MULTIDISZCIPLINÁRIS KIHÍVÁSOK
SOKSZÍNŰ VÁLASZOK

GAZDÁLKODÁS- ÉS SZERVEZÉSTUDOMÁNYI FOLYÓIRAT

MULTIDISCIPLINARY CHALLENGES
DIVERSE RESPONSES

JOURNAL OF MANAGEMENT
AND BUSINESS ADMINISTRATION

18 57
BGE

2026/1.

Online folyóirat

FŐSZERKESZTŐ: Vágány Judit Bernadett, PhD

Borító: FLOW PR

Kiadja: Budapesti Gazdaságtudományi Egyetem
1055 Budapest, Markó utca 29-31.

Felelős kiadó: Prof. Dr. Andor György

ISSN 2630-886X

2026.

ARTIFICIAL INTELLIGENCE-AUGMENTED HR WORKFLOWS FOR MULTICULTURAL INTEGRATION IN A RESOURCE-CONSTRAINED FAMILY FIRM: AN EMPLOYER-SIDE PERSPECTIVE

MESTERSÉGES INTELLIGENCIÁVAL TÁMOGATOTT HR-MUNKAFOLYAMATOK A MULTIKULTURÁLIS INTEGRÁCIÓ SZOLGÁLATÁBAN EGY ERŐFORRÁS-KORLÁTOKKAL MŰKÖDŐ CSALÁDI VÁLLALKOZÁSBAN: MUNKÁLTATÓI PERSPEKTÍVA

LAMPER Ágnes - CZINE Vanda

Kulcsszavak: *mesterséges intelligencia; MI-támogatott HR-munkafolyamatok; hibrid HR-kompetenciák*
Keywords: *artificial intelligence; AI-supported HR workflows; hybrid HR competencies*

JEL-kód: *M53, M54, J24*

https://doi.org/10.33565/MKSV.2026.01.03

ABSTRACT

In Central and Eastern Europe, family-owned companies, which follow the structure of small and medium-sized enterprises (SMEs), are increasingly relying on foreign workers to address structural labour shortages; however, they generally lack the necessary HR infrastructure to support the integration of a multicultural workforce. This study examines how HR workflows augmented with artificial intelligence (AI) shape the integration of a multicultural workforce at a resource-constrained, SME-structured, family-owned company. It also examines the division of tasks, competencies, and organizational conditions that characterize these processes from the employer's perspective. We employed an exploratory, single-case qualitative research design that combined five semi-structured interviews with the analysis of 12 company documents; we applied reflexive thematic analysis to both data sources. Three main themes emerged. First, the organization established a deliberate division of labour in which artificial intelligence handles high-volume, language-intensive tasks across six operational areas, while human actors retain control over decisions that require judgment and are culturally sensitive, thereby creating a complementary collaboration and decision-making architecture between artificial intelligence and humans. Second, HR staff and managers have developed hybrid competencies that combine proficiency in artificial intelligence with intercultural judgment. Third, transparent decision-making authority, the establishment of a consistent complementary framework, and relationship management practices have enabled repeatable, cost-effective integration workflows at the SME level. The results show that affordable, platform-based artificial intelligence tools can narrow the resource and capability gap between small and medium-sized enterprises and large corporations in the area of multicultural integration, provided that human decision-making authority is preserved and clearly delineated. Limitations of this study include its scope, which is limited to a single case; the small sample size; and its focus exclusively on the employer side. Future research should incorporate employee perspectives and adopt comparative, multi-case designs with quantitative integration performance indicators.

ABSZTRAKT

Közép- és Kelet-Európában a kis- és középvállalkozások szerkezetét követő, családi tulajdonban lévő cégek egyre inkább külföldi munkavállalókra támaszkodnak a strukturális munkaerőhiány kezelése érdekében, ugyanakkor általában nem rendelkeznek a multikulturális munkaerő integrációját támogató szükséges HR-infrastruktúrával. Ez a tanulmány azt vizsgálja, hogy a mesterséges intelligenciával (MI) kiegészített HR-munkafolyamatok hogyan alakítják a multikulturális munkaerő integrációját egy erőforrás-korlátokkal küzdő, kkv-szerkezetű, családi tulajdonú vállalatnál. Továbbá azt is, hogy milyen feladatmegosztás, kompetenciák és szervezeti feltételek jellemzik ezeket a folyamatokat a munkáltatói oldal szemszögéből. Feltáró jellegű, egyetlen esetre vonatkozó kvalitatív kutatási tervet alkalmaztunk, *amely öt félig strukturált interjút, valamint 12 szervezeti dokumentum elemzését ötvözte, mindkét adatforrásra reflexív tematikus elemzést alkalmaztuk. Három fő téma rajzolódott ki. Először is, a szervezet szándékos munkamegosztást alakított ki, amelyben a mesterséges intelligencia hat működési területen kezeli a nagy volumenű, nyelvhasználatot igénylő feladatokat, míg az emberi szereplők megtartják a döntéshozatalt igénylő és kulturálisan érzékeny döntések feletti hatalmat, ezáltal létrehozva a mesterséges intelligencia és az ember közötti feladat-kiegészítő jellegű együttműködést és döntéshozatali architektúrát. Másodszor, a HR-munkatársak és a felettesek olyan hibrid kompetenciákat fejlesztettek ki, amelyek ötvözik a mesterséges intelligencia iránti jártasságot az interkulturális ítélőképességgel. Harmadszor, az átlátható döntési jogok, a következetes kiegészítő keret kialakítása és a kapcsolati menedzsment gyakorlatok ismételhető, költséghatékony integrációs munkafolyamatokat tettek lehetővé kkv-méretű vállalkozások szintjén. Az eredmények azt mutatják, hogy a megfizethető, platformalapú mesterséges intelligencia-eszközök szűkíthetik a kis- és középvállalkozások és a nagyvállalatok közötti erőforrás- és képességbeli szakadékot a multikulturális integráció terén, feltéve, hogy az emberi döntéshozatali jogkör megmarad és egyértelműen körülhatárolva van. A tanulmány korlátai közé tartozik az egyetlen esetre korlátozódó hatókör, a kis mintanagyság és a kizárólag a munkáltatói oldalra való összpontosítás. A jövőbeli kutatásoknak be kell vonniuk a munkavállalói perspektívákat is, és összehasonlító, több esetet felölelő terveket kell követniük, kvantitatív integrációs eredménymutatókkal.*

INTRODUCTION

Central and Eastern European firms face acute labour shortages driven by demographic decline, an ageing workforce and emigration. Many family-owned organisations retain small and medium-sized enterprise (SME) characteristics despite having grown beyond formal SME size thresholds, which amplifies resource constraints and limits their capacity to develop formal multicultural human resources (HR) infrastructure (Harney et al., 2022; Csillag et al., 2019; Armstrong and Taylor, 2020). In this article, we refer to such organisations as SME-structured firms: companies that may exceed formal SME size thresholds but preserve core SME-typical structural and governance features including concentrated ownership, informal HR practices and limited functional specialisation. These firms frequently rely on foreign recruitment to sustain operations but typically lack bilingual HR personnel, professional interpreters and dedicated diversity programmes, thereby facing a persistent resource–capability asymmetry relative to large multinationals with capital-intensive, professionally staffed HR functions (Harney et al., 2022; Fachrunnisa and Hussain, 2020; Arroyabe et al., 2024).

In Hungary and the wider CEE region, this asymmetry is sharpened by structural labour shortages and growing dependence on third-country nationals, including workers from Ukraine and selected Asian sending countries (Hickey and Associates, 2024; Astrov et al., 2021). While foreign recruitment offers an immediate response to staffing gaps, SME-structured, family-owned firms often introduce migrant workers into settings where HR systems, communication routines and integration practices were designed for relatively homogeneous, local workforces. The resulting tension between urgent staffing needs and under-developed multicultural HR infrastructure makes these organisations a critical context for examining how technology can support integration-related HR processes under resource constraints.

