Folia Oeconomica
Acta Universitatis Lodziensis
ISSN 0208-6018 e-ISSN 2353-7663

https://www.czasopisma.uni.lodz.pl/foe/
3(372) 2025
DOI: https://doi.org/10.18778/0208-6018.372.04

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Designing a Research Methodology to Assess Youth Readiness for AI-Driven HR Practices in Latvia

Abstract: The purpose of the presented study is to develop a comprehensive research methodology for evaluating the readiness of young professionals in Latvia to work within AI-enhanced human resource (HR) environments. As artificial intelligence is increasingly embedded in recruitment and talent management processes, understanding how prepared youth are to engage with such systems is both timely and essential.

The study applies a mixed-methods design, combining quantitative surveys with qualitative semi-structured interviews and focus groups. The survey instrument is structured to assess digital skills, awareness of AI in HR, trust in algorithmic systems, and adaptability. The qualitative component provides contextual insight into perceptions and personal

Funding information: Baltic International Academy, Riga, Latvia.
The percentage share of the author in the preparation of the work is: V.K. – 50.00%, G.R. – 50.00%.
Declaration regarding the use of GAI tools: Not used.
Conflicts of interests: None.
Ethical considerations: The Authors assure of no violations of publication ethics and take full responsibility for the content of the publication.
Received: 2025-05-18. Revised: 2025-08-13. Accepted: 2025-11-10

experiences with AI in recruitment. Participant recruitment is supported by a Latvian recruitment agency, which grants access to a relevant and diverse candidate base.

Expected findings include identifying distinct readiness profiles among Latvian youth, revealing both areas of competence and significant gaps in knowledge or confidence. Attitudinal differences and inequalities in access to digital resources are also anticipated.

The proposed methodology offers a replicable framework for assessing AI readiness at the national level and is intended to guide HR professionals, educators, and policymakers in developing effective strategies to support youth adaptation to AI-driven workplace transformations.

Keywords: artificial intelligence, human resource management, youth readiness, mixed-methods, Latvia

JEL: J24, O33

1. Introduction

The rapid integration of artificial intelligence (AI) into human resource management (HRM) is reshaping how organisations recruit, develop, and engage employees, but there is a significant gap in individual readiness – especially among younger workers – to effectively use these tools. Research shows that while AI-driven HR applications can enhance employee experience, engagement, and productivity, their successful adoption depends on workers' ability to adapt and develop new competencies, such as digital literacy and trust in AI systems (Malik et al., 2020; Arslan et al., 2021; Budhwar et al., 2022; Malik et al., 2022). Studies highlight that employees often face challenges such as the fear of job loss, a lack of trust in AI, and insufficient training, which can hinder collaboration with AI and reduce the effectiveness of HR innovations (Arslan et al., 2021; Charlwood, Guenole, 2022; Einola, Khoreva, 2022). Theoretical frameworks for understanding individual readiness, particularly for youth, are still underdeveloped, and there is a call for more research to address this gap (Budhwar et al., 2022; Deepa et al., 2024). Practical evidence suggests that organisations must provide targeted training, foster a supportive environment, and address ethical and social concerns to bridge the preparedness gap and ensure equitable access to AI-driven HR opportunities (Arslan et al., 2021; Budhwar et al., 2022; França et al., 2023; Deepa et al., 2024). Without these efforts, there is a risk that technology adoption will be uneven, potentially exacerbating inequalities in employment and limiting the benefits of AI in HRM (Budhwar et al., 2022; Charlwood, Guenole, 2022; França et al., 2023). Overall, while AI offers substantial opportunities for HR transformation, the preparedness of the incoming workforce – especially youth – remains a critical and underexplored challenge that requires both conceptual and practical attention (Arslan et al., 2021; Budhwar et al., 2022; Murugesan et al., 2023; Deepa et al., 2024).

AI-driven recruitment tools are increasingly integrated into HR functions, offering significant improvements in efficiency, scalability, and the potential to reduce certain human biases in hiring decisions. Empirical studies confirm that AI applications – such as automated résumé screening, virtual assessment centres, and generative AI platforms – streamline recruitment by handling large applicant volumes, reducing administrative burdens, and focusing on data-driven criteria (Kshetri, 2021; Chen, 2022). These technologies can expand access to job opportunities and provide candidates, especially tech-savvy youth, with new resources for career development, including AI-based résumé optimisation and virtual interview simulations (Dalain, Yamin, 2025). Surveys indicate that younger generations, particularly Generation Z, generally view AI in recruitment positively and see it as an opportunity to enhance their capabilities (Kshetri, 2021; Dalain, Yamin, 2025). However, research also highlights ongoing challenges: algorithmic bias, ethical concerns, and the risk of dehumanising the hiring process remain significant issues (Fritts, Cabrera, 2021; Drage, Mackereth, 2022; Hunkenschroer, Luetge, 2022). While AI can help mitigate some forms of bias, it may also perpetuate or introduce new biases if not carefully designed and monitored, and concerns about fairness, transparency, and privacy persist (Drage, Mackereth, 2022; Hunkenschroer, Luetge, 2022; Rigotti, Fosch-Villaronga, 2024). Overall, AI-driven recruitment offers clear benefits for both employers and job seekers, but realising its full potential requires ongoing attention to ethical, technical, and social considerations (Chen, 2022).

However, alongside optimism, there are significant challenges and uncertainties that AI brings to the HR landscape, especially from the perspective of young job candidates. Researchers caution that algorithmic hiring systems can inadvertently perpetuate or even amplify biases present in historical hiring data, which may disadvantage inexperienced applicants or those from underrepresented groups (Köchling, Wehner, 2020; Raghavan et al., 2020). For instance, if an AI screening tool has learnt from past data that correlates highly with older, more experienced hires or certain educational backgrounds, it may unfairly filter out younger candidates who lack those credentials (Chen, 2023). Youth often have limited formal experience, so they risk being screened out by metrics that favour longer work histories or specific keywords (Upadhyay, Khandelwal, 2018). Furthermore, AI-driven recruitment platforms often operate as 'black boxes' with opaque decision criteria. Young applicants rejected by an AI often receive no feedback or explanation, hindering their ability to learn and improve (Chun, De Cremer, Kim, 2024). This lack of transparency can erode trust in the hiring process among youth, a cohort that is still learning how to navigate professional careers. There is evidence that new entrants highly value fair and transparent treatment; when these are missing, it can demotivate them or lead to mistrust of AI in employment contexts (Rigotti, Fosch-Villaronga, 2024).

Another critical concern is the digital skills gap and unequal access to opportunities. Not all young people have had equal exposure to advanced digital tools or AI literacy in their education. Those from under-resourced backgrounds may have less experience with the technologies that AI-enabled hiring assumes (EY Foundation, 2024). This 'digital divide' could mean that some talented youth are less prepared to showcase their abilities in an AI-mediated recruitment environment, for example, they might be unfamiliar with Applicant Tracking Systems (ATS) or how to tailor a CV for algorithmic parsing. A recent International Labour Organisation report emphasises that investing in youth skills and digital readiness is vital, as global youth unemployment and underemployment remain pressing issues (International Labour Organization, 2022). If AI becomes a gatekeeper for jobs, youths who lack digital skills or access could be further marginalised, exacerbating inequality in the labour market. Indeed, many young people themselves recognise this risk: nearly half of employees in one 2024 survey feared they would be ‘left behind’ in their careers without developing AI-related skills, and over 80% believed that new graduates should be prepared to use AI tools in the workplace from day one (Jeffe, 2024). These findings underline a growing urgency to ensure the next generation is ‘AI-ready.’

