent with an augmentation technology absorbed into the existing HR function rather than a substitution shock or a generative engine of new specialist roles. This reading should be weighed against the early, pilot-dominated stage of adoption.

Fifth, readiness underlies the whole configuration. Organizational AI maturity rises monotonically across the adoption gradient, is associated with the depth of HR-AI penetration, and accompanies the breadth that in turn predicts adoption. Perceived barriers fall as adoption advances, and the motivation throughout is an efficiency imperative. The Slovak case adds a distinctive regional signal in the unusual prominence of state support among perceived barriers. These propositions hang together. A readiness-linked, portfolio-embedded adoption logic helps explain why HR is reached late and by the broadest, most mature firms; a wide but thin application architecture is what one expects of a function in early, exploratory expansion; engaged ambivalence is the appraisal posture of firms thinking seriously about a consequential technology; and a quiet employment footprint is a plausible near-term accompaniment of pilots that have not yet scaled. The account is internally consistent, and that consistency is what gives the descriptive portrait its coherence.

10.2 Dialogue with the literature

The findings both confirm and qualify the international evidence. On determinants, the study confirms the centrality of readiness emphasized by the AI-maturity literature (Jöhnk et al., 2020; Uren & Edwards, 2022) but qualifies the size- and sector-centred findings common in TOE-based SME studies (Badghish & Soomro, 2024; Shahadat et al., 2023): when the analysis is conditioned on prior AI use and resolved to the HR function, demographic determinants give way to programme breadth. This is a genuinely novel result enabled by the function-resolved design, and it suggests that the determinants of functional AI diffusion differ from the determinants of whether a firm uses AI at all, a distinction the literature has largely elided.

On applications, the talent-acquisition primacy documented here echoes the recruitment-and-selection focus of the HR-AI literature (Mori et al., 2024; Chen, 2023; Pillai & Sivathanu, 2020), but the finding that the acquisition bundle is adopted no more deeply than the development bundle tempers the common assumption that AI in HR is essentially AI in hiring. The pilot dominance aligns with the “gap between promise and reality” that Tambe et al. (2019) identified, and with the early-stage, exploratory character that reviews of generative AI in HRM anticipate (Budhwar et al., 2023; Chowdhury et al., 2024).

On appraisal, the duality finding contributes something the fairness/ethics and acceptance literatures imply but rarely test at the organizational level. Those literatures document, separately, the substantial benefits (Huang et al., 2023; Votto et al., 2021) and the serious risks (Fabris et al., 2024; Sánchez-Monedero et al., 2020; Tursunbayeva et al., 2021) of algorithmic HRM. The present study shows that adopting firms hold both in view at once, that benefit and risk perceptions are positively correlated rather than traded off, and that the relational and fairness risks foregrounded by critics are the ones firms rate most significant. This benefit-risk duality is a feature of how firms perceive and appraise the technology, and it should be distinguished from Meijerink and Bondarouk’s duality of algorithmic management, which concerns the consequences of algorithmic control for worker autonomy and for value creation and capture. That perceived risks do not brake adoption resonates with the acceptance literature’s emphasis on perceived benefits and managerial confidence as the active correlates of use (Cao et al., 2021; Dabbous et al., 2021), while raising the governance concern that risk awareness alone may not translate into risk mitigation.

On employment, the quiet footprint is consistent with the augmentation pole of the automation-augmentation debate (Raisch & Krakowski, 2021; Acemoğlu & Restrepo, 2019). It should be read, though, alongside Raisch and Krakowski’s central argument that automation and augmentation are interdependent and cannot be cleanly separated: the same tools that augment HR work also automate parts of it, and the two move together rather than as rival poles a firm simply selects between. The absence of a layoff association and the lower new-role creation together suggest that, for the HR function at least, AI is currently more a tool for doing existing work efficiently than a driver of either displacement or task reinstatement, consistent with the view that AI’s labour-market effects are mediated by the stage and breadth of deployment (Frank et al., 2019) and may lag adoption considerably.