AI presents a potential pathway to narrow this asymmetry by augmenting HR tasks such as translation, compliance research and visual communication at the SME scale. However, the automation–augmentation paradox highlights a dual effect: AI can deliver efficiency gains while simultaneously creating new demands for culturally informed human judgement that AI tools cannot reliably supply (Charlwood and Guenole, 2022; Fenwick et al., 2024). Augmentation is therefore contingent on organisational design choices that explicitly allocate decision rights between humans and AI, provide transparency about how AI recommendations are generated, and frame AI as a tool that supports rather than replaces professional judgement (Raisch and Krakowski, 2021; Tambe et al., 2019; Davenport and Ronanki, 2018).

Three theoretical gaps motivate this study. First, AI–HRM research predominantly examines large, well-resourced organisations, leaving implementation dynamics in SME-structured, resource-constrained contexts underexplored (Ayinaddis, 2025; Jiang et al., 2025). Second, augmentation theory remains weakly specified for multicultural settings where AI outputs must be interpreted and adapted by humans with situated cultural knowledge, precisely the domain in which human capabilities are least substitutable (Mäkelä et al., 2024; Blodgett et al., 2020; Bender et al., 2021). Third, there is limited case-level evidence on how platform-based generative AI enables SME-structured, family-owned firms in CEE to cope with structural labour shortages and increasing reliance on third-country nationals without proportional investments in HR infrastructure (Hickey and Associates, 2024; Astrov et al., 2021; Vidovic, 2022; Chowdhury et al., 2023).

Based on this context, we address the following research question: *How do AI-augmented HR operations shape multicultural workforce integration workflows in*

SME-structured, family-owned firms, and what competencies, workflows and organisational conditions characterise these AI-augmented HR processes from an employer-side perspective?
To answer this question, we conduct an exploratory single-case study of a Hungarian SME-structured packaging firm that integrated 30 Filipino workers between 2023 and 2025 using AI-augmented HR operations. Drawing on five semi-structured interviews and organisational artefacts, we trace how AI-augmented HR workflows were designed and enacted, and how they interacted with existing organisational structures, cultural norms and resource constraints.

THEORETICAL FRAMEWORK

The AI Augmentation–Automation Paradox in HR Functions

Augmentation-oriented perspectives on human–AI collaboration argue that AI and humans should be designed to complement rather than replace one another, creating capabilities that neither could achieve alone (Raisch and Krakowski, 2021). In this view, augmentation differs from automation by treating AI as a partner that expands human capacity while preserving human authority over judgement-intensive tasks. AI is reshaping HRM strategy across recruitment, training and human–machine collaboration, yet the concrete mechanisms through which AI is embedded in HR workflows remain empirically underspecified (Vrontis et al., 2021). Existing work is divided on whether AI primarily augments human capabilities or erodes relational HR functions: proponents highlight the potential to relieve professionals of routine tasks and refocus them on uniquely human competencies such as cultural intelligence, relationship-building and ethical judgement (Aguinis et al., 2024), while critics emphasise automation bias, cultural insensitivity in training data, eroded trust from machine-mediated interactions and resistance linked to job-displacement fears (Arslan et al., 2022; Charlwood and Guenole, 2022). The automation–augmentation paradox captures this duality by showing how efficiency gains often coincide with new demands for culturally sensitive judgement that AI tools cannot reliably supply, making explicit human–AI decision boundaries essential for preserving relational trust while leveraging technological scale (Fenwick et al., 2024).

Human–AI Complementarity and Hybrid Competencies

Augmentation theory thus posits that human-AI collaboration generates capabilities that neither party could realise independently (Raisch and Krakowski, 2021). Mäkelä et al.'s (2024) AI Complementarity Framework, based on 12 million

U.S. job postings from 2018–2023, distinguishes complementary skills that gain value with AI, such as critical thinking and intercultural communication, from supplementary skills that AI tends to automate, including data processing and scheduling. Demand grows faster for the former, and hybrid expertise that combines human judgment with AI literacy commands wage premiums. For multicultural integration, this implies reskilling trajectories in which AI manages translation and routine documentation, while humans provide contextual adaptation, cultural sensitivity and trust-building. Symbiosis models further specify that AI contributes data volume and workflow consistency, whereas humans supply judgment, emotional intelligence and ethical reasoning (Huang and Rust, 2022; Rahwan et al., 2019). In resource-constrained family firms, platform-based AI may therefore partially substitute for missing infrastructure such as bilingual staff or interpreters and help approximate the integration outcomes of better-resourced organizations without proportional headcount increases (Sánchez et al., 2025).

Cultural Background of the Migrant Workforce

In this study, we examine AI-augmented HR workflows for non-Hungarian, third-country national workers whose first language and cultural background differ from those of the existing local workforce. Cross-cultural research shows that, in many such contexts, migrant workers often come from more collectivistic and hierarchical cultures, where maintaining harmony, avoiding open confrontation and protecting others' face through indirect communication and deference to authority figures are valued norms (Hofstede, 2001). In the case under study, these general patterns are visible among Filipino production workers and shape how they respond to feedback, voice concerns or signal misunderstanding, particularly in interactions with foreign supervisors. We therefore treat these cultural characteristics as a sensitising background for understanding how AI-generated messages are received and adapted in HR workflows, rather than as deterministic traits tied to any specific nationality and use them primarily to contextualise specific episodes in the empirical material.

Critical Research Gaps

Despite rapid growth in AI-HRM research, three gaps persist. First, empirical work focuses mainly on large, well-resourced firms, leaving resource-constrained contexts underexamined (Ayinaddis, 2025). Second, augmentation theory remains weakly specified for multicultural settings where AI outputs must be interpreted through situated cultural knowledge (Mäkelä et al., 2024; Blodgett et al., 2020; Bender et al., 2021). Third, there is little case-level evidence on how platform-based generative AI narrows resource–capability gaps in CEE firms recruiting non-EU labour (Vidovic, 2022; Chowdhury et al., 2023). This single-case study addresses that gap by tracing AI-augmented HR practices in a resource-constrained, SME-structured, family-owned firm.

Integrated Framework and Research Expectations

The framework assumes that AI improves integration only when technological inputs are mediated by clear organisational mechanisms. Figure 1 summarises this four-step logic by distinguishing what AI provides (speed, scale) from the human and organisational controls that convert those inputs into HR outcomes. Mediators play a particularly AI-specific role:

- Clear decision rights: predefined rules regarding which communications and decisions can be automated, and which remain within human jurisdiction.
- Hybrid competencies: the requirements for prompting, error detection, and output evaluation in AI tools demand new, combined skills—technical AI knowledge and cultural judgment simultaneously.
- Validation logs: Recording the versioning and human modifications of AI-generated content reduces the risk of automation bias and blurred accountability.
- Transparent framing: Leadership communication that positions AI as a support tool helps maintain trust and employee acceptance.