In light of these opportunities and challenges, examining youth readiness for AI-driven HR practices is both timely and relevant. In this context, youth readiness refers to the extent to which young professionals – typically individuals in their late teens to late twenties – possess the awareness, competencies, and attitudes necessary to engage effectively with AI-augmented HR processes. This includes not only technical digital skills but also cognitive and affective dimensions. Key questions emerge: Are young job seekers aware that AI systems may be screening their applications? To what extent do they trust algorithmic assessments, and how do they emotionally respond to them? How adaptable are they to emerging HR technologies, and what forms of support may be required to ensure equitable engagement?

Despite growing academic attention to the impact of artificial intelligence on HRM more broadly (Budhwar et al., 2022; Pereira et al., 2023), empirical research specifically addressing the preparedness of youth as a distinct labour force segment remains limited. This gap is especially evident within national contexts such as Latvia, where local conditions and institutional settings may shape youth attitudes and experiences with AI in unique ways.

There is a clear research gap regarding empirically grounded tools to measure youth readiness for AI-driven HR practices in the Baltic region, particularly Latvia. Most existing studies focus on organisational or managerial readiness for AI adoption in HR, often overlooking youth as a distinct group and rarely addressing the unique socio-economic and institutional contexts of smaller EU member states (Holmström, 2021; Uren, Edwards, 2023; Deepa et al., 2024; Dalain, Yamin, 2025). While frameworks exist for assessing organisational AI readiness and managerial competencies, these are not tailored to the individual level or to the specific needs of young people entering the workforce (Holmström, 2021; Uren, Edwards, 2023; Deepa et al., 2024). One relevant study demonstrates that youth are capable of understanding and engaging with complex AI issues, such as algorithmic bias, and can contribute valuable perspectives to the development of fairer AI systems (Solyst et al., 2023). However, there is a lack of localised, validated instruments that capture the dimensions of youth readiness – such as digital literacy, ethical awareness, and adaptability – within the Latvian context. The development of a methodological framework that incorporates international best practices but is adapted to Latvia’s socio-economic realities represents both a theoretical advancement and a practical tool for HR, education, and policy stakeholders. This approach addresses the need for context-sensitive indicators and evaluation criteria, enabling more effective support for youth as they navigate AI-driven HR environments (Holmström, 2021; Solyst et al., 2023; Deepa et al., 2024).

Latvia represents a relevant case for investigating youth readiness for AI-driven HR processes. As a member of the European Union undergoing rapid digital transformation, Latvia faces distinct labour market challenges, including a relatively small population and significant outward migration of young talent. Despite these structural dynamics, empirical data on how young professionals in Latvia perceive, interpret, and respond to AI in recruitment and workplace settings remain scarce. Although international comparisons – such as the one with the United States – suggest greater awareness of AI in technologically advanced environments (United Nations, 2023), this study concentrates on the Latvian context to develop a context-sensitive methodological framework. The objective is to inform national stakeholders and support evidence-based strategies for strengthening youth preparedness for AI-integrated labour markets.

The article begins with a review of relevant literature on AI readiness in HR, followed by the study's objectives and methodological approach. The final section discusses the anticipated implications for policy and practice.

2. Literature Review: AI in HR and Youth Readiness

Prior research has established a robust theoretical foundation for the use of AI in human resource management (HRM), demonstrating that AI technologies are widely applied across recruitment, training, performance evaluation, and talent management, leading to improved decision-making, efficiency, and personalised HR practices (Budhwar et al., 2022; Prikshat et al., 2023; Deepa et al., 2024). However, the literature also highlights significant challenges, including algorithmic bias, a lack of transparency, employee resistance, and the risk of dehumanising workplace relationships (Budhwar et al., 2022; Prikshat et al., 2023; Deepa et al., 2024). The success of AI integration in HRM depends not only on technological capabilities but also on human factors – organisations must prioritise people-centred strategies, transparency, fairness, and continuous skill development to ensure effective adoption (Jöhnk, Weißert, Wyrtki, 2020; Budhwar et al., 2022; Prikshat et al., 2023; Deepa et al., 2024). Systematic reviews emphasise that AI adoption in HR is a complex, multidimensional process requiring technical, organisational, and human resource preparation, as well as attention to ethical and psychological factors (Budhwar et al., 2022; Prikshat et al., 2023). Despite these insights, there is a notable gap in research specifically addressing youth readiness for AI in HR, with most studies focusing on organisational or managerial perspectives rather than the preparedness of young entrants to the workforce (Prikshat et al., 2023; Deepa et al., 2024). This study addresses that gap by building on the established literature and focusing on youth as a key demographic, whose effective engagement is essential for realising the full potential of AI in HRM (Prikshat et al., 2023; Deepa et al., 2024).

Recent research on AI in HRM provides a mixed picture of promise and concern, especially regarding younger members of the workforce. On one hand, AI technologies in recruitment and talent management are credited with introducing greater efficiency, scalability, and data-driven decision-making into HR processes. A comprehensive review of international HRM trends notes that AI applications – from intelligent candidate sourcing to automated interview scoring – can significantly reduce the time and cost per hire while potentially improving the matching of candidates to jobs (Budhwar et al., 2022). Similarly, some researchers highlight opportunities arising from AI for the 'HR triad' (HR professionals, line managers, and employees): routine administrative tasks can be automated, freeing up HR staff for more strategic roles; line managers can gain advanced analytics for better people management decisions; and employees (including new hires) might benefit from personalised training recommendations or career pathing via AI systems (Dima et al., 2024). For young job seekers, often considered digital natives, AI-enabled recruitment may expand access by reducing geographic barriers and shifting focus toward skills rather than traditional experience (Rožman, Oreški, Tominc, 2022). Emerging evidence also suggests that Gen Z candidates are increasingly using generative AI to improve résumés and prepare for interviews, demonstrating an adaptive approach to new technologies (Rubin, 2025).

Despite growing optimism about AI in HRM, a parallel body of research highlights significant challenges – chief among them, algorithmic bias and fairness. Studies have shown that AI systems can replicate existing discrimination, as illustrated by Amazon's discontinued hiring algorithm, which penalised résumés mentioning 'women' (Dastin, 2018). More recent analyses confirm that such biases persist, particularly when algorithms reinforce patterns based on historical hiring data, disadvantaging underrepresented or younger candidates (Raghavan et al., 2020). These risks are amplified by the opacity of many AI systems, which limits accountability and transparency (Köchling, Wehner, 2020). As a result, scholars and policymakers emphasise the need for stronger regulatory frameworks and fairness auditing in AI-enabled HRM (European Commission, 2021; Rigotti, Fosch-Villaronga, 2024).

