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From AI adoption to productive use: building organizational AI capability in Latvia

Artificial intelligence is spreading rapidly across organizations, but access to AI tools does not automatically translate into productivity gains or business value. Drawing on interviews with senior executives from medium and large organizations in Latvia, this brief examines how firms adopt AI and develop the organizational and workforce capabilities required to use it effectively. The analysis identifies a consistent pattern: organizations have made substantial progress in deploying AI tools, developing management awareness, assigning responsibility, and establishing governance, while less so in areas requiring deeper organizational adaptation - data readiness, measurement of business impact, task and role redesign, strategic workforce planning, and organization change. The next stage of AI readiness lies in embedding AI into organizational processes and translating its use into measurable value. For business leaders, this requires stronger foundations and measurement, systematic redesign of work and greater integration of workforce planning into AI implementation. For policymakers, the task is to extend Latvia's existing infrastructure for digitalization, experimentation, and AI skills towards the organizational capabilities required for productive AI use.

AI adoption is accelerating, but is it creating value?

AI adoption among European businesses has accelerated sharply. In 2025, 20.0 percent of EU enterprises with at least 10 employees reported using AI technologies, up from 13.5 percent in 2024. Latvia remained below the EU average, at 12.2 percent (Eurostat, 2026). The aggregate figure, however, masks substantial differences by company size: AI was used by 19.8 percent of medium-sized Latvian enterprises and by 47.1 percent of large enterprises in 2025.

These figures indicate that AI is already relevant to most organizations with sufficient scale to make structured investments in technology and workforce development. Yet adoption statistics reveal little about what happens after an organization begins using AI. A company may purchase licenses, launch pilots, or introduce AI tools without substantially changing how work is organized or being able to demonstrate that the investment improves performance.

The medium and large organizations in Latvia examined in this study reflect this shift. Most have deployed general-purpose or specialized AI tools, and some have developed extensive portfolios of AI applications. Senior executives generally demonstrate a pragmatic understanding of AI and increasingly distinguish between applications offering concrete value and those driven primarily by technological hype. The management architecture around AI is also developing: responsibility has usually been assigned, working groups or steering structures are common, and many organizations have dedicated budgets, internal guidelines, and processes for moving AI ideas from experimentation towards common use.

However, organizations struggle to integrate fragmented data, determine whether AI investments improve performance, redesign tasks and jobs around new technologies, and translate technological change into systematic workforce planning. This is the challenge of organizational embedding – integrating AI into workflows and organizational routines, adapting tasks and roles, developing appropriate workforce capabilities and establishing mechanisms for assessing whether AI creates value. AI adoption is progressing faster than organizational embedding.

Evidence base and analytical framework

The underlying research (Nīgale, Kalniņa and Vārpiņa, 2026) is based on semi-structured interviews conducted in Spring 2026 with senior executives from 22 medium and large organizations in Latvia, supplemented by interviews with AI and digital-transformation practitioners. Organizations were purposively selected across major sectors of the Latvian economy. The sample deliberately focused on organizations with evidence of AI engagement and was designed for cross-sectoral qualitative trend comparison rather than for statistical representativeness. The findings should therefore be read as patterns, not prevalence estimates.