10.3 Theoretical contributions

Three theoretical contributions follow. The first is the concept of portfolio-embedded functional adoption: the proposition that the spread of a general-purpose technology into a particular organizational function is associated less with the firm's characteristics than with the breadth of the technology's deployment across the firm's other functions. This reframes functional AI adoption as a diffusion process within the firm, paralleling the inter-firm diffusion that the adoption literature usually studies, and it raises the possibility that interventions aiming to promote AI in a sensitive function such as HR may be more effective if they broaden the firm's overall AI programme than if they target the function directly. The breadth-HR association is open to a mechanical or selection-based reading, and the non-significant breadth-depth correlation among adopters means the concept is offered as an interpretive frame rather than a demonstrated causal mechanism.

The second is the duality model of technology appraisal. Where an implicit trade-off model would treat benefit and risk perceptions as inversely related, the study offers evidence for a duality model in which they are distinct, positively correlated dimensions, and in which engagement appears to amplify awareness of both. The associated empirical typology of enthusiast, skeptic, indifferent and ambivalent firms provides a parsimonious way to characterize organizational stances toward a contested technology, and the finding that the ambivalent stance is both modal and most behaviourally engaged matters for how we understand responsible adoption.

The third is a readiness-as-substrate account that integrates maturity, breadth and depth. Maturity does not act as a simple gatekeeper to HR-AI adoption. It accompanies the breadth of the AI programme, which is associated in turn with AI reaching HR, and it is independently associated with the depth of HR-AI penetration once a firm has crossed the threshold. This layered role, enabling breadth and predicting depth, is a more nuanced account than the binary "ready/not ready" framing common in maturity-model work.

10.4 A note on coherence across angles

A final observation concerns the internal coherence of the account. The efficiency imperative that dominates the adoption-driver battery (Chapter 9) reappears as the leading perceived benefit of AI in HR (Chapter 7); the pilot dominance of the application architecture (Chapter 6) is mirrored in the recency of AI projects (Chapter 4) and the quiet employment footprint (Chapter 8); and the readiness gradient (Chapter 4) is bound up with the determinants (Chapter 5), the appraisal-linked depth (Chapter 7) and the barrier profile (Chapter 9). The four analyses draw on one sample and one organizational informant, so their agreement cannot be treated as independent corroboration that the portrait is real rather than an artefact of shared method. What the agreement does show is that the descriptive account is internally consistent across the angles from which the data were examined, with no single analytic choice generating the picture on its own.

11. Implications, limitations and future research

The preceding chapters have documented AI adoption in human resource management from several complementary perspectives, examining where organizations adopt AI, how they deploy it across HR functions, how they evaluate its benefits and risks, and whether early employment consequences are already observable. Considered together, these findings suggest that AI implementation in HR is neither a purely technological nor a purely organizational phenomenon. Rather, it represents a gradual process through which enterprises expand their AI capabilities into increasingly complex and socially consequential organizational domains.

Moving from empirical findings to practical recommendations requires a corresponding shift in perspective. The statistical relationships reported throughout the monograph should not be interpreted as deterministic rules for organizational decision-making. Instead, they identify patterns that consistently characterize enterprises further advanced in their AI journey. In this respect, the results point less toward isolated technological solutions than toward the broader organizational conditions that enable responsible and sustainable AI adoption. Organizational readiness, managerial commitment and governance capacity emerge repeatedly across the analyses as recurring characteristics of enterprises that have progressed furthest in integrating AI into human resource management.

This chapter therefore translates the empirical evidence into implications for organizational practice and public policy while recognizing the methodological boundaries within which those implications should be interpreted. It first discusses lessons for managers and HR professionals responsible for planning and governing AI implementation, then considers implications for technology policy in Slovakia and the wider Central and Eastern European region. The chapter subsequently revisits the principal limitations of the research design and concludes by outlining priorities for future research that can build upon the analytical foundation established by the AI-ImpactSK project.

11.1 Implications for management and HR practice

Several practical lessons follow from the integrated account. The first is to treat AI in HR as part of an AI programme rather than a stand-alone HR project. Because HR-AI adoption is portfolio-embedded, HR leaders in firms with narrow AI footprints should expect resistance and limited traction from isolated HR-AI initiatives, and may achieve more by participating in, and learning from, the firm's broader AI efforts. Executives leading firm-wide AI programmes face the mirror image of this point: HR will likely be reached as the programme broadens, so they should plan deliberately for the distinctive governance demands of the HR domain rather than letting AI enter people-management by default.