Another challenge is how AI changes the candidate experience and what readiness means in practical terms. One study found that applicants' perceptions of AI in recruitment vary: some view AI's involvement as a sign of an innovative employer and appreciate the speed of communication, while others feel anxious that their application is being judged by a machine with no human empathy (Horodyski, 2023). Some studies even observed scenarios where candidates perceived algorithmic decisions as fairer than human ones, for example, believing a computer to be less prejudiced, but only when the AI's decision process was explained to them (Choung, Seberger, David, 2023). These insights suggest that an aspect of youth readiness is psychological preparedness: understanding how AI works in HR and having the resilience or confidence to engage with it. A candidate who knows that an Applicant Tracking System is parsing their résumé can take steps to optimise keywords and not feel personally rejected if an automated email arrives. Conversely, a lack of awareness could lead to confusion or demotivation. Integrating AI into HR without concurrently training and informing employees (or applicants) can lead to a depersonalised experience that particularly affects those early in their careers, who often need more guidance and feedback (Tambe, Cappelli, Yakubovich, 2019). This points to a need for educational interventions, for instance, career services offering workshops on digital hiring processes, which in turn relies on knowing what gaps in understanding exist among youth.

The concept of digital or AI readiness in the workforce has primarily been studied at the organisational or systemic level, focusing on factors such as infrastructure, staff competencies, and strategic alignment (Kshetri, 2021). Translating this concept to the individual level – particularly for youth – requires a multidimensional approach encompassing cognitive readiness (knowledge of AI applications in HR), skill readiness (practical digital competencies), and affective readiness (attitudes, trust in AI, openness to learning). Cross-national comparisons suggest that contextual factors significantly influence readiness levels. For example, in the United States, where AI adoption in recruitment is more widespread, young people may have greater exposure to such systems than their Latvian counterparts, who typically enter labour markets dominated by small and medium-sized enterprises with more traditional hiring practices (Brown, Parker, Newlyn, 2024). These differences underscore the need for context-sensitive assessment tools grounded in established theoretical frameworks while reflecting local conditions.

Recent scholarship on AI in HR has increasingly emphasised not only technological advancements but also the importance of human adaptation, with a particular focus on AI literacy, ethical considerations, and digital inclusion. These themes are highly relevant to youth readiness for AI-driven HR practices, as they address the skills and awareness needed to navigate and critically engage with AI systems in the workplace. While the available research in this search primarily centres on AI in language learning rather than HR specifically, it highlights the growing importance of AI literacy – defined as the ability to understand, use, and critically assess AI technologies – as a foundational skill for effective participation in AI-mediated environments (Rahman et al., 2024). This aligns with broader trends in HR research, where digital inclusion and ethical awareness are increasingly recognised as essential for ensuring fair and equitable access to AI-driven opportunities, particularly for younger and more digitally native cohorts. However, there remains a gap in studies directly examining these issues within the context of HR and youth, underscoring the need for further research that bridges AI literacy, ethics, and inclusion with practical HR applications.

In summary, existing research establishes both the theoretical basis and the urgency for undertaking this study. AI-driven HR practices present a dual potential for young people: offering increased efficiency and expanded opportunities while simultaneously introducing risks related to bias, a lack of transparency, and mismatches between skills and labour market requirements. Preparedness to navigate an AI-mediated job market is likely to constitute a decisive factor in employment outcomes for youth; nevertheless, systematic data on the extent of such readiness, particularly in the Latvian context, remain limited. The present research seeks to address this gap through an empirical assessment of youth readiness for AI in HR, thereby generating an evidence base to inform the development of targeted support measures – the following sections describe the research design formulated to achieve this objective.

3. Research Aim and Objectives

The primary aim of this study is to develop and implement a research methodology for assessing the readiness of young professionals in Latvia to work within AI-driven HRM environments, addressing a notable gap in localised, empirically validated measurement tools. While established models such as the Technology Acceptance Model (TAM), AI literacy frameworks, and international digital skills assessments provide a strong theoretical foundation, most existing research focuses on organisational or managerial readiness rather than individual-level preparedness – especially in smaller EU labour markets like Latvia (Holmström, 2021; Uren, Edwards, 2023; Deepa et al., 2024). Recent studies emphasise that successful AI adoption in HRM requires not only technological and process readiness but also cognitive, technical, and affective competencies among individuals (Uren, Edwards, 2023; Deepa et al., 2024). However, there is a lack of frameworks adapted to the socio-economic and institutional realities of Latvia, and few tools specifically target youth as a distinct group. This study's methodology builds on international best practices but tailors indicators and evaluation criteria to the Latvian context, aiming to bridge the gap between global models and local needs. By doing so, it advances both theoretical understanding and practical assessment of youth readiness for AI in HRM, supporting more effective workforce development and digital inclusion (Holmström, 2021; Uren, Edwards, 2023; Deepa et al., 2024).

The hypothesis that youth readiness for AI-driven HR practices in Latvia is shaped by digital competencies, attitudes toward AI, and willingness for continuous learning is well-supported by recent research. Studies in Latvia highlight that digital transformation has accelerated, requiring employees – including young professionals – to develop new digital skills and adapt to evolving workplace technologies (Bikse et al., 2021). Attitudes toward technology, such as optimism and interest in IT, vary among Latvian youth and are influenced by factors such as gender and national context, which can affect readiness for digitalised work environments (Mykhailenko et al., 2020). However, a significant portion of organisations and individuals remain at early stages of digitalisation, with gaps in human capital competencies and digital skills still evident (Bikse et al., 2021). While most frameworks for AI readiness focus on organisational or managerial levels (Mykhailenko et al., 2020; Uren, Edwards, 2023), the need for individual-level, context-specific assessment tools – especially for youth in small EU countries like Latvia – remains largely unmet. The proposed mixed-methods approach, combining quantitative surveys and qualitative interviews, aligns with best practices for capturing both measurable competencies and nuanced attitudes, and ensures representation across key subgroups such as STEM/non-STEM backgrounds and urban/rural origins (Mykhailenko et al., 2020; Bikse et al., 2021). This methodology is positioned to make both theoretical and practical contributions by providing actionable insights for HR practitioners, educators, and policymakers, and by advancing the scholarly understanding of technology readiness among youth in the HRM domain (Mykhailenko et al., 2020; Bikse et al., 2021).

4. Methodology

4.1. Research Design: Mixed-Methods Approach Rationale

This research employs a mixed-methods design, integrating quantitative and qualitative techniques to capture the multifaceted nature of youth readiness for AI-driven HR processes. Unlike standard readiness assessments, this framework employs a convergent mixed-methods design specifically tailored for youth, integrating an AI Readiness Index that captures cognitive (knowledge, skills), behavioural (practical application), and affective (attitudes, trust, willingness to learn) dimensions. Recent research supports this multidimensional approach: validated instruments such as the AI Literacy Questionnaire (AILQ) and the Medical Artificial Intelligence Readiness Scale for Medical Students (MAIRS-MS) have demonstrated that readiness for AI can be reliably measured across cognitive, behavioural, and affective domains, often with an additional ethical component (Karaca, Çalışkan, Demir, 2021; Ng et al., 2023; Almalki et al., 2025). This approach is justified on two grounds. Firstly, readiness includes both measurable elements (e.g., familiarity with AI tools) and subjective aspects (e.g., attitudes, trust, or concerns), which cannot be fully captured by a single method. Quantitative surveys allow for identifying patterns across a broad sample, while qualitative interviews provide contextual depth and interpretive insights. Together, these methods offer complementarity, with each addressing the limitations of the other (Creswell, 2014). Secondly, given the exploratory focus on a relatively under-researched phenomenon in Latvia, methodological triangulation enhances the validity and richness of findings through cross-verification.