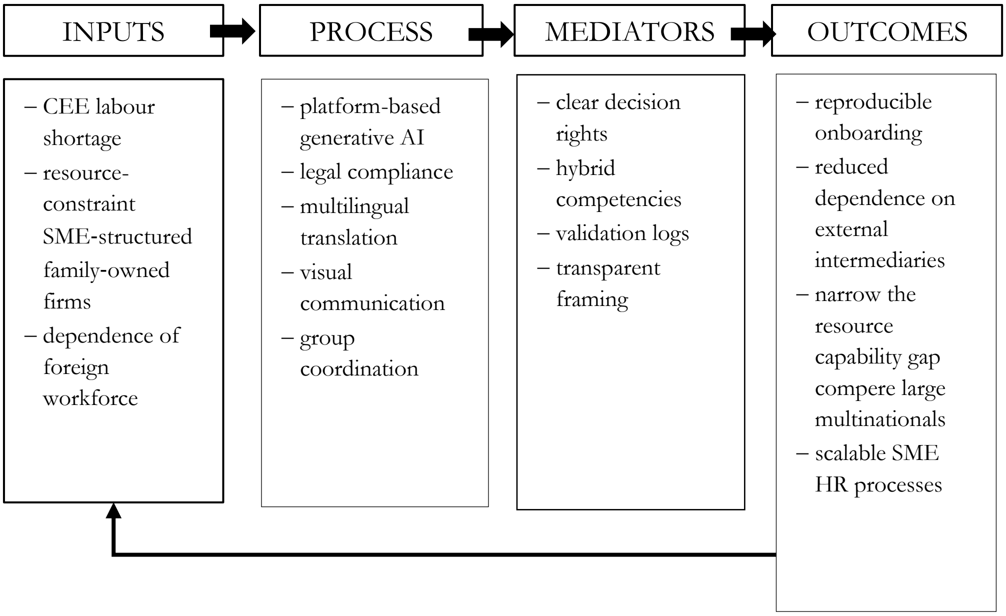

Figure 1: From contextual constraints to scalable HR processes via AI and mediators.
Source: Authors' own

Based on this model, we formulate three interrelated expectations:
Expectation 1: Task complementarity. AI takes over high-volume, language-intensive, routine HR tasks (translation, document drafts, compliance summaries), but their use only improves integration if human decision-making boundaries are clearly defined and adhered to.
Expectation 2: Hybrid competencies. HR staff and line managers develop hybrid competencies that combine AI literacy (prompting, output critique, validation exercises) with intercultural judgment, enabling the adaptation of machine recommendations to local cultural norms.
Expectation 3: Organizational conditions. If the organization employs documented decision-making authorities, validation logs, and consistent managerial framing, AI-supported workflows can become reproducible and scalable at the SME level, reducing dependence on external intermediaries and narrowing the resource–capability gap compared to larger organizations.
This four-step logic highlights both the point of technological intervention and the conditions for success: AI's speed and scale translate into lasting outcomes only through these mediators.

METHODOLOGY

Research design

This study adopts an exploratory single-case study design (Yin, 2018) to examine how AI-augmented HR operations shape multicultural workforce integration workflows in a resource-constrained organisation from an employer-side, process-focused perspective. The case is instrumental in Stake's (1995) sense: the focal organisation is examined not for its own sake, but as a tool for understanding how SME-structured firms can leverage AI to address structural capability gaps in multicultural integration. Following established guidance on rigorous qualitative case research (Yin, 2018), the design draws on two complementary data sources – semi-structured interviews and organisational documents – to enable data source triangulation and strengthen the credibility of the findings (Creswell and Creswell, 2018; Nowell et al., 2017; Shenton, 2004).

Case selection and context

The organisation was selected as an information-rich, theoretically relevant single case rather than as a statistically representative one (Yin, 2018; Stake, 1995). It is a privately owned Hungarian packaging company in Békés County, one of Hungary's most rapidly shrinking regions, where the population declined by approximately 12–13 per cent (almost 45,000 people) between the 2011 and 2022 censuses—the highest rate among Hungarian counties (Hungarian Central Statistical Office, 2023). This regional setting is characterised by severe labour shortages, demographic decline, population ageing and outward migration, making it a particularly informative context for studying foreign workforce integration in a resource-constrained organisation (Alhloul and Kiss, 2022; Pedron, 2022). The firm employs around 468 people and has annual revenue of €47.2 million. Although it exceeds the European Commission's quantitative SME threshold of 250 employees (European Commission, 2003; Armstrong and Taylor, 2020), it displays core features of an SME-structured, family-owned context: concentrated decision-making, informal HR practices, limited functional specialisation and a single generalist HR role rather than dedicated diversity or international HR functions (Harney and Dundon, 2006; Harney et al., 2022; Csillag et al., 2019). Operating in a severely constrained local labour market characterised by demographic decline, ageing and outward migration (Alhloul and Kiss, 2022; Pedron, 2022), the company recruited and integrated 30 Filipino workers between 2023 and 2025, representing around 6.4 per cent of the workforce. This profile, rather than headcount alone, distinguishes it from the well-resourced multinationals that dominate the AI-in-HRM literature (Budhwar et al., 2022) and makes it an information-rich, theoretically relevant single case for examining AI-augmented multicultural integration under resource constraints (Csillag et al., 2019; Garavan et al., 2016; Adla et al., 2019).

Data collection

Data collection combined semi-structured interviews and organisational documents to enable triangulation (Yin, 2018; Creswell and Creswell, 2018). Five face-to-face interviews were conducted between October 2025 and January 2026 with the HR Generalist, three shift supervisors and the CEO. Interviewees were selected for their direct involvement in integration practices and AI-supported HR workflows (Palinkas et al., 2015; Elmusharaf et al., 2017). Interviews covered AI use across HR functions, implementation barriers, competency change, trust-building, validation practices and organisational conditions shaping human–AI collaboration.

Organisational documents complemented interviews by providing independent evidence of AI-augmented practice. From a 2023–2025 corpus of 25 items, 12 documents with explicit AI involvement were selected to cover recruitment, onboarding, workplace communication, training and quality control. These included translated HR policies, visual materials, e-learning modules, internal messages and validation logs, which were used to corroborate how AI outputs were reviewed, adapted and embedded in routine HR work.

Document excerpts were coded within the same framework as interview data, and several codes—notably *tone softening*, *visual layering* and *validation logs*—originated primarily in documents. In the final structure, all three themes drew on both interview and document segments. Illustrative quotations were translated into English with DeepL Translator and lightly edited by the researchers for clarity.

Data analysis

Interview transcripts and organisational materials were analysed using reflexive thematic analysis (Braun and Clarke, 2006; Braun and Clarke, 2019). Hungarian-language transcripts were read repeatedly and coded line by line using a combination of deductive codes derived from the three expectations and inductive codes capturing unanticipated patterns. Related codes were then grouped into three themes: (1) AI–human task complementarity and decision architecture, (2) hybrid competency development and work reallocation, and (3) organisational capability building and implementation conditions.

Analysis proceeded abductively (Dubois and Gadde, 2002), moving iteratively between data and theory. Unexpected incidents—for example, overreliance on AI-generated messages or misunderstandings in communication with foreign workers—were revisited in light of the study's core concepts. Claims from interviews were systematically cross-checked against documents, and coding and theme development were reviewed collaboratively by both authors.

Because the interviews were conducted after much of the 2023–2025 integration process had already unfolded, the material is partly retrospective in nature. This timing enabled participants to reflect on the process as a whole but also raises the risk of recall bias and post hoc rationalisation. To mitigate this limitation, participants were encouraged to provide concrete examples rather than broad retrospective evaluations, and these accounts were triangulated with concurrent organisational documentation.

Perplexity Pro was used only in later stages of analysis as a supplementary tool on anonymised, already coded excerpts, for minor labelling support such as alternative theme wording, overlap flags and brief pattern summaries, in line with guidance on transparent AI use in qualitative research (James et al., 2024; Országos Doktori Tanács, 2026). No full transcripts or identifiable organisational data were uploaded; identifiers were removed and quotations reduced to short, non-identifiable summaries before any AI-assisted step. The system was never used as an independent coder or interpretive authority: all suggestions were jointly reviewed against the original coded material by both authors, and only those consistent with their reflexive thematic analysis were adopted, thereby minimising circularity despite analysing AI-augmented workflows with an AI tool and preserving a researcher-led analytic process (Braun and Clarke, 2019).