A second lesson concerns readiness. Maturity is the most consistent correlate of adoption and depth, and the sample's "enthusiasm-ahead-of-embedding" profile, strong on culture and technology but weak on organizational embedding, strategy and ethics, identifies where investment is most likely to help. For AI in HR, the under-developed ethics and organizational dimensions are not peripheral. They are the capabilities that make

responsible deployment possible. One caveat applies here with particular force. The maturity–adoption link is cross-sectional and probably runs in both directions: building readiness may open the way to adoption, but adopting AI may also build readiness as firms learn by doing, and the data cannot establish that investing in readiness first will produce adoption later. The practical case for readiness rests on its consistent association with adoption and depth, not on a demonstrated temporal sequence.

A third lesson is to govern the relational and fairness risks proactively, because awareness alone will not. The study’s most cautionary finding is that perceived risks, concentrated on diversity, social cohesion, management–employee relations and discrimination, do not slow adoption. Firms proceed on the strength of perceived benefits and maturity even as they recognize substantial human and fairness hazards. Because risk awareness is decoupled from risk restraint, mitigation has to be built in deliberately: bias auditing of selection tools, human oversight of consequential decisions, transparency with employees, and attention to the relational texture of work that employees themselves most fear losing. That deep adoption coincides with high risk awareness among ambivalent firms is an opportunity, since these firms are primed to act on governance if given the tools.

A fourth lesson is to manage the transition from pilot to routine consciously. With most applications still at the pilot stage and the employment footprint correspondingly quiet, firms are in a window in which governance practices, employee communication and evaluation routines can be established before AI becomes consequential at scale. The quiet present is an opportunity to prepare for a noisier future, not a guarantee that the future will stay quiet.

11.2 Building Organizational AI Readiness and Governance for Human Resources

The findings presented throughout this monograph consistently indicate that successful adoption of artificial intelligence in human resource management depends on considerably more than technological capability alone. Although AI applications themselves provide the immediate tools through which organizations automate, augment and support HR processes, their successful and responsible implementation is ultimately conditioned by organizational readiness and governance. Across the empirical analyses, enterprises that progressed furthest in AI adoption were characterized not primarily by their size, ownership or sector, but by broader organizational capabilities, including higher AI maturity, dedicated investment, wider organizational experience with AI and stronger managerial commitment. Taken together, these findings suggest that AI implementation in HR should be understood as an organizational capability-building process rather than as a sequence of isolated technological projects. Organizational AI readiness therefore represents a strategic prerequisite for sustainable AI adoption. Readiness extends beyond technological infrastructure to encompass organizational culture, strategic alignment, leadership commitment, employee competencies, governance arrangements and the quality of organizational data. The AI-ImpactSK results illustrate that many Slovak enterprises currently display an imbalanced readiness profile. Respondents reported comparatively favourable levels of technological preparedness and organizational enthusiasm for AI, while considerably weaker results emerged for strategic embedding, organizational structures,

ethical preparedness and governance-related dimensions. This suggests that organizations often invest in acquiring AI technologies faster than they develop the organizational capabilities necessary to govern those technologies effectively.

The practical implication is that managers should avoid approaching AI implementation as a collection of independent departmental initiatives. Instead, AI should be managed as a coordinated organizational programme spanning multiple business functions. The empirical analyses demonstrated that HR adoption rarely emerges in isolation. Organizations typically introduce AI first in commercially oriented or operational functions before extending it into human resource management as organizational experience, managerial confidence and technological competence accumulate. This gradual pattern indicates that successful HR-AI implementation benefits substantially from organizational learning generated by previous AI projects elsewhere in the enterprise.

Consequently, strengthening organizational AI readiness should become a continuous managerial activity rather than a one-time preparation phase. Leadership commitment provides strategic direction, organizational structures allocate responsibilities, employee development strengthens internal capabilities, and governance mechanisms ensure that technological innovation remains aligned with organizational objectives. Organizations that periodically assess their maturity across these complementary dimensions are better positioned to identify capability gaps before they become implementation barriers and are more likely to achieve sustainable AI adoption over time.