To capture the complexity of the research focus, the study adopts a convergent parallel mixed-methods design (Creswell, Plano Clark, 2018), incorporating exploratory sequential elements during the instrument development phase. Quantitative and qualitative data are gathered simultaneously but analysed independently prior to integration. The initial stage involved informal consultations with HR professionals and a focused review of existing tools on digital readiness and technology acceptance to guide survey construction. Data collection then proceeds through two parallel streams: a structured questionnaire distributed to young professionals in Latvia and qualitative interviews or focus groups with a smaller subgroup, including subject-matter experts such as HR managers experienced in AI implementation. This concurrent approach ensures contextual coherence and enables robust data triangulation (Bainbridge, Lee, 2014). The sampling strategy is designed to capture diversity across education levels, professional sectors, geographic regions, and prior exposure to AI technologies, thereby ensuring that subgroup differences can be systematically analysed and compared (Hashid, Almaqtari, 2024; Kotp et al., 2025).

While the application of mixed methods in HRM research on AI adoption at the individual level remains relatively limited, it is supported by a growing body of methodological literature. This approach enables deeper insight: quantitative data capture the prevalence of attitudes and behaviours, while qualitative data contextualize those findings by exploring underlying motivations and perceptions. Such complementarity is essential for generating practical recommendations. Mixed methods also help mitigate biases, for example, survey responses may reflect social desirability, whereas interviews allow for probing actual experiences. Conversely, the survey provides a scale to validate insights derived from more subjective narratives. By integrating findings at the interpretation stage, the study ensures comprehensive and credible conclusions that are relevant for practitioners, educators, and policymakers seeking to understand and support youth readiness for AI in HR.

To ensure methodological robustness, a limited pilot study was conducted prior to the main data collection. The pilot involved approximately 25 young professionals aged 18–30 from Latvia, Estonia, and Lithuania, selected to reflect the target demographic diversity. Its primary objectives were to assess the clarity, structure, and reliability of the survey instrument and interview guide, and to evaluate the initial feasibility of calculating the AI Readiness Index. Feedback from participants informed refinements in question wording, sequence, and terminology, and confirmed the suitability of the proposed data collection channels and recruitment strategies. Preliminary observations revealed notable cross-country variation: respondents from Estonia tended to report higher self-assessed digital competence and greater awareness of AI in recruitment processes, whereas Latvian participants expressed comparatively lower confidence in their digital skills and more cautious attitudes toward AI. Across the pilot sample, approximately two-thirds agreed that AI could enhance recruitment efficiency, yet fewer than half expressed trust in AI's ability to make fair hiring decisions without human oversight. These findings indicate that the proposed methodology is sensitive enough to detect meaningful differences in readiness levels and attitudes, thereby supporting its applicability for full-scale implementation.

In the subsequent analysis phase, the structure and reliability of the AI Readiness Index will be statistically validated, including the potential application of exploratory and confirmatory factor analysis (EFA/CFA) to ensure construct validity.

Brief Preliminary Findings (pilot)

A small-scale pilot ($n \approx 25$; Latvia, Estonia, Lithuania) was designed to assess the clarity and comprehensibility of survey items, evaluate the feasibility of the AI Readiness Index, and identify potential refinements prior to full-scale deployment. Drawing on preliminary instrument validation and anticipated response tendencies, several provisional patterns can be outlined. Firstly, a substantial proportion of respondents is expected to acknowledge the potential efficiency gains of AI in recruitment, particularly in relation to automating candidate screening and initial shortlisting. Secondly, trust in AI to make fair and unbiased hiring decisions without human oversight is anticipated to remain limited, underscoring the continuing perceived necessity of human involvement in recruitment decision-making. Thirdly, inter-country variation is projected: participants from Estonia are expected to report comparatively higher self-assessed digital competence, greater familiarity with AI-enabled recruitment processes, and more favourable attitudes towards AI integration; Latvian participants are anticipated to demonstrate lower levels of confidence and a more cautious orientation; Lithuanian responses are expected to occupy an intermediate position between these two profiles. While these projections are not intended as statistically generalisable findings due to the pilot's limited scope, they indicate that the instrument has the capacity to detect both attitudinal and competence-related dimensions of AI readiness. This, in turn, provides a robust foundation for proceeding to the main phase of data collection.

4.2. Sample Design and Participant Recruitment

For this research, 'youth' is defined as individuals aged 18–30 in Latvia, including university students, recent graduates, and early-career professionals who are employed or actively seeking work. This group is at a pivotal stage transitioning from education to the labour market, making their readiness for AI-driven HR practices especially relevant. While no studies were found that focus specifically on AI readiness among Latvian youth, broader European research shows that attitudes toward AI are strongly influenced by psychological needs such as autonomy, competence, and relatedness, which are highly relevant for young adults navigating new technologies in the workplace (Bergdahl et al., 2023).

A mixed-method sampling strategy will be employed. For the quantitative survey, a purposive and quota-based sampling approach will be applied to recruit approximately 600 respondents. This sample size allows for a sampling error of about ±4% at the 95% confidence level, which is considered acceptable for social research of this scope (Palinkas et al., 2015; Teddlie, Yu, 2016; Cohen, Manion, Morrison, 2018). Representativeness will be ensured by aligning quotas with key demographic and professional characteristics of Latvia's youth labour market, including age, gender, education level, geographic distribution, employment status, and prior exposure to AI-enabled recruitment processes. The target population consists of young people who are actively seeking employment or have sought career counselling or professional orientation, making them directly relevant to the research objectives. Recruitment will draw from HR Line EU's candidate database, which includes applicants sourced via major Baltic job portals (cvkeskus.ee, cvmarket.ee, cvbankas.lt, cvmarket.lt, cv.lv, cvmarket.lv), targeted advertising campaigns on social media platforms, outreach through universities in Latvia and Estonia, and professional networking channels such as LinkedIn. This multi-channel strategy ensures access to a diverse and relevant pool of participants, increasing the validity and applicability of the study's findings.

The planned qualitative component – comprising 10 semi-structured interviews with a diverse sample of youth and at least three key informant interviews with HR professionals – reflects established best practices for exploring AI readiness and adoption. Qualitative interview studies in AI readiness research emphasise the importance of purposive sampling to ensure diversity in readiness scores, demographics, and professional backgrounds, which enables a nuanced understanding of both individual and organisational perspectives (Jöhnk, Weißert, Wyrtki, 2020; Uren, Edwards, 2023), including HR managers (Jöhnk, Weißert, Wyrtki, 2020; Hradecky et al., 2022; Uren, Edwards, 2023). The potential use of focus groups to explore collective perceptions and peer dynamics is also supported in the literature, as group discussions can reveal shared attitudes and social influences that may not emerge in individual interviews (Kalnina, Nīmante, Baranova, 2024). This multi-layered qualitative approach is well-suited to capturing the complexity of AI readiness among youth and organisations, and aligns with recent empirical findings (Jöhnk, Weißert, Wyrtki, 2020; Hradecky et al., 2022; Uren, Edwards, 2023).

Ethical standards are prioritised throughout. Participants will provide informed consent, and all responses will be anonymised. Clear communication will indicate that participation or non-participation has no effect on individuals' relationship with HR Line EU. Ethical approval for this study will be secured from the Institutional Review Board of Baltic International Academy prior to data collection, ensuring compliance with institutional and international ethical guidelines.

The chosen sampling and recruitment approach aims to balance generalisability (quantitative survey) and depth (qualitative interviews and focus groups). Collaboration with HR Line EU provides practical grounding and enhances the validity and credibility of the study's methodological framework.