Employer-side scope and implications

This study is intentionally positioned as an employer-side, process-focused investigation: its aim is to document how AI-augmented HR operations were designed, enacted and governed from the perspective of HR staff and supervisors in an SME-structured, family-owned firm. As such, the empirical material primarily reflects managerial and supervisory accounts rather than worker-level experiences.

Ethical considerations

The study followed established ethical principles for organisational research (Bryman, 2016; Saunders et al., 2019). All interviewees gave informed consent after being briefed on the study's purpose, voluntariness, confidentiality and right to withdraw. Organisational consent was secured from the CEO, including agreement on anonymisation, secure storage and factual review of outputs.

Anonymisation included use of a pseudonym for the company, masking identifying details in quotations and documents, and aggregating demographic information where needed. Audio files and transcripts are stored on password-protected servers accessible only to the researchers, and participants could request removal of specific data segments before publication.

Formal ethics committee approval was not sought because the study involved voluntary participation by professional adults, no deception, no sensitive personal data and rigorous anonymisation before any external processing. AI-assisted analysis was limited to anonymised excerpts and was consistent with institutional ethical guidelines and emerging recommendations on responsible AI use in research.

While full anonymity of the organisation cannot be absolutely guaranteed in a small regional context, the case was included with the CEO's informed agreement that the company has no misconduct to conceal and may benefit from being presented as an illustrative good-practice example. In this sense, the limited risk of organisational identification was judged proportionate to the potential learning benefits for similar firms.

FINDINGS

Thematic analysis of interview transcripts and organisational materials identified three core themes describing how AI-augmented HR operations shape multicultural workforce integration workflows in an SME-structured, family-owned firm: (1) AI–human task complementarity and decision architecture, (2) hybrid competency development and work reallocation, and (3) organisational capability building and implementation conditions. These themes map directly onto the theoretical expectations introduced in the framework.

AI–Human Task Complementarity and Decision Architecture. Interview data reveal a deliberate division of labour between AI systems and human actors across six operational domains: legal compliance research, multilingual translation, visual communication, cultural content creation, real-time interpretation and group coordination. AI tools provided speed, consistency and volume for routine, language-intensive tasks, while humans retained authority over relationship-building, cultural mediation and judgement-dependent communication.

The HR Generalist described a typical translation workflow in which AI generated first drafts that were then systematically reviewed before distribution. Supervisors reported layered communication practices combining English, gestures and, when needed, interpreter support. As SV1 explained, *"I'll say it once in English, then show you with gestures, and if accuracy is important, we'll reinforce it with an interpreter."* Critical interactions such as performance feedback, conflict resolution and disciplinary conversations remained strictly human-led. When SV1 discovered that a safety rule had been misunderstood, the supervisor involved HR and used iterative dialogue rather than additional AI-generated messages.

AI support enabled integration of foreign workers without proportional HR headcount growth. As the CEO noted, the company now needs *"fewer external interpreters and consultants, achieving cost savings."* However, outcomes depend on human oversight, and the material also shows clear limits of automation. In one case, an AI-generated performance feedback message labelled a worker "not reliable" which supervisors perceived as too direct and was replaced by a more cautious, dialogic approach, with the supervisor slowing down communication, checking understanding and revising phrasing with HR: *"for sensitive topics I speak slowly, ask for confirmation, and manually revise phrases with HR before communicating."* (SV1.) Across accounts, AI handled routine tasks in the six domains, but integration quality depended on active, culturally informed human oversight, particularly in high-stakes interpersonal interactions where tone and relational nuance were central.

As Table 1 summarises, the organisation established a deliberate complementary division of labour that assigned routine, scalable work to AI tools while locating culturally sensitive judgement, relational trust-building and high-stakes decisions with human actors. This pattern is consistent with theoretical Expectation 1, which posits that strategic AI deployment operates within preserved boundaries of human decision authority.

AI Role	Operational Domain	Human Role	Outcome
Data collection and synthesis	Legal compliance research	Validity verification; local context adaptation	Faster, accurate compliance research; reduced legal risk
First-draft generation (multilingual)	Multilingual translation	Tone refinement; cultural sensitivity check	Faster onboarding; reduced reliance on external interpreters; improved comprehension
Infographic and icon generation	Visual communication	Cultural appropriateness assessment; context adjustment	Cross-cultural accessibility; clearer instructions for low-English proficiency workers
Neutral phrasing suggestions	Culturally sensitive content	Sensitivity screening; personalization; finalization	Trust preservation; fewer misunderstandings in high-stakes interactions
Synchronous speech translation	Real-time interpretation	Gestures; facial expressions; non-verbal communication	Immediate comprehension; smoother on-site coordination
Message distribution; template management	Hub-and-spoke coordination	Group leader decisions; conflict resolution; escalation	Scalable, reproducible workflows; cost savings; maintained human decision authority

Table 1. AI-Human task division framework

Source: Authors' own

Hybrid Competency Development and Work Reallocation.

Supervisors and HR staff developed new hybrid competencies that combine intercultural sensitivity with critical AI literacy, rather than either traditional HR skills or narrow technical AI proficiency alone. Supervisors described learning *"patience and conscious communication"* and coming to view AI and translation tools as additional channels rather than substitutes for their own responsibility, while the HR Generalist emphasised judgement about the cultural appropriateness of machine-generated content.

Routine tasks such as translation, document generation, compliance searches, and scheduling increasingly flow through AI systems, freeing human capacity for relational work. The HR Generalist highlighted that AI accelerated translation-heavy preparation phases, and one supervisor described an initial sense of AI as *"extra burden"* that shifted over time toward perceiving it as support, because it enabled closer observation of social dynamics during breaks. Together, these accounts suggest that AI augmentation catalysed a distinctive hybrid competency profile and a gradual reallocation of human effort from transactional tasks toward relational and integrative activities, while leaving ultimate responsibility with human actors.

Organizational Capability Building and Implementation Conditions.

The organization developed reproducible AI-augmented workflows in the six domains listed above, each with clearly defined points of human decision authority. Supervisors anchored these workflows in a small set of transferable practices that paired foreign workers with experienced Hungarian "buddies", relied on iterative feedback in which workers repeated back key messages, treated nonverbal cues as indicators of understanding, and used clear escalation paths to HR alongside informal relationship-building during breaks. The CEO signalled intent to further formalize these routines, for example by allowing employees to *"ask chatbots about regulatory topics"* under defined guidelines; together, these developments amount to SME-scale capabilities that historically required large-organization resources and thereby narrow the resource–capability asymmetry in multicultural integration.

Two organisational conditions emerged as critical enablers: transparent communication and clear decision rights, and consistent augmentation framing. The HR leader "*personally walked the entire organization through the strategy"* specifying which decisions remain strictly human, while SV1 stressed that *"these tools work well only if I, as leader, pay attention"* and leaders repeatedly framed AI as enhancing rather than replacing human roles, emphasising that Filipino colleagues are *"equal team members"*. Despite these enablers, vulnerabilities persist: SV2 warned that *"if we don't continuously attend to communication, invisible walls could develop"*, automation bias risks remain (Charlwood and Guenole, 2022; Fenwick et al., 2024), non-English-speaking supervisors face higher coordination costs, and the long-term sustainability of reliance on external AI platforms versus in-house solutions is unresolved. These tensions underscore that sustained organisational attention, supervisory vigilance and transparent decision-rights architecture are non-negotiable for keeping AI-augmented HR workflows functioning reliably. The firm's SME-scale integration capabilities ultimately rest on these workflows being anchored in clear human authority and inclusive leadership messaging.