The empirical findings also demonstrate that organizational readiness alone is insufficient unless accompanied by appropriate governance mechanisms. One of the most noteworthy results of this monograph is that organizations with the highest levels of AI adoption frequently report both substantial perceived benefits and substantial perceived risks. Awareness of ethical and organizational risks therefore does not automatically constrain AI implementation. Rather, successful organizations appear capable of simultaneously recognizing these risks while continuing adoption through appropriate governance arrangements. This finding shifts managerial attention from the question of whether organizations recognize AI-related risks to whether they possess the organizational capacity to manage them responsibly. Human resource management represents one of the most governance-sensitive organizational domains because AI increasingly contributes to decisions concerning recruitment, employee evaluation, career development, workforce planning and other activities directly affecting individuals. Errors, unintended discrimination or opaque decision-making in these processes may influence not only organizational performance but also employee trust, organizational legitimacy and regulatory compliance. For this reason, AI governance should be regarded as an integral component of organizational AI maturity rather than as a separate compliance function introduced only after implementation.

This interpretation aligns closely with the evolving international governance frameworks for artificial intelligence. The European Union Artificial Intelligence Act adopts a risk-based approach under which many AI systems supporting employment-related decisions are classified as high-risk applications requiring systematic governance throughout their

lifecycle. Similarly, ISO/IEC 42001 promotes organizational AI management through clearly defined responsibilities, documented decision-making processes, continuous monitoring and ongoing organizational improvement. The OECD AI Principles likewise emphasize transparency, accountability, robustness and human-centred AI, principles that closely correspond with the organizational capabilities identified throughout the empirical analyses as supporting mature AI adoption.

Viewed through the lens of the present findings, these governance frameworks should not be interpreted primarily as regulatory obligations but as organizational mechanisms that strengthen the long-term sustainability of AI implementation. Organizations capable of embedding governance into everyday managerial practice are likely to be better equipped to maintain employee trust, demonstrate accountability and support continuous organizational learning as AI technologies evolve. Several governance principles emerge directly from the empirical evidence presented in this monograph. Human oversight should remain an essential component of all AI-supported HR decisions carrying significant consequences for employees. AI systems may substantially improve analytical capacity and decision consistency, yet responsibility for employment-related decisions should remain clearly assigned to appropriately qualified human decision-makers. Transparency and explainability should likewise become routine organizational practices. Employees should understand when AI contributes to organizational decisions, how algorithmic recommendations are generated and how these recommendations are incorporated into managerial judgement. Such transparency is likely to strengthen organizational trust while reducing unnecessary uncertainty surrounding AI implementation.

Equally important is the establishment of organizational mechanisms supporting accountability and auditability. AI-supported HR decisions should be documented sufficiently to permit subsequent review, validation and improvement. Maintaining an appropriate audit trail not only facilitates regulatory compliance but also enables organizations to learn systematically from implementation experience. Similarly, bias monitoring should become a continuous organizational process rather than an isolated technical assessment. Recruitment, promotion, performance evaluation and other HR processes should be regularly reviewed for unintended disparities arising from algorithmic models or underlying training data. Finally, organizations should maintain comprehensive documentation describing the objectives, intended use, limitations, validation procedures and governance responsibilities associated with each AI system deployed within HR.

Ultimately, the evidence presented throughout this monograph suggests that responsible AI adoption in human resource management depends on balancing technological innovation with organizational capability development and effective governance. Organizations that treat governance as an enabler of innovation rather than a constraint upon it are likely to be better positioned to extend AI confidently into increasingly sensitive HR activities while maintaining employee trust, organizational legitimacy and long-term strategic value. In this sense, organizational AI readiness and AI governance should not be viewed as separate managerial challenges but as complementary dimensions of the same organizational capability required for successful and sustainable AI adoption.