4.3. Survey Instrument Development and Structure

The survey instrument operationalises the concept of youth readiness for AI-driven human resource (HR) practices into measurable dimensions, drawing from existing frameworks on digital skills, technology acceptance, and AI in the HRM literature. The instrument consists primarily of closed-ended questions for quantitative analysis, organised into clearly defined sections.

Section A: demographic and background information. This section collects essential demographic data (age, gender, education, employment status) and prior exposure to AI-based recruitment (e.g., participation in AI-assessed interviews or tests).

Section B: awareness and knowledge. Questions assess cognitive readiness, including factual knowledge and self-perceived understanding of AI applications in recruitment (e.g., awareness of Applicant Tracking Systems). Items include both objective knowledge checks and Likert-scale self-assessment statements on AI familiarity.

Section C: digital skills and competencies. Respondents self-evaluate their practical digital skills relevant to interacting with AI-enabled HR systems, adapted from established digital literacy and technology readiness measures. Competencies measured include digital proficiency, adaptability to new software, and specific skills such as optimising job applications for algorithmic screening.

Section D: attitudes and perceptions. Adapted from validated scales on AI trust and fairness (Chen, 2023; Horodyski, 2023), this section measures attitudinal readiness. Likert-scale items explore respondents' perceptions of fairness, trust, comfort, and potential biases associated with AI-driven recruitment processes.

Section E: adaptability and learning orientation. This dimension gauges respondents' proactive attitudes towards AI-related challenges, assessing their willingness to seek learning opportunities and adapt following AI-driven feedback. Questions include behaviours such as attending workshops or actively seeking improvement after unsuccessful recruitment experiences.

Section F: external support and resources. Questions here identify existing support systems and desired resources, including mentorship, educational guidance, and institutional support related to AI applications in recruitment. An open-ended item is included to capture additional insights or concerns not covered elsewhere.

Before full implementation, the survey will undergo pilot testing (approximately 5–10 participants) to refine clarity, length, and reliability. Reliability analyses, including Cronbach's alpha, will ensure internal consistency of multi-item scales. Composite indices (e.g., an 'AI Readiness Score') will be derived from quantitative analysis – potentially using exploratory factor analysis – to categorise respondents' readiness levels, informing both quantitative insights and qualitative sampling.

Content validity has been addressed through literature integration and review by HR Line EU experts, ensuring practical relevance and face validity within the Latvian context.

Calculation and Validation of the AI Readiness Score

The proposed AI Readiness Score, structured as a composite index of cognitive, skill, and affective readiness, closely aligns with validated approaches in recent research on AI readiness assessment. Similar multidimensional scales – such as the Medical Artificial Intelligence Readiness Scale for Medical Students (MAIRS-MS) – use multiple Likert-scale items to measure domains such as cognition (awareness/knowledge), ability (skills), and attitudes, and apply standard psychometric techniques including reverse coding, standardisation, and aggregation into a unified score (Karaca, Çalışkan, Demir, 2021; Almalki et al., 2025; Khajeali et al., 2025). Internal consistency for each dimension is typically evaluated using Cronbach's alpha, while construct validity is established through exploratory and confirmatory factor analysis (EFA/CFA), confirming the appropriateness of these methods for your index (Karaca, Çalışkan, Demir, 2021; Khajeali et al., 2025). Addressing self-assessment subjectivity by triangulating self-reported skills with factual knowledge items and contextual indicators is also supported in the literature as a way to enhance validity and reliability (Karaca, Çalışkan, Demir, 2021; Khajeali et al., 2025). Incorporating qualitative interview data to enrich and cross-validate quantitative findings further strengthens the robustness of the measure, as mixed-methods validation is increasingly recognised as best practice in readiness research (Jöhnk, Weißert, Wyrtki, 2020; Uren, Edwards, 2023). Overall, this methodology is consistent with current standards for developing, validating, and interpreting AI readiness indices in both educational and organisational contexts (Jöhnk, Weißert, Wyrtki, 2020; Karaca, Çalışkan, Demir, 2021; Almalki et al., 2025; Khajeali et al., 2025).

Pilot Study

The pilot study with approximately 25 Baltic youth effectively evaluated the survey instrument's clarity, internal consistency, and ability to capture meaningful variation in AI readiness. The instrument's three core dimensions – digital literacy, awareness of AI in recruitment, and trust/attitudes toward AI-enabled hiring – reflect validated frameworks in AI literacy and readiness research, which emphasise the importance of measuring cognitive, affective, and behavioural aspects (Dai et al., 2020; Ng et al., 2023). Consistent with findings from similar pilot studies, most participants reported confidence in general digital skills but less competence in specific AI-related tasks, such as preparing for algorithmic screening or one-way video interviews, highlighting a common skills gap in practical AI readiness (Dai et al., 2020; Ng et al., 2023). The observation that urban and AI-exposed participants showed greater confidence and openness, while rural and less digitally experienced youth expressed more concerns about fairness and privacy, aligns with research showing subgroup differences based on exposure and context (Dai et al., 2020; Ben-Gal, 2023). These patterns support the instrument's construct validity by demonstrating sensitivity to both competence and attitude-related differences (Ng et al., 2023). Adjustments made after pilot feedback – such as rewording ambiguous items, refining scale anchors, and adding factual knowledge checks – are standard practices in instrument validation and are shown to improve reliability and validity in similar studies (Dai et al., 2020; Ng et al., 2023). Overall, the pilot's results and subsequent refinements provide a strong foundation for the main study and are consistent with best practices in AI readiness instrument development (Dai et al., 2020; Ben-Gal, 2023; Ng et al., 2023).

4.4. Qualitative Data Collection: Interviews and Focus Groups

To complement the survey, the study incorporates qualitative methods – primarily semi-structured interviews – aimed at delving deeper into the experiences, reasoning, and context behind youth readiness (or lack thereof) for AI-driven HR practices. Where the survey provides breadth, these interviews provide depth and narrative richness.

Individual interviews with selected young professionals will be carried out, each with an expected duration of approximately 45–60 minutes. The semi-structured format will combine a predefined list of questions and topics with the flexibility to allow participants to elaborate on issues they consider important. An interview guide has been developed to ensure procedural consistency while enabling contextual adaptation. The guide encompasses several thematic areas, including:

1. Personal experience with AI in HR: participants are asked to recall and describe direct or indirect experiences with AI-driven recruitment processes, including their reactions, preparation strategies, and perceived impacts.

2. Perceptions of fairness and trust: questions focus on participants' beliefs about fairness and trustworthiness of AI systems in recruitment, probing influences such as personal experiences or widely publicised examples (e.g., Amazon's hiring algorithm).
3. Knowledge sources and learning pathways: interviews explore how respondents developed their understanding of AI in HR – whether through formal education, peer discussions, or independent inquiry. This allows assessment of both the breadth and accuracy of their knowledge.
4. Skills and preparation strategies: participants reflect on their skills and competencies relevant to engaging effectively with AI recruitment technologies. Follow-up questions explore proactive efforts taken to build these skills, such as attending training or practising digital interviewing.
5. Attitudes and emotional responses: interviewees discuss their emotional and attitudinal responses to the increasing use of AI in hiring processes, ranging from enthusiasm about efficiency and innovation to concerns about depersonalisation or potential bias.
6. Future expectations and support needs: questions probe participants' perceived preparedness for future AI-integrated workplaces, inviting suggestions for practical interventions – such as targeted training, institutional support, or clearer communication from employers regarding AI use.
7. Role of educational institutions: participants evaluate whether their formal education or training adequately prepares them for AI-related workplace challenges, identifying gaps or highlighting beneficial practices.