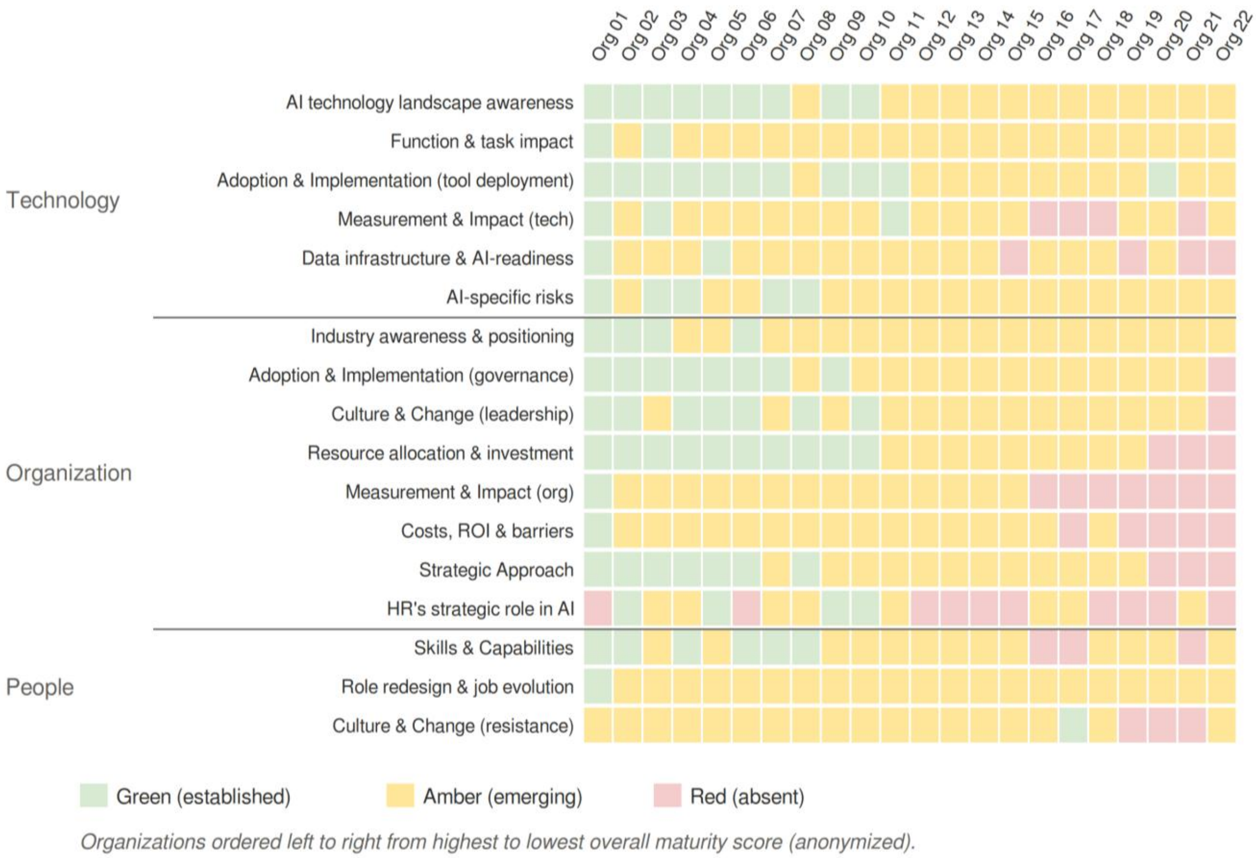
The interviews were analyzed using an adapted Technology–Organization–People (TOP) framework, based on Tursunbayeva and Chalutz-Ben Gal (2024). The framework treats AI adoption as a multilevel process shaped by the technologies being introduced, the organizational conditions in which they are deployed, and the people who use them. The adapted framework covers 17 capability areas: six related to technology (T), eight to organization (O), and three to people (P).

Interview evidence was classified using a Red-Amber-Green (RAG) assessment. Red indicates that a capability is largely absent or dependent on individual initiative; Amber – the relevant activity exists but remains partial, informal, or inconsistently embedded; and Green – the capability is integrated into organizational practice, with defined ownership or a clear implementation path.

AI adoption is ahead of organizational embedding

The heatmap in Figure 1 reveals differences between organizations, but the stronger pattern appears across capability areas. Capabilities associated with the visible adoption of AI tend to be comparatively well developed. Tools are being deployed, management understands the evolving AI landscape, responsibility is assigned, governance structures are emerging, and resources are committed.

Figure 1. Patterns of AI readiness across 22 medium and large organizations actively engaging with AI in Latvia



Source: Nīgale, Kalniņa and Vārpiņa, 2026. Note: The assessment summarizes qualitative evidence from executive interviews and is intended to reveal patterns of relative strength and weakness.

Areas that depend on broader organizational adaptation show a different pattern. Measurement of business impact, data foundations, HR's strategic involvement, and behavioral change are consistently less developed. Task and role redesign has begun in many organizations but has rarely developed into systematic practice. In the RAG assessment, these areas are dominated by emerging rather than established capabilities.

This suggests an important difference between two types of organizational capability. A management team can make a relatively discrete decision to purchase licenses, authorize expenditure, appoint an AI lead or introduce a governance policy. Integrating organizational data, redesigning work, changing employee behavior, and developing reliable outcome measures require sustained coordination across functions and changes in organizational practice.

The challenge is therefore less about acquiring AI than about what organizations can do with it.