11.3 Implications for technology policy in Slovakia and the CEE region

The barrier analysis carries a clear regional policy signal. Slovak enterprises rate the adequacy of state financial, technical and training support as barriers on par with internal cost and integration obstacles, a pattern less prominent in Western SME studies. Public policy therefore has substantial leverage. Targeted instruments that lower the cost and risk of AI adoption, including grants and co-financing for AI projects, technical advisory support for SMEs that lack in-house expertise, and subsidized workforce training in AI competencies, address barriers that firms themselves identify as binding. Because adoption is readiness-linked and portfolio-embedded, support that helps firms broaden and deepen their overall AI programmes may carry AI into HR and other functions indirectly. At the same time, the concentration of perceived HR-AI risks on fairness and discrimination, together with the EU's treatment of many HR uses of AI as high-risk, argues for regulatory clarity and capacity-building, that is, clear guidance and accessible compliance support, so that legal and regulatory uncertainty, the second-highest-rated barrier overall, neither chills beneficial adoption nor drives unguided adoption of poorly governed tools.

11.4 Limitations

The conclusions are bounded by the study's design, as flagged in Chapter 3 and reiterated here with their specific consequences. The cross-sectional design precludes causal inference: the central associations, of maturity with adoption, benefits with depth, and barriers with adoption stage, are almost certainly bidirectional, and the data cannot adjudicate direction. The reliance on self-report from a single organizational informant raises the possibility of common-method variance, particularly within the sentiment, maturity and impact batteries, and of social-desirability bias in reporting on sensitive matters such as layoffs and fairness. The internal consistency of the descriptive account across analyses does not address this concern, since all the analyses draw on the same informant and the same instrument; common-method variance would, if anything, tend to produce exactly such consistency. The screened, non-probability sample generalizes to established, non-micro, private/foreign/mixed-owned Slovak enterprises, not to micro-firms, start-ups or the public sector, and the absence of design weights means descriptive proportions should be read as sample, not population, estimates; agreement among the analyses does nothing to license inference beyond the achieved sample. The primary HR analytic sample of 100 firms, though substantial for this topic and region, limits power for complex multivariable models and fine subgroup analysis, which is why effect sizes, confidence intervals and multiplicity corrections have been emphasized throughout and why borderline results, particularly the new-role finding, are reported as borderline. The HR module is conditional on the D3 functional-area flag, a broad indicator of having "implemented or tested" AI in HR; the finding that a fifth of flagged firms have no function yet in active or pilot use shows that this flag captures intent and experimentation as much as live deployment, so the analyses of the HR module describe a population of engaged firms at varying stages rather than uniformly active users. Finally, the instrument was administered in Slovak, and the English wording used here is a documented translation; subtle connotations may differ across languages, and one documentation inconsistency (the

sentiment scale length) and one variable-naming artefact were identified and resolved transparently.

11.5 Directions for future research

Six directions would extend this work most productively. Longitudinal designs that re-survey the same firms would convert the cross-sectional associations into trajectories and test whether the quiet employment footprint persists as pilots scale into routine use, the single most important open question. Multi-informant designs that pair organizational reporting with employee-level data would test whether the firm-reported engaged ambivalence is matched by employees' own experiences and fears, and would address the common-method limitation directly. Cross-country CEE comparison would establish whether the portfolio-embedded adoption logic, the duality appraisal and the state-support barrier signal are Slovak peculiarities or regional regularities, and would calibrate the external validity of the dominant Western findings against a set of structurally similar economies. Function-comparative analysis, applying the same adoption-ladder and impact instruments to marketing, operations and finance, would test whether the broad-but-shallow architecture and the duality appraisal are specific to HR or general features of early functional AI adoption. Process and qualitative research into how ambivalent firms actually reconcile recognized risks with continued adoption would illuminate the decoupling of risk awareness from risk restraint that this study documents but cannot explain. And causal or quasi-experimental designs, exploiting policy variation in state support or the staggered roll-out of AI tools, would move beyond association toward the effects of adoption on productivity, fairness and employment. The dataset analysed here, with its rich functional and perceptual instrumentation, provides a strong baseline for several of these extensions.

12. Conclusion

Artificial intelligence has rapidly become one of the defining technologies shaping contemporary organizations, yet its organizational consequences remain only partially understood. While public debate frequently oscillates between technological optimism and concerns about widespread workforce displacement, empirical evidence capable of explaining how organizations actually integrate AI into human resource management has remained comparatively limited, particularly in Central and Eastern Europe. This monograph set out to address that gap by providing a comprehensive organization-level analysis of AI adoption in HR among Slovak enterprises, drawing on one of the largest enterprise surveys on artificial intelligence conducted in the region.