Corroborating Evidence from Organizational Materials.

Analysis of organizational materials complemented interview insights. Examination of AI-generated and human-revised multilingual HR documents revealed systematic patterns in where human oversight added value. AI generally handled technical terminology accurately, human reviewers routinely softened tone and added contextual clarifications. In one safety document, the AI-generated phrase *"Failure to comply will result in immediate consequences"* was revised to *"Please ensure compliance with this procedure to maintain workplace safety for everyone,"* reflecting sensitivity to more indirect, inclusive communication.

Visual communication artifacts produced with Canva AI prioritized cross-cultural accessibility. Infographics paired clear icons with minimal text, and a machine operation workflow diagram used numbered pictorial steps with short English captions such as *"1. Check material"* and *"2. Press green button,"* supporting comprehension for workers with limited English proficiency. Together, these documents corroborate supervisor accounts of layered communication strategies that combine visual, gestural and AI-mediated verbal channels in the integration process. Document analysis thus confirmed that effective AI-augmented communication operated through multiple complementary channels, with human reviewers consistently adding value by softening tone, contextualising content and ensuring cross-cultural accessibility.

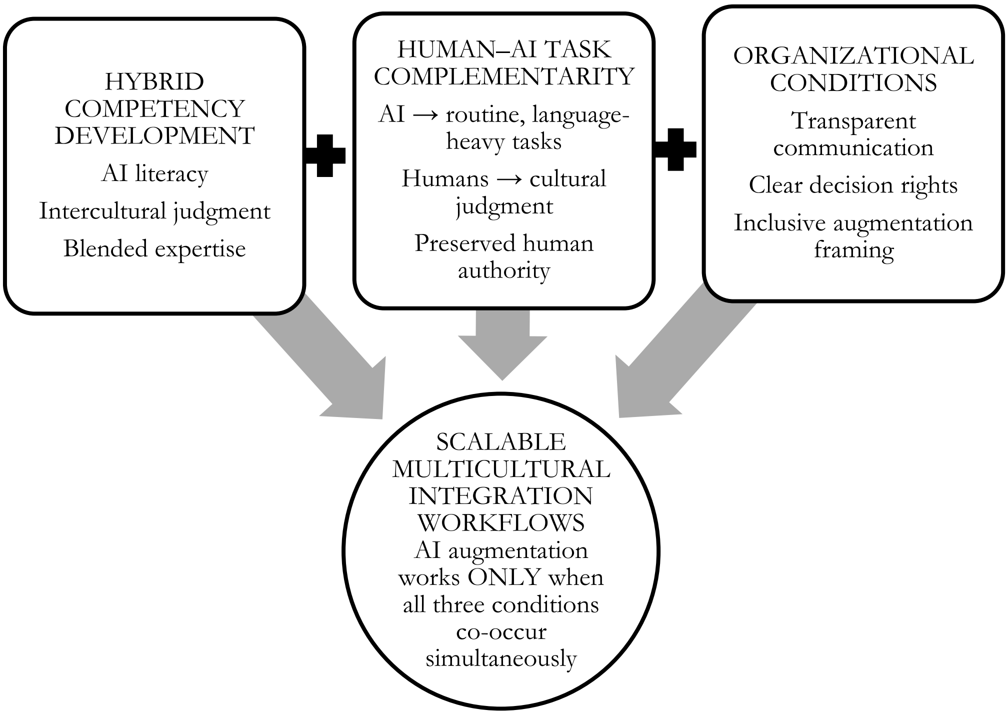

Figure 2. Requirements for AI-augmented multicultural integration
Source: Authors' own

Across the three themes, interview and documentary evidence converge on a consistent pattern: AI augmentation can help resource-constrained firms scale multicultural integration workflows, but only when three conditions co-occur simultaneously. As Figure 2 illustrates, each contributes a distinct functional layer: (1) hybrid competency development couples AI literacy with intercultural judgment as blended expertise, (2) human–AI task complementarity assigns routine, language-heavy tasks to AI while preserving human authority over culturally sensitive decisions while (3) organisational conditions provide the institutional scaffolding through transparent communication, clear decision rights, and inclusive augmentation framing. The convergent arrows in Figure 2 represent a simultaneity condition, not a sequential pipeline: the absence of any single element undermines the system as a whole. These patterns are grounded in a CEE labour market context characterised by chronic shortages and reliance on third-country nationals, and in an SME-structured, family-owned firm with informal HR infrastructure, where dedicated HR and IT functions are largely absent and AI adoption proceeds through informal, emergent processes rather than structured implementation frameworks.

DISCUSSION

The strongest empirical pattern from this exploratory case study is that deliberate augmentation appears to produce more effective integration-related HR workflows than either pure automation or purely manual effort in an SME-structured, family-owned firm facing structural capability constraints. In this case, pure automation and purely manual effort both fall short. This aligns with augmentation-focused perspectives on human–AI collaboration, which argue that AI is most beneficial when it supports rather than replaces human judgment (Davenport and Westerman, 2018; Tambe et al., 2019).

SV1's critical incident with machine-generated performance feedback: *"you are not reliable"*, illustrates that technically correct English can still be culturally inappropriate in high-stakes interpersonal contexts. Similar concerns about how AI-mediated communication can undermine trust have been highlighted in prior work on human reactions to algorithmic decision-making (Longoni et al., 2019). Only because the supervisor understood Filipino communication norms and the relational stakes did he recognize the problem and change practice: speaking more slowly, seeking confirmation, and co-editing sensitive phrasing with HR. These dynamics refine augmentation theory, as in multicultural contexts effective AI augmentation requires cultural judgment applied to AI outputs themselves, extending beyond high-level decisions (Orlikowski and Scott, 2008; Tambe et al., 2019). The cost savings the CEO reported reflect both automation efficiency and the organisation's investment in developing this judgment capability. The result is a form of capability democratization in which SME-scale budgets sustain large-firm-like cultural mediation through relatively inexpensive digital tools (Bharadwaj et al., 2013; Kane et al., 2015).

The data also clarify how hybrid competencies emerge. Both AI literacy and intercultural sensitivity developed together through situated problem-solving at the technology–culture interface (Seeber et al., 2020; Boyatzis, 2008). Supervisors experimented with AI tools and discovered when automated translation was sufficient and when human judgment was needed. They simultaneously deepened their understanding of Filipino communication norms—indirectness, relational focus, face-saving—because these norms became directly relevant to evaluating AI-generated outputs (Earley and Ang, 2003; Markus and Kitayama, 1991). The

HR Generalist's *"judgment about cultural appropriateness of machine-generated content"* represents a new professional competency category: cultural intelligence applied to AI-mediated communication. This points toward emerging hybrid skill profiles in AI-augmented HR roles (Ekuma, 2024).

A further pattern concerns the shift from transactional to relational work, which is evident but temporally nuanced. In early phases, AI adoption increased workload, as supervisors had to learn tools, validate outputs and troubleshoot failures. Only after workflows stabilized did time savings materialize, consistent with Job Demands–Resources logic, in which new technologies initially raise demands before functioning as capability-expanding resources (Bakker and Demerouti, 2007). Over time, automation of translation and documentation freed capacity for relational work: the HR Generalist invested more in monitoring inclusion, while SV1 shifted attention toward observing social dynamics during breaks. Supervisors came to experience AI as *"mainly help,"* because it allowed them to concentrate on more meaningful, human-centric activities. This redistribution enabled greater focus on empowerment and relationship-building, factors linked to engagement in diverse teams (Spreitzer, 1995; Rich et al., 2010).