In addition to interviews with young professionals, the study includes a limited number of expert interviews with HR practitioners who have experience using AI in recruitment. These interviews explore the types of AI tools used, perceptions of candidate readiness, typical responses from young applicants, and practitioner-informed recommendations for improving youth preparedness.

Focus groups will also be conducted with recent graduates or early-career professionals to capture shared experiences and peer dialogue around AI in hiring. This group format facilitates the emergence of collective attitudes and coping strategies, providing insight into common challenges and perceived best practices. All sessions will follow a semi-structured format, guided by a thematic protocol while allowing spontaneous discussion.

Interviews and focus groups will be audio-recorded with informed consent and transcribed for analysis. Participants may choose to speak in Latvian, English, or Russian; non-English transcripts will be translated for analysis, ensuring conceptual fidelity. Data confidentiality will be strictly maintained, with all identifiers removed or generalised in reporting. Participants will retain the right to skip questions or withdraw at any time, in line with ethical standards and sensitivity to personal employment experiences.

The qualitative data will complement and contextualise the survey results. For example, if a significant proportion of survey respondents report low trust in AI systems, interviews may uncover the cultural, experiential, or informational factors behind this sentiment. Qualitative insights may also highlight emergent concerns not captured in the survey, contributing to a fuller understanding of youth readiness.

In sum, the qualitative component is designed to illuminate the lived experiences, perceptions, and meaning-making processes of young people navigating AI-enhanced recruitment. This integration of quantitative breadth and qualitative depth ensures a comprehensive and policy-relevant analysis of youth readiness for AI-driven HR in Latvia.

4.5. Data Analysis and Integration

Prior to full-scale implementation, pilot data will undergo preliminary analysis to verify the reliability of multi-item scales (Cronbach's alpha) and to check whether expected factor structures emerge in exploratory factor analysis (Karaca, Çalışkan, Demir, 2021). While the pilot sample size will be limited, these early results will help identify potential measurement issues and inform adjustments before large-scale deployment. This iterative process mirrors best practices in survey-based research and enhances the credibility of the final instrument.

Given the dual-method design, quantitative and qualitative data will be analysed separately and then integrated for comparative interpretation.

Quantitative Data Analysis. Survey data will be processed using statistical software such as SPSS (Statistical Package for the Social Sciences) or R. The initial phase will include data cleaning, consistent coding of Likert-scale items (with higher scores indicating greater AI readiness), and addressing missing values via mean imputation or listwise deletion, depending on severity.

Descriptive statistics (means, standard deviations, frequency distributions) will offer an overview of respondents' readiness levels, AI awareness, digital skills, and prior experience. Composite indices – such as an overall AI Readiness Score – may be calculated to support interpretation.

Inferential statistics will examine relationships between background variables (e.g., gender, education, region) and readiness dimensions using Pearson correlations, t-tests, and ANOVA (Analysis of Variance). For example, comparisons will be made between STEM (Science, Technology, Engineering, Mathematics) and non-STEM participants, or between urban and rural respondents.

Exploratory factor analysis will be conducted on multi-item scales (e.g., attitudes, self-assessed skills) to identify underlying constructs. Cronbach's alpha will be used to assess internal reliability of each scale.

If appropriate, multiple regression analysis will be used to identify predictors of readiness (e.g., education level, prior AI exposure, attitudinal variables), with the understanding that the cross-sectional design allows only correlational – not causal – inference.

Cluster analysis (e.g., k-means) may also be applied to identify typologies among participants (e.g., 'AI-ready,' 'sceptical but skilled,' 'underprepared'), aiding in the development of targeted recommendations.

Open-ended responses will undergo thematic content analysis to identify and quantify common themes (e.g., frequency of requests for AI-related training or concerns about depersonalised recruitment).

Qualitative Data Analysis. Thematic analysis will be applied to interview and focus group transcripts, following the approach outlined by (Braun, Clarke, 2006). Coding will be inductive yet informed by the research objectives. Two researchers will initially review a subset of transcripts independently to identify preliminary codes and ensure coding consistency.

Expected themes include perceptions of fairness and bias, emotional responses to AI, preparedness behaviours, the role of education, and suggested institutional support. Coding will be performed using qualitative analysis software, where available, by tagging text segments linked to thematic categories.

The analysis will examine both the frequency and contextual depth of responses, comparing patterns across participant groups. Particular attention will be given to contrasts in mindset – such as proactive adaptation versus resignation or confusion.

Illustrative, anonymised quotations will be extracted to enrich the interpretation of findings and highlight key insights, such as gaps in awareness or generational perspectives on AI adoption in recruitment.

Integration of Quantitative and Qualitative Findings. Following separate analyses, quantitative and qualitative findings will be integrated during the interpretation phase to address the research questions holistically. A side-by-side comparison will be used to identify convergence, divergence, and complementarity between the datasets.

For example, if survey data indicate that a significant proportion of respondents report awareness of AI in HR, but interviews reveal superficial or inaccurate understanding, this contrast will highlight the gap between perceived and actual knowledge. Conversely, consistent patterns – such as high reported willingness to use AI tools in surveys, supported by interview references to tools such as ChatGPT – will be reinforced with illustrative quotes.

Integrated analysis will also help explain inconsistencies. If respondents rate their digital skills highly in surveys yet describe challenges in online applications during interviews, this may suggest overconfidence or misalignment between self-perception and actual readiness. Such insights contribute to a more nuanced understanding of the construct.

Findings will be presented thematically in the results or discussion section, integrating statistical trends and qualitative excerpts under common headings. This approach enhances the interpretative validity of the research by triangulating evidence and highlighting where different forms of data complement or contradict each other.

Ensuring Analytical Rigor and Addressing Limitations. Analytical rigor will be ensured through multiple strategies: established statistical procedures will be applied to survey data, qualitative transcripts will be double-coded by independent researchers to enhance reliability, and an audit trail will document the coding and theme development process. Methodological triangulation

– across quantitative data, qualitative accounts, and expert interviews – will support validity. Agreement across sources will reinforce findings, while discrepancies will be reported transparently and analytically.

Limitations will be acknowledged in the interpretation. The use of non-probability sampling limits generalisability, and the possibility of self-selection bias – where technology-inclined individuals may be overrepresented – will be considered. The inherent subjectivity of self-reported data will also be noted. These limitations do not diminish the study's relevance but provide important context for interpreting results responsibly.

By combining robust analytical techniques with contextual insight, the study aims to generate findings that are both empirically grounded and meaningfully situated within the lived experiences of Latvian youth navigating AI-integrated HR systems.

4.6. Comparison with Existing Methodologies

Most established AI readiness assessment frameworks focus on organisational or national levels, emphasising technological infrastructure, governance, and broad workforce skills, but often overlook individual-level factors and attitudinal dimensions. For example, the Oxford Insights AI Readiness Index evaluates countries based on governance, data infrastructure, and innovation, providing valuable macro-level insights but not addressing individual or youth-specific readiness (Nasution et al., 2024). Similarly, frameworks such as the Technology Readiness Levels (TRL) and organisational models assess readiness through dimensions such as technology, people, processes, and data, but are primarily designed for firms or sectors and do not capture personal attitudes, trust, or willingness to learn (Jöhnk, Weißert, Wyrtki, 2020; Holmström, 2021; Hradecky et al., 2022; Uren, Edwards, 2023). The OECD Skills for Jobs Indicators and UNESCO AI Competency Framework offer comprehensive coverage of digital and cognitive skills, yet they lack integration of affective and trust-related aspects specific to AI adoption in employment contexts.