Rather than approaching AI adoption as a single technological event, the analyses consistently demonstrated that AI implementation in human resource management represents one element of a broader organizational transformation. Across the different analytical perspectives presented throughout the monograph, a remarkably coherent picture emerged. Organizations do not introduce AI into HR in isolation, nor do they adopt it solely because technological opportunities become available. Instead, HR adoption appears to evolve alongside wider organizational AI programmes, supported by accumulated implementation experience, organizational readiness and managerial capability. Artificial intelligence therefore spreads across organizational functions progressively rather than simultaneously, with human resource management occupying what this monograph describes as a second-wave position within enterprise AI diffusion.

One of the most important empirical contributions concerns the determinants of HR-AI adoption. Contrary to much of the broader AI adoption literature, traditional organizational characteristics such as firm size, ownership structure and industrial sector proved to be relatively poor predictors once organizations had already adopted AI elsewhere. Instead, the strongest determinant was the breadth of enterprise AI deployment itself. Organizations applying AI across multiple business functions were substantially more likely to extend these technologies into HR. This finding suggests that successful HR adoption is closely linked to organizational learning accumulated through previous AI implementations rather than to static organizational characteristics. The analyses further demonstrated that AI adoption within HR is considerably more heterogeneous than suggested by many conceptual discussions. Organizations rarely implement AI as a comprehensive HR solution. Instead, AI appears as a portfolio of applications progressing through different stages of maturity across recruitment, employee development, performance management, workforce planning, HR analytics and administrative support. Most observed implementations remain at pilot or early deployment stages, indicating that organizational experimentation currently exceeds full-scale operational integration. This broad-but-shallow pattern represents one of the defining characteristics of contemporary enterprise AI adoption in HR.

The monograph also provides evidence that organizations evaluate AI through a more complex decision logic than is often assumed. Benefits and risks are not perceived as opposite ends of a single continuum but as distinct dimensions that frequently coexist.

Many organizations simultaneously recognize substantial opportunities for improving efficiency, decision quality and organizational performance while also expressing concern regarding fairness, discrimination, transparency and employee relations. Importantly, heightened awareness of these risks does not appear to discourage adoption. Instead, organizations exhibiting the greatest maturity often report both the strongest perceived benefits and the highest awareness of organizational risks. This finding supports an interpretation of organizational AI adoption based on informed managerial ambivalence rather than either technological enthusiasm or technological resistance. Equally noteworthy are the findings concerning employment. Public debate frequently frames AI primarily as a threat to jobs, particularly within administrative functions such as HR. The evidence presented here provides a considerably more nuanced picture. AI adoption in HR was not associated with significantly higher levels of workforce reductions, nor with elevated employee concern relative to organizations applying AI elsewhere. At the same time, AI-related creation of entirely new roles remained limited. Rather than producing immediate substitution or rapid expansion of employment, AI currently appears to function primarily as an augmentative organizational technology supporting existing HR processes. These findings should not be interpreted as evidence that employment consequences will remain negligible indefinitely. Instead, they characterize an early stage of organizational AI adoption in which implementation remains predominantly exploratory.

Beyond the individual empirical findings, this monograph advances a broader conceptual interpretation of AI adoption in human resource management. The integrated conceptual framework developed in Chapter 10 proposes that organizational AI readiness constitutes the foundation upon which enterprise AI adoption expands across organizational functions before reaching HR, generating both organizational benefits and governance challenges while simultaneously creating opportunities for continuous organizational learning. This framework integrates determinants, implementation patterns, organizational perceptions and employment consequences into a single organizational capability perspective. In doing so, it moves beyond fragmented explanations that treat technological, organizational or human factors independently and instead conceptualizes AI adoption as an iterative process of organizational capability development.

The practical implications follow naturally from this interpretation. Successful AI implementation depends not merely on acquiring advanced technological solutions but on developing the organizational conditions that enable those technologies to create sustainable value. Organizational readiness, leadership commitment, employee capability development, governance arrangements and systematic learning repeatedly emerged as more informative than purely technological characteristics. Consequently, organizations seeking to expand AI within human resource management should view governance not as a constraint imposed upon innovation but as one of its principal organizational enablers. Responsible AI implementation requires transparency, accountability, human oversight and continuous evaluation alongside technological development if organizations are to maintain employee trust while realizing the benefits AI can offer.