The third insight is that technology alone is not enough. Clear communication, clear decision rights, supportive framing, and psychological safety helped employees accept and use AI tools (Edmondson, 1999; Rogers, 2003; Venkatesh et al., 2003). Workers who received clear messaging understood AI tools as support rather than monitoring devices. Supervisory practices – *"buddy"* systems, iterative feedback, attention to nonverbal cues and informal relationship-building - functioned as low-tech counterweights to high-tech change (Schein, 2010; Kotter, 1995).

Trust fragility deserves particular attention. Algorithmic language lacks the embodied cues of tone, facial expression and pacing that signal benevolence and repair misunderstandings (Mayer et al., 1995; Schoorman et al., 2007). Workers receiving AI-generated messages in sensitive areas may attribute harshness to the supervisor even when wording originated from an algorithm (Longoni et al., 2019). The evidence points to a tiered deployment model: AI suits policies, training materials and compliance, while performance feedback, conflict resolution and trust-building require human-led interaction with AI as background support only. Organizations that combine these domains risk undermining the trust that integration depends on (Dirks and Ferrin, 2001).

Taken together, these findings contribute to three theoretical conversations. First, they extend AI augmentation research into SME-structured family-owned firm contexts, illustrating how augmentation is accessible beyond large-firm settings. Such firms can approximate similar capabilities through widely available, low-cost tools and deliberate human–AI task design (Birkinshaw and Ansari, 2015; Levy and Powell, 1998; Thong, 1999). Second, they help to enrich competency development theory: AI literacy and intercultural competence emerge as a unified hybrid competency through situated practice rather than formal training alone (Boyatzis, 2008; Eraut, 2004). Third, they propose context-specific implementation conditions for multicultural AI augmentation, where standard best practices of transparency, decision-rights clarity and augmentation framing require supplementation with psychological safety, relational infrastructure and inclusive leadership messaging to translate technological potential into sustained organizational capability (DeLone and McLean, 2003; Edmondson, 1999; Ployhart and Moliterno, 2011).

These contributions are grounded in a CEE labour market context characterised by chronic labour shortages, demographic decline and growing reliance on third-country nationals, and in an SME-structured, family-owned firm with informal HR infrastructure. As such, they should not be generalised to all organisational contexts, but they illustrate how generative-AI tools can reconfigure HR workflows in resource-constrained settings that lack the HR and IT capacity typically assumed in AI-HRM research.

Implications

SME-structured firms may treat AI as a core enabler of multicultural integration when it is deployed with a clear augmentation focus. AI tends to work best for high-volume, low-ambiguity tasks such as document translation, onboarding materials, scheduling and compliance research. Judgment-intensive, relational work remains human-led. This study deliberately focuses on the employer's perspective. The paper primarily provides insight into organizational planning, decision-making authority, and validation practices.

For HR practitioners in family-owned, SME-structured firms facing labour shortages, four practical implications follow. First, use AI for routine translation and document preparation, and ensure that culturally sensitive communication is reviewed and rewritten by staff with local and intercultural knowledge. Second, define clear human–AI decision boundaries: AI can handle volume and standardisation, while supervisors and HR retain authority over performance feedback, conflict resolution and other people decisions. Third, invest in hybrid competencies that combine AI literacy with intercultural judgment, particularly for HR generalists and frontline supervisors working directly with migrant employees. Practice-oriented training using real organizational documents and role-plays builds cultural intelligence faster than theoretical instruction. Fourth, communicate transparently about why AI is introduced, who holds final decision authority and how data are used. Buddy systems, iterative feedback loops and leadership messages that frame AI as enhancing rather than replacing human roles serve as essential social infrastructure for psychological safety in diverse teams. Overall, this is an exploratory single-case study, and its findings are not intended to be statistically generalisable, but to provide analytically rich insight into how AI-augmented HR workflows may operate in SME-structured, resource-constrained firms in CEE.

CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

This exploratory case study illustrates how deliberate AI augmentation can help a medium-sized Hungarian manufacturer to integrate a cohort of foreign workers under severe resource constraints. Prorok (2024) argues that AI-driven decision support systems enable more informed managerial decisions and deeper insights; this case complements that claim by showing how AI-augmented HR workflows preserve human judgement while scaling routine language and documentation tasks. When AI tools automate routine, language-intensive tasks and human actors retain responsibility for culturally sensitive, judgement-dependent decisions, SME-structured firms may approximate integration-related HR capabilities more commonly associated with large organisations. Hybrid competencies emerge at the intersection of technology use and cultural mediation, while organisational conditions, especially transparent communication, augmentation framing and relational practices, shape whether AI lightens or intensifies the human burden of integration work. The findings are necessarily provisional, reflecting one organisation, one migrant population and a specific technological moment in a CEE labour market context characterised by chronic labour shortages and reliance on third-country nationals. As AI systems evolve and migration patterns shift, both the opportunities and risks of AI-mediated integration are likely to change. The evidence here should be read as illustrative of what is possible under particular conditions rather than as a universal blueprint. Future research could proceed in three main directions. First, longitudinal studies following multicultural teams over time could assess whether AI-augmented approaches have durable effects on retention, career trajectories, cohesion and well-being. Second, comparative research across industries, cultural pairings and national contexts could clarify which elements of augmentation-oriented integration travel across settings and which remain context-specific. Third, worker-centred studies foregrounding migrant employees' perspectives would show when AI-mediated communication is experienced as supportive or alienating, and under what conditions it strengthens or undermines belonging. Together, such work would move debates beyond abstract optimism or pessimism toward a more precise, human-centred understanding of how technology and organisational design can jointly support inclusive, sustainable multicultural workplaces in SME-structured, resource-constrained firms.

REFERENCES

1. Adla, L., Gallego-Roquelaure, V. & Calamel, L., 2019. Human resource management and innovation in SMEs, *Personnel Review*, 49(8), pp. 1519–1535. https://doi.org/10.1108/PR-09-2018-0328.
2. Aguinis, H., Beltran, J. R. & Cope, A., 2024. How to use generative AI as a human resource management assistant, *Organizational Dynamics*, 53(1), 101029. https://doi.org/10.1016/j.orgdyn.2024.101029.
3. Alhloul, A. & Kiss, E., 2022. Industry 4.0 as a challenge for the skills and competencies of the labor force: A bibliometric review and a survey, *Sci*, 4(3), p. 34. https://doi.org/10.3390/sci4030034.
4. Armstrong, M. & Taylor, S., 2020. *Armstrong's handbook of human resource management practice*. 15th edn. London: Kogan Page.
5. Arroyabe, M. F., Arranz, C. F. A., Fernandez de Arroyabe, I. & Fernandez de Arroyabe, J. C., 2024. Analyzing AI adoption in European SMEs: A study of digital capabilities, innovation, and external environment, *Technology in Society*, 79, 102733. https://doi.org/10.1016/j.techsoc.2024.102733.
6. Arslan, A., Cooper, C., Khan, Z., Golgeci, I. & Ali, I., 2022. Artificial intelligence and human workers interaction at team level: A conceptual assessment of the challenges and potential HRM strategies, *International Journal of Manpower*, 43(1), pp. 75–88. https://doi.org/10.1108/IJM-01-2021-0052.
7. Astrov, V., Grieveson, R., Hanzl-Weiss, D., Leitner, S., Mara, I., Zavarska, Z. & Vidovic, H., 2021. *How do economies in EU-CEE cope with labour shortages?* wiiw Research Report No. 452. Vienna: Vienna Institute for International Economic Studies (wiiw). Available at: https://wiiw.ac.at/how-do-economies-in-eu-cee-cope-with-labour-shortages-dlp-6406.pdf (Accessed: 8 March 2026).
8. Ayinaddis, S. G., 2025. Artificial intelligence adoption dynamics and knowledge in SMEs and large firms: A systematic review and bibliometric analysis, *Journal of Innovation & Knowledge*, 10(3), 100682. https://doi.org/10.1016/j.jik.2025.100682.