From adoption to embedding

Foundations and measurement remain weak

Data-related constraints emerge repeatedly as a barrier to more advanced AI use. Companies report fragmented information, interoperability problems, and unclear data ownership. In many organizations, the visible layer of AI tools has advanced more quickly than the data infrastructure and processes needed to make more integrated applications work. One AI director summarized the challenge:

> *"AI by itself is an enabler. Value is created when prerequisites are in order: data and its quality, technologies, processes, data governance, and AI governance."* (AI Director, Retail)

The implication is that further investment in AI tools cannot substitute for the organizational foundations on which those tools depend.

Measurement represents an equally important weakness. Companies can frequently identify how many licenses have been purchased, how many employees have attended training, or how many pilots have been launched. Much less common is systematic measurement connecting AI use with productivity, quality, costs, customer outcomes or other organizational objectives. One executive described a particularly difficult measurement problem:

> *"Only the employee themselves knows how much time they have actually saved using AI. The manager cannot see this. This asymmetric information problem is significant."* (CEO, Shared Services Center)

This helps explain why individual productivity gains can remain largely invisible at the organizational level. Without credible evidence about what AI delivers, management has a weaker basis for deciding which applications to scale, modify, or discontinue. The distinction between measuring activity and measuring outcomes therefore becomes central to effective AI management.

AI is being added to jobs faster than jobs being redesigned around AI

Organizations generally recognize which business functions are being affected by AI, particularly IT, marketing, customer service, legal functions, and HR. Yet systematic task-level analysis remains rare. Respondents do not describe widespread efforts to map which individual activities within jobs can be automated or augmented, which should remain predominantly human, and how responsibilities should be reorganized as AI capabilities expand.

A similar pattern appears in workforce development. General AI training is relatively widespread, particularly around common tools and prompting. Some organizations provide more advanced or role-specific programs. Still, very few systematically map AI-related capabilities across different occupations or functions, and none of the organizations studied uses a structured capability framework of this kind.

The issue does not end with identifying tasks that AI can perform faster. Organizations also need to decide what happens to the capacity that AI releases. As one CEO put it:

> *"Motivation is the key: what does the organization want the employee to do with the saved time? That question must have a clear answer." (CEO, Shared Services Center)*

The answer might be client development, higher-value analytical work, innovation, additional output, or further professional development. Without such decisions, faster task completion does not automatically become higher organizational productivity. AI implementation therefore requires a conversation about work, rather than simply about technology.

Workforce transformation often lacks strategic ownership

Most organizations have relatively clear ownership of the AI program itself. Responsibility for the workforce transformation accompanying AI is less developed. HR is frequently involved in organizing training, recruitment or communication after major AI-related decisions have already been taken. It is less consistently involved in defining future capability needs, analyzing task change or redesigning roles. In some organizations, the difficulty begins even earlier:

> *"Currently, HR involvement in AI processes has not been relevant for us. We ourselves cannot yet clearly define AI skills." (Director, Manufacturing)*

This suggests that limited HR involvement is more than an HR problem. In some organizations, AI implementation has not yet been translated into sufficiently clear questions about tasks, capabilities, and future workforce needs for HR to address strategically.

The finding also does not imply that HR should independently own AI transformation. AI-related workforce change requires collaboration between business leadership, technology functions, process owners and HR. The central issue is that organizations frequently have clearer ownership of technology adoption than of the organizational and workforce changes required to make that technology productive.

Employee behavior is a further constraint. Some respondents describe a substantial gap between providing access to AI and seeing employees incorporate it meaningfully into everyday work. Limited time to experiment, established routines, uncertainty about usefulness, and concerns about future roles can all impede adoption. Training matters, but it is unlikely to create sustained organizational change if employees remain uncertain about how AI should alter their work or what the organization expects them to do with the resulting efficiency gains.

Latvia's AI support ecosystem is developing

These organizational gaps need to be considered against a policy environment that has already evolved considerably. Latvia already has a range of instruments supporting business digitalization and AI adoption.

The latest Latvian Investment and Development Agency (LIAA) program for process digitalization and AI solutions supported both digital business-process transformation and the development and implementation of AI solutions. Demand was high: applications requested €25.5 million against €18.6 million available. Applications closed in November 2025, and LIAA indicates that no new call is currently planned, although approved projects continue to be implemented (LIAA, 2026).