The findings also carry broader significance for technology policy. The evidence presented throughout the monograph suggests that organizations require not only technological

infrastructure but also institutional support capable of strengthening organizational readiness and governance capabilities. In countries such as Slovakia, where many enterprises remain in the early stages of AI adoption, policies supporting organizational capability development may prove at least as important as investments in technological infrastructure alone. Encouraging organizational learning, managerial competencies and responsible AI governance is therefore likely to accelerate sustainable AI adoption more effectively than technology-centred interventions in isolation. Like every empirical investigation, this study reflects a particular moment within an evolving technological landscape. Artificial intelligence is developing rapidly, organizational capabilities continue to mature and regulatory frameworks are simultaneously becoming more sophisticated. The predominantly pilot-stage implementations observed throughout the present study suggest that many of the organizational consequences associated with AI have yet to unfold fully. Future longitudinal research will therefore be essential for determining whether the patterns documented here remain stable as AI becomes more deeply embedded within enterprise operations.

Ultimately, the principal message of this monograph is neither that artificial intelligence will fundamentally transform human resource management nor that its impact will remain modest. Rather, the evidence suggests that the trajectory of AI in HR will depend primarily on organizations themselves. Technology provides the capability; organizations determine how that capability is translated into managerial practice. The enterprises most advanced in AI adoption are distinguished not simply by greater technological sophistication but by stronger organizational readiness, broader implementation experience, more deliberate governance and greater capacity for organizational learning. Artificial intelligence in human resource management should therefore be understood not as a technological destination but as an ongoing organizational journey requiring continuous adaptation, responsible leadership and sustained institutional development.

In this sense, the contribution of the present monograph extends beyond documenting the current state of AI adoption in Slovak enterprises. It offers an empirically grounded framework for understanding how organizations progress from technological readiness to organizational transformation and from isolated AI applications to responsible enterprise-wide capability. As artificial intelligence continues to reshape the future of work, this organizational perspective may prove as important as the technologies themselves.

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Appendix A. Human-resources module: item wording

HR functions assessed on the five-point AI adoption ladder (1 = no use and no plans; 2 = considering for the more distant future; 3 = planning within two years; 4 = already using on a pilot or occasional basis; 5 = using actively and regularly):

- Workforce planning and job design
- Recruitment
- Screening of CVs and personnel documents
- Matching candidates to job requirements
- Predicting candidate success probability and career planning
- Personalized educational programs, simulations, active and multitasking learning
- Personalized onboarding plans (reception, adaptation and integration)
- Automated employee evaluation and feedback
- e-HRM
- Employee satisfaction management
- Employee turnover prediction
- Employee compensation

Perceived positive impacts of AI in HR (rated 1 = not at all significant to 5 = very significant):

- Job optimization
- Speeding up the recruitment process
- Saving HR team time and automating routine processes
- Better allocation of workers
- Personalization of educational programs and increasing learning efficiency
- Faster adaptation of new employees (personalized onboarding)
- Increasing the objectivity and regularity of employee evaluations
- Reducing administrative burden and more efficient management of personnel data
- Early identification of problems and improvement of the working environment
- Identification of turnover factors and proactive problem solving in HR
- Fairer compensation based on performance, market benchmarks and historical data
- Increasing the efficiency of internal communication

Perceived negative impacts of AI in HR (rated 1 = not at all significant to 5 = very significant):

- Reducing individuality and overlooking employees' unique abilities
- Risk of discrimination and unfairness in recruitment and evaluation
- Overlooking unconventional candidates and limiting diversity
- Limited consideration of soft skills and cultural compatibility
- Biased or inaccurate predictions affecting career opportunities
- Decreased social interaction and weakened teamwork

- Impersonal onboarding without capturing the informal company culture
- Weakening of relations between employees and management
- Loss of employee trust due to constant monitoring
- Problems with IT infrastructure outages and dependence on AI systems
- Stigmatization of employees incorrectly identified as at-risk
- Excessive automation of compensation without taking into account individual factors

AI maturity dimensions (each rated on a five-stage scale):