9. Bakker, A. B. & Demerouti, E., 2007. The job demands–resources model: State of the art, *Journal of Managerial Psychology*, 22(3), pp. 309–328. https://doi.org/10.1108/02683940710733115.

10. Bender, E. M., Gebru, T., McMillan-Major, A. & Shmitchell, S., 2021. On the dangers of stochastic parrots: Can language models be too big?, in *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency (FAccT '21)*. New York: ACM. https://doi.org/10.1145/3442188.3445922.

11. Blodgett, S. L., Barocas, S., Daumé III, H. & Wallach, H., 2020. Language (technology) is power: A critical survey of "bias" in NLP, in *Proceedings of ACL 2020*. https://doi.org/10.18653/v1/2020.acl-main.485.

12. Boyatzis, R. E., 2008. Competencies in the 21st century, *Journal of Management Development*, 27(1), pp. 5–12.

13. Braun, V. & Clarke, V., 2006. Using thematic analysis in psychology, *Qualitative Research in Psychology*, 3(2), pp. 77–101. https://doi.org/10.1191/1478088706qp063oa.

14. Braun, V. & Clarke, V., 2019. *Thematic analysis: A practical guide*. London: SAGE Publications.

15. Bryman, A., 2016. *Social research methods.* 5th edn. Oxford: Oxford University Press.

16. Budhwar, P., Malik, A., De Silva, M. T. T. & Thevisuthan, P., 2022. Artificial intelligence – challenges and opportunities for international HRM: A review and research agenda, *The International Journal of Human Resource Management*, 33(6), pp. 1065–1097. https://doi.org/10.1080/09585192.2022.2035161.

17. Charlwood, A. & Guenole, N., 2022. Can HR adapt to the paradoxes of artificial intelligence?, *Human Resource Management Journal*, 32(4), pp. 729–742. https://doi.org/10.1111/1748-8583.12433.

18. Chowdhury, S. et al., 2023. Unlocking the value of artificial intelligence in human resource management through AI capability framework, *Human Resource Management Review*, 33(1), 100899. https://doi.org/10.1016/j.hrmr.2022.100899.

19. Creswell, J. W. & Creswell, J. D., 2018. *Research design: Qualitative, quantitative, and mixed methods approaches*. 5th edn. Thousand Oaks, CA: SAGE Publications.

20. Csillag, S., Csizmadia, P., Hidegh, A. L. & Szászvári, K. Á., 2019. Typical features of family-owned SME's HR practices, *Prosperitas*, 6(1), pp. 54–75. https://doi.org/10.31570/Prosp_2019_01_3.

21. Davenport, T. H. & Ronanki, R., 2018. Artificial intelligence for the real world, *Harvard Business Review*, 96(1), pp. 108–116.

22. Davenport, T. H. & Westerman, G., 2018. Why so many high-profile digital transformations fail, *Harvard Business Review*, 9 March. Available at: https://hbr.org/2018/03/why-so-many-high-profile-digital-transformations-fail (Accessed: 1 March 2026).

23. DeLone, W. H. & McLean, E. R., 2003. The DeLone and McLean model of information systems success: A ten-year update, *Journal of Management Information Systems*, 19(4), pp. 9–30. https://doi.org/10.1080/07421222.2003.11045748.

24. DeepL GmbH, 2024. DeepL Translator [computer software].

25. Dirks, K. T. & Ferrin, D. L., 2001. The role of trust in organizational settings, *Organization Science*, 12(4), pp. 450–467. https://doi.org/10.1287/orsc.12.4.450.10640.

26. Dubois, A. & Gadde, L.-E., 2002. Systematic combining: An abductive approach to case research, *Journal of Business Research*, 55(7), pp. 553–560. https://doi.org/10.1016/S0148-2963(00)00195-8.

27. Earley, P. C. & Ang, S., 2003. *Cultural intelligence: Individual interactions across cultures.* Stanford, CA: Stanford University Press.

28. Edmondson, A., 1999. Psychological safety and learning behavior in work teams, Administrative *Science Quarterly*, 44(2), pp. 350–383. https://doi.org/10.2307/2666999.

29. Ekuma, K., 2024. Artificial Intelligence and Automation in Human Resource Development: A Systematic Review, *Human Resource Development Review*, 23(2), pp. 199-229. https://doi.org/10.1177/15344843231224009.

30. Elmusharaf, K., Byrne, E., Manandhar, M., Hemmings, J. & O'Donovan, D., 2017. Participatory ethnographic evaluation and research: Reflections on the research approach used to understand the complexity of maternal health issues in South Sudan, *Qualitative Health Research*, 27(9), pp. 1345–1358. https://doi.org/10.1177/1049732316673975.

31. Eraut, M., 2004. Informal learning in the workplace, *Studies in Continuing Education*, 26(2), pp. 247–273. https://doi.org/10.1080/158037042000225245.

32. European Commission, 2003. Commission Recommendation 2003/361/EC of 6 May 2003 concerning the definition of micro, small and medium-sized enterprises. *Official Journal of the European Union*, L124, pp. 36–41. Available at: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32003H0361 (Accessed: 8 March 2026).

33. Fachrunnisa, O. & Hussain, F. K., 2020. Blockchain-based human resource management practices for mitigating skills and competencies gap in workforce, *International Journal of Engineering Business Management*, 12, 184797902096640. https://doi.org/10.1177/1847979020966400.

34. Fenwick, A., Molnar, G. & Frangos, P., 2024. Revisiting the role of HR in the age of AI: Bringing humans and machines closer together in the workplace, *Frontiers in Artificial Intelligence*, 6, 1272823. https://doi.org/10.3389/frai.2023.1272823.

35. Garavan, T., Watson, S., Carbery, R. & O'Brien, F., 2016. The antecedents of leadership development practices in SMEs: The influence of HRM strategy and practice, *International Small Business Journal: Researching Entrepreneurship*, 34(6), pp. 870–890. https://doi.org/10.1177/0266242615594215.

36. Hickey and Associates, 2024. Where next? Migration in CEE, *Hickey and Associates Blog*, 2 April. Available at: https://www.hickeyandassociates.com/blog/hickey-where-next-migration-in-cee (Accessed: 10 March 2026).

37. Hofstede, G. H., 2001. *Culture's consequences: Comparing values, behaviors, institutions, and organizations across nations*. 2nd edn. Thousand Oaks, CA: SAGE Publications. Available at: https://books.google.hu/books?id=w6z18LJ_1VsC (Accessed: 2 March 2026).

38. Hungarian Central Statistical Office, 2023. *Preliminary data from the 2011 and 2022 censuses for Békés County*. Budapest: Hungarian Central Statistical Office. Available at: https://www.ksh.hu/ (Accessed: 10 March 2026).

39. Huang, M.-H. & Rust, R. T., 2022. A framework for collaborative artificial intelligence in marketing, *Journal of Retailing*, 98(2), pp. 209–224. https://doi.org/10.1016/j.jretai.2021.03.001.

40. James, T. G., Guetterman, T. C. & Molina-Azorín, J. F., 2024. Increasing transparency on the use of artificial intelligence and automated tools in mixed methods studies, *Journal of Mixed Methods Research*, 18(4), pp. 425–429. https://doi.org/10.1177/15586898241287294.

41. Jiang, Y., Cai, Z. & Wang, X., 2025. Leverage generative AI for human resource management: Integrated risk analysis approach, *The International Journal of Human Resource Management*, 36(11), pp. 1929–1959. https://doi.org/10.1080/09585192.2025.2544972.