Latvia's European Digital Innovation Hubs provide another layer of support. The Digital Accelerator of Latvia offers digital maturity assessments, transformation roadmaps, training, consulting, and test-before-invest services. The European Commission's Digital Maturity Assessment covers digital business strategy, digital readiness, human-centered digitalization, data management and connectivity, automation and AI, and green digitalization (Digital Accelerator of Latvia, 2026). The Latvian IT Cluster EDIH also offers AI-oriented services, including an AI Studio implementation workshop that helps firms analyze business processes, identify AI use cases, define pilots, and develop an implementation roadmap (Latvian IT Cluster EDIH, 2026).

At EU level, the EDIH network has been refocused as Experience Centers for AI, with a stronger role in supporting companies and public-sector organizations to test, deploy, and develop skills around AI. The AI Skills Academy began operations in May 2026 and is intended to support AI and generative-AI upskilling and reskilling, including for professionals in SMEs (European Commission, 2026a, 2026b).

The competence-framework landscape has also advanced. DigComp 3.0, released in late 2025, systematically integrates AI competence across the European Digital Competence Framework. It defines competence in terms of knowledge, skills, and attitudes and is designed to be adapted for employment, education, and training contexts, including sectoral and role-specific competence profiles (Cosgrove and Cachia, 2025).

Finally, Latvia's Artificial Intelligence Center provides an institutional platform linking the public sector, private sector, and higher education. Its statutory tasks include promoting AI application in public and private organizations, strengthening AI skills, providing consultations and guidelines, coordinating projects and supporting responsible and safe implementation (Likumi.lv, 2025).

These initiatives already address technology adoption, experimentation, skills, data, and elements of organizational development. As firms move beyond initial adoption, the support ecosystem needs to evolve accordingly, from enabling AI adoption towards enabling productive organizational use.

Priorities for business leaders

The findings suggest three priorities for organizations seeking to move from AI experimentation towards productive use.

1. Strengthen foundations and measurement before scaling. Companies should ensure that reliable data, interoperability, access rights, data ownership, security and governance are in place alongside AI deployment. Expected outcomes should also be defined before pilots are scaled. Monitoring licenses, usage, or participation in training shows whether AI activity is occurring. Management also needs evidence about whether AI improves productivity, quality, customer outcomes or other business objectives.

2. Redesign tasks and define how efficiency gains will be used. Organizations should analyze tasks and workflows to determine which activities can be automated or augmented, which should remain human-led, and how work should be reorganized. Management should explicitly consider how released employee capacity will be used. Without this step, time saved on individual tasks is absorbed rather than converted into output.

3. Strengthen HR's role in AI implementation. HR should participate beyond training delivery and administrative support. Strategic workforce planning, capability development, task and role redesign, and change management should form part of AI implementation from an early stage. Workforce transformation should be jointly owned by business leadership, technology functions, process owners and HR.

These priorities reinforce one another. Better measurement provides evidence about where AI creates value. Task analysis identifies how work needs to change. Workforce planning and capability development then help organizations implement those changes.

Priorities for policymakers: from supporting adoption to supporting embedding

Three corresponding priorities emerge for national and EU policymakers.

1. Extend AI support towards organizational embedding. Future digitalization and AI support should increasingly address the organizational capabilities required to translate technology into productive use. Existing maturity assessments, roadmaps and support instruments provide a natural starting point. These instruments could place greater emphasis on data readiness, task and process redesign, workforce implications, organizational ownership and outcome measurement. This is an extension of the current support system rather than a call for a separate new program.

2. Translate European competency frameworks into practical workforce tools. Developing another general AI competency framework is unlikely to be the best use of resources. DigComp 3.0 and related European initiatives already provide a substantial conceptual foundation. The next step is to translate these into tools employers can use for role-specific skills mapping, capability assessment, training pathways and workforce planning. Such tools could be developed with EDIHs, employer organizations, education providers and the Artificial Intelligence Centre, with particular attention to organizations lacking dedicated workforce-planning capacity.

3. Strengthen public sector capability. Public sector institutions should also strengthen their own capacity to adopt AI effectively. This should include systematic task and process redesign, workforce capability development, and measurement of productivity gains, allowing the public sector to demonstrate practical approaches to AI-enabled organizational change. Demonstration cases should document organizational changes as well as the technology introduced, including how tasks changed, how employees were prepared, and whether productivity or service quality improved. Latvia's Artificial Intelligence Center is well positioned to support the dissemination of such approaches given its mandate across the public and private sectors.

These recommendations do not necessarily require a new large-scale public program. They point instead towards extending and redirecting existing instruments as organizations progress from experimentation towards wider AI use.

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