- Culture And Mindset
- Strategy
- Organization
- Technology
- Data
- Ethics
- Privacy

Appendix B. Descriptive statistics and survey overview

Table B1. Sample composition (N = 816)

Characteristic	n	%
10–49 employees	222	27.2%
50–249 employees	246	30.1%
250+ employees	348	42.6%
Private Slovak	391	47.9%
Foreign-owned (registered in SK)	326	40.0%
Mixed ownership	99	12.1%
5–10 years	248	30.4%
11+ years	568	69.6%

Table B2. AI adoption status (N = 816)

Status	n	%
Use in multiple areas	135	16.5%
Use in specific processes	216	26.5%
Testing / piloting	211	25.9%
Plan within 1 year	59	7.2%
Plan within 2 years	29	3.6%
Plan in 3+ years	43	5.3%
No use, no plans	123	15.1%

Table B3. Functional areas of AI application among AI users (n = 562)

Functional area	n	% of users
Marketing and Sales	209	37.2%
Production and Operational Processes	157	27.9%
Logistics	142	25.3%
Research, Development and Innovation	121	21.5%
Human Resources	100	17.8%
Management	91	16.2%
ICT security	78	13.9%
Finance	75	13.3%
Other	44	7.8%

Table B4. AI maturity index by adoption group

Group	Mean	SD	n
Non-adopters	1.27	0.61	123
Planners	2.14	0.70	131
Other AI users	2.85	0.87	462
HR-AI adopters	3.03	0.79	100

Table B5. HR-AI adoption by function (n = 100)

HR function	Mean stage	SD	% in use (≥4)	% active (=5)
Recruitment	3.20	1.07	40%	12%
Personalized educational programs, simulations, active and multitasking learning	3.12	1.04	30%	12%
Screening of CVs and personnel documents	3.09	1.08	40%	7%
Matching candidates to job requirements	3.06	1.02	36%	6%
Personalized onboarding plans (reception, adaptation and integration)	3.06	1.12	36%	10%
Automated employee evaluation and feedback	3.00	1.13	40%	6%
Workforce planning and job design	2.91	1.16	32%	9%
Employee satisfaction management	2.89	1.11	31%	7%
Predicting candidate success probability and career planning	2.86	1.04	23%	6%
e-HRM	2.86	1.13	28%	7%
Employee turnover prediction	2.86	1.15	31%	8%
Employee compensation	2.82	1.12	30%	7%

Table B6. Perceived positive impacts of AI in HR (n = 100)

Positive impact	Mean	SD
Reducing administrative burden and more efficient management of personnel data	3.72	0.95
Increasing the objectivity and regularity of employee evaluations	3.67	0.91
Speeding up the recruitment process	3.66	0.88
Faster adaptation of new employees (personalized onboarding)	3.65	0.94
Early identification of problems and improvement of the working environment	3.64	0.88
Increasing the efficiency of internal communication	3.64	0.82
Personalization of educational programs and increasing learning efficiency	3.63	0.87
Better allocation of workers	3.57	0.91

Saving HR team time and automating routine processes	3.54	0.95
Identification of turnover factors and proactive problem solving in HR	3.52	0.95
Fairer compensation based on performance, market benchmarks and historical data	3.45	1.00
Job optimization	3.41	0.96

Table B7. Perceived negative impacts of AI in HR (n = 100)

Negative impact	Mean	SD
Overlooking unconventional candidates and limiting diversity	3.68	0.95
Decreased social interaction and weakened teamwork	3.65	0.86
Weakening of relations between employees and management	3.56	0.98
Risk of discrimination and unfairness in recruitment and evaluation	3.53	1.02
Loss of employee trust due to constant monitoring	3.52	0.97
Limited consideration of soft skills and cultural compatibility	3.49	0.96
Biased or inaccurate predictions affecting career opportunities	3.49	0.93
Impersonal onboarding without capturing the informal company culture	3.46	1.01
Excessive automation of compensation without taking into account individual factors	3.46	1.01
Stigmatization of employees incorrectly identified as at-risk	3.41	1.01
Reducing individuality and overlooking employees' unique abilities	3.40	0.99
Problems with IT infrastructure outages and dependence on AI systems	3.36	1.02