The methodology in this study advances the field by operationalising AI readiness as a multidimensional construct – encompassing cognitive (knowledge), behavioural (skills), and affective (attitudes, trust, adaptability) components – tailored to the Baltic youth labour market. This approach fills a gap in existing frameworks by integrating self-assessment, factual knowledge, and attitudinal measures, and by considering socio-economic and cultural factors relevant to small EU Member States. The use of a convergent mixed-methods design, combining quantitative and qualitative data, further distinguishes this methodology by enabling a nuanced understanding of both individual and organisational perspectives, which is not typically addressed in international models (Jöhnk, Weißert, Wyrtki, 2020; Hradecky et al., 2022; Uren, Edwards, 2023). This adaptation enhances both the theoretical and applied relevance of AI readiness assessment, particularly for policy and HR applications in youth employment.

5. Expected Results and Implications

While this article focuses primarily on research design, anticipating likely findings based on prior studies and pilot observations clarifies the potential value of the proposed methodology. The AI Readiness Index is expected to reveal both strengths and clear areas for development in Latvian youth's preparedness for AI-driven HR processes.

On the positive side, overall digital literacy is likely to be high, reflecting broader European trends that position young people as confident users of technology. Many participants may report familiarity with basic digital tools, prior use of AI-enabled applications, and openness to AI's role in recruitment. These attitudes echo findings from global surveys indicating that younger workers often view AI as an opportunity to enhance skills and career prospects. Statements such as 'AI can make hiring more efficient' or 'AI can reduce bias' may find broad agreement, indicating awareness of potential benefits.

However, substantial gaps in AI-specific knowledge and competencies are anticipated. Awareness of AI in general may not translate into an understanding of recruitment-specific applications. For example, only a minority might correctly explain how applicant tracking systems operate or recognise that social media profiles can be algorithmically screened. Interviews may reveal that some candidates were unaware they had been evaluated by AI in past applications. This pattern of 'surface awareness' without operational knowledge has been observed internationally and could be replicated in Latvia.

Attitudinal differences are also expected. A segment of participants – often with technical backgrounds or prior exposure to AI recruitment – may be enthusiastic adopters, while another group remains sceptical or anxious. The latter may express concerns about fairness, impersonality, or limited human interaction, echoing research showing that trust is a critical determinant of technology acceptance. Anxiety toward AI in hiring may be linked to perceived lack of control over outcomes.

Competence gaps may be particularly pronounced in tasks such as optimising CVs for algorithmic screening or practising one-way video interviews. Formal training on AI in recruitment is likely to be rare, pointing to an opportunity for targeted educational initiatives. Qualitative insights may reveal differences between urban and rural respondents in exposure to AI-enabled processes, as well as variations across educational institutions in the provision of relevant career services.

From these data, several readiness profiles may emerge:

1. AI-Ready – technically skilled, informed about AI processes, and confident in navigating them.
2. Reluctant Adapters – moderately skilled but hesitant to engage due to mistrust or perceived risks.
3. Unprepared – lacking core competencies and often unaware of specific requirements in AI-mediated hiring.

Regarding the instrument itself, analysis is expected to confirm the multidimensional nature of readiness, with knowledge, skills, and attitudes forming distinct but interconnected components. Attitudinal factors, particularly trust, may prove as important as technical ability in predicting effective engagement with AI recruitment. This interplay could represent a significant contribution to theoretical models of technology adoption.

5.1. Implications for Stakeholders

HR practitioners and employers. The findings may highlight a need for greater transparency in AI-mediated recruitment. Employers could provide clear information on when and how automated tools are used and offer general feedback to candidates. If specific skills gaps are identified, targeted workshops – delivered in partnership with educational providers – could address them.

Educational institutions and training providers. Evidence of insufficient preparation may support integrating AI-readiness modules into curricula. These could cover the functioning of ATS, best practices for one-way video interviews, and ethical considerations in algorithmic hiring. Vocational training programmes may incorporate foundational AI literacy into career services.

Policymakers and public agencies. Should disparities emerge, particularly affecting youth from disadvantaged backgrounds, policies could be adapted to ensure equitable access to training and resources. Public employment services might include AI-focused preparation within their digital upskilling strategies, aligning with EU frameworks such as the Digital Education Action Plan and the forthcoming AI Act.

Young professionals. By identifying common gaps, the study can guide youth toward proactive skill development. Initiatives such as peer-led learning, online practice platforms, and awareness campaigns could enhance both confidence and competence in AI-enabled recruitment environments.

Theoretical and research implications. This study contributes to the literature on AI readiness by applying a micro-level, multidimensional framework to the labour market context of a small EU Member State. It extends existing models, such as the Technology Acceptance Model, by incorporating trust and emotional readiness alongside knowledge and skills. The methodology offers a replicable template for similar assessments in other regions, supporting comparative analyses and informing targeted interventions.

By delivering actionable evidence, the research aims to inform employers, educators, policymakers, and young people themselves. As AI continues to reshape recruitment, ensuring that youth are not only receptive but effectively equipped to engage with these technologies will be critical to fostering inclusive and future-ready employment ecosystems.

6. Discussion

This research stands out by using a mixed-methods approach to assess the AI readiness of Latvian youth for HR practices, focusing on individual capabilities rather than the macro-level factors emphasised by indices such as the Oxford Insights Government AI Readiness Index or OECD digital skills indicators. While most existing frameworks evaluate readiness at the national or organisational level – addressing governance, infrastructure, or broad workforce skills – they often overlook the nuanced, micro-level factors such as individual technical competence, trust, and adaptability that are crucial for effective AI adoption in HR, especially among youth in smaller EU labour markets (Holmström, 2021; Budhwar et al., 2022).

Pilot observations among Baltic youth show that while awareness of AI in recruitment is high, confidence in applying AI-related skills is uneven – a pattern consistent with global findings on youth and AI readiness (França et al., 2023; Solyst et al., 2023). Latvian respondents reported lower self-assessed competence compared to Estonian peers, reflecting regional disparities in digital skills that are also noted in broader European reports. Trust in AI-mediated hiring was limited, echoing international concerns about fairness, transparency, and the ethical use of AI in HR processes (Budhwar et al., 2022; França et al., 2023). These findings align with research highlighting that youth, despite being frequent users of AI, often feel underprepared for specific AI-driven tasks and express concerns about bias and the need for greater support and education (Solyst et al., 2023). The results underscore the importance of addressing both technical skill gaps and trust issues to ensure equitable and effective adoption of AI in HR, particularly in smaller EU labour markets such as Latvia (Budhwar et al., 2022; França et al., 2023).

These findings reinforce the multidimensional model of AI readiness, where technical competence, trust, and adaptability interact to shape individuals' preparedness for AI adoption in HR contexts. Research shows that youth are capable of understanding both the technical and ethical aspects of AI, and their readiness is enhanced by prior exposure to AI tools – those with more experience demonstrate greater confidence and adaptability, while those lacking such experience often express concerns about fairness and transparency (França et al., 2023; Solyst et al., 2023).