42. Kane, G. C., Palmer, D., Phillips, A. N., Kiron, D. & Buckley, N., 2015. Strategy, not technology, drives digital transformation, *MIT Sloan Management Review*, 56(3), pp. 1–25.

43. Kotter, J. P., 1995. Leading change: Why transformation efforts fail, *Harvard Business Review*, 73(2), pp. 59–67.

44. Levy, M. & Powell, P. L., 1998. SME flexibility and the role of information systems, *Small Business Economics*, 11, pp. 183–196. https://doi.org/10.1023/A:1007912714741.

45. Longoni, C., Bonezzi, A. & Morewedge, C. K., 2019. Resistance to medical artificial intelligence, *Journal of Consumer Research*, 46, pp. 629–650. https://doi.org/10.1093/jcr/ucz013.

46. Mäkelä, E., Bone, M., Sehrer, M., Nanji, F. & Stephany, F., 2024. Complement or substitute? How AI increases the demand for human skills (Version 4), *arXiv*. https://doi.org/10.48550/ARXIV.2412.19754.

47. Markus, H. R. & Kitayama, S., 1991. Culture and the self: Implications for cognition, emotion, and motivation, *Psychological Review*, 98(2), pp. 224–253. https://doi.org/10.1037/0033-295X.98.2.224.

48. Mayer, R. C., Davis, J. H. & Schoorman, F. D., 1995. An integrative model of organizational trust, *Academy of Management Review*, 20(3), pp. 709–734. https://doi.org/10.2307/258792.

49. Nowell, L. S., Norris, J. M., White, D. E. & Moules, N. J., 2017. Thematic analysis: Striving to meet the trustworthiness criteria, *International Journal of Qualitative Methods*, 16, 1609406917733847. https://doi.org/10.1177/1609406917733847.

50. Orlikowski, W. J. & Scott, S. V., 2008. Sociomateriality: Challenging the separation of technology, work and organization, *Academy of Management Annals*, 2(1), pp. 433–474. https://doi.org/10.1080/19416520802211644.

51. Országos Doktori Tanács, 2026. *A mesterséges intelligencia (MI) doktori képzésben és fokozatszerzésben való alkalmazásának alapelvei.* Available at: https://doktori.hu/hirek/54-a-mesterseges-intelligencia-mi-doktori-kepzesben-es-fokozatszerzesben-valo-alkalmazasanak-alapelvei (Accessed: 1 March 2026).

52. Palinkas, L. A., Horwitz, S. M., Green, C. A., Wisdom, J. P., Duan, N. & Hoagwood K., 2015. Purposeful sampling for qualitative data collection and analysis in mixed method implementation research, *Administration and Policy in Mental Health and Mental Health Services Research*, 42(5), pp. 533–544. https://doi.org/10.1007/s10488-013-0528-y.

53. Pedron, Z., 2022. Small businesses to overcome skill shortages and talent mismatches, in Biginas, K. et al. (eds.) *Small business management and control of the uncertain external environment*. Bingley: Emerald Publishing Limited, pp. 111–135. https://doi.org/10.1108/978-1-83909-624-220211008.

54. Perplexity AI (2024) Perplexity Pro [computer software].

55. Ployhart, R. E. & Moliterno, T. P., 2011. Emergence of the human capital resource: A multilevel model, *Academy of Management Review*, 36(1), pp. 127–150. https://doi.org/10.5465/amr.2009.0318.

56. Prorok, M., 2024. Az innováció ösztönzése mesterséges intelligenciával támogatott menedzsmenten keresztül, *Multidiszciplináris Kihívások, Sokszínű Válaszok*, (2), pp. 74–109. https://doi.org/10.33565/MKSV.2024.02.04.

57. Rahwan, I., Cebrian, M., Obradovich, N., Bongard, J., Bonnefon, J-F., Breazal, C., Crandall, J. W., Christakis, N. A., Couzin, I. D., Jackson, M. O., Jennings, N. R., Kamar, E., Kloumann, I. M., Larochelle, H., Lazer, D., McElreath, R., Mislove, A., Parkes, D. C., Pentland, A., Roberts, M. E., Shariff, A., Tenenbaum, J. B. & Wellmann, M., 2019. Machine behaviour, *Nature*, 568(7753), pp. 477–486. https://doi.org/10.1038/s41586-019-1138-y.

58. Raisch, S. & Krakowski, S., 2021. Artificial intelligence and management: The automation–augmentation paradox, *Academy of Management Review*, 46(1), pp. 192–210. https://doi.org/10.5465/amr.2018.0072.

59. Rich, B. L., Lepine, J. A. & Crawford, E. R., 2010. Job engagement: Antecedents and effects on job performance, *Academy of Management Journal*, 53(3), pp. 617–635. https://doi.org/10.5465/AMJ.2010.51468988.

60. Rogers, E. M. (2003) *Diffusion of innovations.* 5th edn. New York: Free Press.

61. Sánchez, E., Calderón, R. & Herrera, F., 2025. Artificial intelligence adoption in SMEs: Survey based on TOE–DOI framework, primary methodology and challenges, Applied Sciences, 15(12), 6465. https://doi.org/10.3390/app15126465.

62. Saunders, M. N. K., Lewis, P. & Thornhill, A., 2019. *Research methods for business students*. 8th edn. Harlow: Pearson.

63. Schoorman, F. D., Mayer, R. C. & Davis, J. H., 2007. An integrative model of organizational trust: Past, present, and future, *Academy of Management Review*, 32(2), pp. 344–354. https://doi.org/10.5465/amr.2007.24348410.

64. Seeber, I., Bittner, E., Briggs, R. O., de Vreede, T., de Vreede, G., Elkins, A., Maier R., Merz, A. B., Oeste-Reiß, S., Randrup, N., Schwabe, G. & Söllner, M., 2020. Machines as teammates: A research agenda on AI in team collaboration, *Information & Management*, 57(2), 103174. https://doi.org/10.1016/j.im.2019.103174.

65. Shenton, A. K., 2004. Strategies for ensuring trustworthiness in qualitative research projects, *Education for Information*, 22(2), pp. 63–75. https://doi.org/10.3233/EFI-2004-22201.

66. Spreitzer, G. M., 1995. Psychological empowerment in the workplace: Dimensions, measurement, and validation, *Academy of Management Journal*, 38(5), pp. 1442–1465. https://doi.org/10.2307/256865.

67. Stake, R. E., 1995. *The art of case study research*. Thousand Oaks, CA: SAGE Publications.

68. Tambe, P., Cappelli, P. & Yakubovich, V., 2019. Artificial intelligence in human resources management: Challenges and a path forward, *California Management Review*, 61(4), pp. 15–42. https://doi.org/10.1177/0008125619867910.

69. Venkatesh, V., Morris, M., Davis, G. & Davis, F., 2003. User acceptance of information technology: Toward a unified view, *MIS Quarterly*, 27(3), p. 425. https://doi.org/10.2307/30036540.

70. Vidovic, H., 2022. How do economies in EU-CEE cope with labour shortages? — Study update from *wiiw Research Report* 452. Vienna: Vienna Institute for International Economic Studies. Available at: https://wiiw.ac.at/how-do-economies-in-eu-cee-cope-with-labour-shortages-an-update-pj-278.html (Accessed: 2 March 2026).

71. Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A. & Trichina, E., 2021. Artificial intelligence, robotics, advanced technologies and human resource management: A systematic review, *The International Journal of Human Resource Management*, 33(3), pp. 1-30. https://doi.org/10.1080/09585192.2020.1871398.

72. Yin, R. K., 2018. *Case study research and applications: Design and methods*. 6th edn. Thousand Oaks, CA: SAGE Publications.

ISSN 2630-886X

BGE