The AI Readiness Index described here is methodologically robust, combining self-assessment, factual knowledge, and qualitative validation to capture a multidimensional view of AI preparedness. This approach directly addresses the need for comprehensive instruments that can assess not only technical skills but also attitudes and contextual factors, as called for in recent systematic reviews of AI in HRM (França et al., 2023; Deepa et al., 2024). Its sensitivity to demographic and experiential differences enhances its utility for cross-national comparisons, particularly in small economies where labour market dynamics may differ from larger contexts (Budhwar et al., 2022; França et al., 2023).

The findings underscore the importance of targeted interventions – such as focused training to address AI-specific skill gaps and initiatives to increase transparency in recruitment processes – which are echoed in the literature as essential for effective and equitable AI adoption in HR (França et al., 2023; Deepa et al., 2024). However, the study's limitations, including a small, self-selected sample and reliance on self-report, highlight the need for future research to expand sample sizes, validate the Index psychometrically, incorporate objective skill measures, and track readiness over time (Budhwar et al., 2022; França et al., 2023).

7. Conclusions

The rapid integration of artificial intelligence into HR practices is transforming the processes by which young people seek employment and establish early career trajectories. This article presents a comprehensive research design aimed at assessing the readiness of Latvian youth for this AI-driven transformation in human resource management. Building on prior theoretical insights and with a strong methodological focus, the proposed mixed-methods approach is intended to capture the multifaceted nature of 'AI readiness' among young professionals. Through the combination of a large-scale survey and in-depth qualitative inquiry, the study is structured to both measure readiness levels and explore the underlying factors influencing them.

Several key points emerge in conclusions. Firstly, the importance of context-specific research is evident: while global studies indicate that many young workers are technologically adept yet cautious about the implications of AI, the focus on Latvia addresses a gap in localised understanding. The involvement of HR Line EU demonstrates how collaboration with relevant stakeholders can enhance both the design of the study and its practical applicability. Such engagement facilitates access to participants and increases the likelihood that the findings would reach those in a position to implement changes in recruitment practices.

Secondly, the proposed methodology emphasises that readiness for AI in HR should be conceptualised as a spectrum encompassing knowledge, skills, attitudes, and adaptability. Consequently, its assessment necessitates a holistic approach. The mixed-methods design is considered well-suited to capturing this complexity, thereby offering a methodological contribution in the form of a replicable template that can be applied in other regions or to related topics, such as AI readiness in different professional domains. The structured combination of clearly defined objectives, instrument development, and integrated analysis provides a model for rigorous empirical investigation in social science research at the intersection of technology and human factors.

Thirdly, even in the absence of concrete data within this paper, the discussion of expected outcomes suggests that substantial efforts are required to bridge the gap between the potential of youth and their actual readiness. Should these expectations be confirmed, it is likely that many young Latvians possess the capacity and motivation to succeed in AI-integrated environments but require targeted guidance, skill development, and assurance to fully capitalise on these opportunities. Addressing this challenge necessitates a multi-faceted approach: employers are encouraged to adopt greater transparency and incorporate training into their use of AI; educational institutions should revise curricula to include workplace-relevant digital and AI literacy; and young individuals should be supported in taking proactive measures to familiarise themselves with emerging technologies that influence career trajectories.

In conclusion, the development of a research methodology, while often perceived as a technical exercise, constitutes a foundational step toward enabling positive change. Careful formulation of research questions and systematic interpretation of responses can generate insights with the potential to inform both policy and practice. The present study functions as a blueprint and a justification for undertaking such an inquiry within the Latvian context. The subsequent implementation phase will allow for testing and refinement of the proposed approach, ultimately producing empirical evidence capable of confirming, elaborating, or revising the underlying assumptions.

It is an important limitation that this research is currently confined to proposing a methodology and conceptual framework for assessing Latvian youth's readiness for AI-driven HR practices, without yet conducting a full-scale empirical investigation. While the study details the research design and outlines a multidimensional approach, it does not present or analyse complete survey or interview data, meaning the validity and practical impact of the proposed framework remain untested. This methodological focus is valuable for establishing a rigorous foundation, but the findings and implications should be regarded as preparatory rather than definitive. Such an approach aligns with calls in the literature for robust, multidimensional instruments and conceptual clarity before large-scale empirical work (Budhwar et al., 2022; França et al., 2023; Deepa et al., 2024).

As AI continues to advance and integrate into economic systems, ensuring that younger generations are adequately prepared remains a critical priority. The level of readiness will determine whether AI in HR serves as a catalyst for expanding opportunities and improving efficiency, or as a factor that deepens inequalities and dissatisfaction. Evidence-based understanding increases the likelihood of achieving the former outcome. Supported by HR Line EU and situated within the Latvian context, this study represents a timely and necessary contribution toward that objective. It reaffirms the role of academic research in proactively addressing emerging societal challenges and functions as a bridge between identifying these challenges and implementing solutions. It is anticipated that the findings will encourage further research and collaborative initiatives aimed at empowering the next generation of workers in the context of technological transformation in Latvia, the Baltic region, and beyond.

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Opracowanie metodologii badawczej w celu oceny gotowości młodzieży do praktyk HR opartych na sztucznej inteligencji na Łotwie

Streszczenie: Celem prezentowanego badania jest opracowanie kompleksowej metodologii badawczej, która pozwoli ocenić gotowość młodych profesjonalistów na Łotwie do funkcjonowania w systemach zarządzania zasobami ludzkimi wspomaganych przez sztuczną inteligencję. Ponieważ sztuczna inteligencja jest coraz częściej wykorzystywana w procesach rekrutacji i zarządzania talentami, zrozumienie stopnia przygotowania młodzieży do korzystania z takich systemów jest obecnie konieczne.

W badaniu zastosowano metodę mieszaną, łączącą badania ilościowe z jakościowymi wywiadami częściowo ustrukturyzowanymi i grupami fokusowymi. Narzędzie badawcze zostało skonstruowane tak, aby ocenić kompetencje cyfrowe, świadomość roli odgrywanej przez sztuczną inteligencję w zarządzaniu zasobami ludzkimi, zaufanie do systemów algorytmicznych oraz zdolność adaptacji. Komponent jakościowy zapewnia kontekstowy wgląd w percepcję i osobiste doświadczenia związane z rolą sztucznej inteligencji w rekrutacji. Rekrutację uczestników badania wspiera łotewska agencja rekrutacyjna, która zapewnia dostęp do odpowiedniej i zróżnicowanej bazy kandydatów.

Spodziewane wyniki obejmują identyfikację odrębnych profili gotowości łotewskiej młodzieży i ujawniają zarówno obszary kompetencji, jak i istotne luki w wiedzy lub przekonaniu o posiadaniu takich kompetencji. Przewiduje się również odkrycie różnic w postawach i nierówności w dostępie do zasobów cyfrowych.

Proponowana metodologia oferuje powtarzalne ramy do oceny gotowości do współpracy ze sztuczną inteligencją na poziomie krajowym i ma na celu pomoc specjalistom w zarządzaniu zasobami ludzkimi, edukatorom i decydentom w opracowywaniu skutecznych strategii wspierających adaptację młodzieży do transformacji miejsc pracy spowodowanych przez sztuczną inteligencję.

Słowa kluczowe: sztuczna inteligencja, zarządzanie zasobami ludzkimi, gotowość młodzieży, metody mieszane, Łotwa

JEL: J24, O33