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AI Transformation in Polish Organisations: The Gap Between Individual Adoption and Organisational Maturity

Abstract

This article diagnoses the state of AI transformation in Polish organisations and explores whether leader education is associated with organisational readiness. The study employs an exploratory, mixed-methods design based on data source triangulation: a survey of 179 leaders, a qualitative analysis of 539 AI projects, and a descriptive contrast between graduates of an AI leadership programme ($n = 102$) and a market comparison group ($n = 66$); the remaining 11 respondents, programme graduates, are included only in aggregate analyses. The results indicate a pronounced gap between individual AI adoption (83% of leaders use AI daily) and organisational maturity (roughly 70% of organisations have not progressed beyond pilots). The study offers three contributions: (1) the Awareness Paradox, whereby leaders with higher competencies evaluate their organisations more critically despite reporting stronger, albeit self-reported, implementation indicators; (2) exploratory evidence of patterns consistent with a cascading effect of leader education; and (3) an inverted build-versus-buy pattern, in which internal builds achieve markedly higher PoC effectiveness than purchased SaaS. Barriers prove primarily organisational rather than technological; change management, the only dimension in which the two groups do not differ, emerges as a systemic barrier requiring whole-organisation intervention.

Keywords: artificial intelligence, AI transformation, organisational maturity, AI readiness, leader education, Shadow AI, change management, Polish enterprises

Introduction

Artificial intelligence (AI) has become one of the defining catalysts of digital transformation. Enterprise spending on generative AI surged from $1.7 billion in 2023 to $37 billion in 2025 (Tully et al., 2025), yet only about 5% of companies globally generate substantial value from AI at scale, while 60% fail to achieve measurable returns (Apotheker et al., 2025). This split between escalating expenditure and modest outcomes raises fundamental questions about the systemic causes of AI transformation failures.

In Poland, AI transformation is entering a decisive phase. KPMG (2025a) data indicate that the share of Polish enterprises declaring some degree of AI implementation surged from 28% to 82% within a single year. Concurrently, EY (2025) reports that over 70% of Polish companies are taking steps to comply with the EU AI Act, though only 31% have actually begun implementation. Poland is among the most mature AI markets in Central and Eastern Europe (KPMG, 2025c), yet, as our data show, roughly 70% of organisations have not progressed beyond pilots and experiments.

The literature increasingly identifies a 'widening AI value gap' (Apotheker et al., 2025) and a 'valley of death' between the proof-of-concept (PoC) stage and production deployment (Deloitte, 2026): McKinsey (2025) reports that 88% of global respondents use AI, but only 6% qualify as 'high-performing AI organisations.' In parallel, Shadow AI – the unauthorised use of AI tools by employees – has emerged as a critical governance challenge (Cisco, 2025; KPMG, 2025b), reflecting deeper deficits in governance frameworks, change management capabilities, and leadership competencies.

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Research Problem

Although individual adoption of AI tools among Polish leaders is near-universal, most Polish organisations cannot convert this momentum into systemic, production-scale deployments – and it is unclear which organisational mechanisms (strategy, ownership, competencies, change management) account for this gap, or whether educating leaders can help close it. Theoretically, maturity and readiness models developed for mature Western markets (Holmström, 2022; Jöhnk et al., 2021) have rarely been examined in a market combining very low SME-level adoption (OECD, 2025b) with very high individual-level adoption. Empirically, Polish studies linking leader education to organisational readiness remain scarce. Practically, organisations entering the EU AI Act enforcement period need evidence on where transformation stalls and which interventions are worth investing in.

The aim of the study is therefore to diagnose the state of AI transformation in Polish organisations and to explore the relationship between leader education and organisational readiness. Three research questions are addressed: (1) What is the current level of AI maturity in Polish organisations, and what are the primary barriers to transformation? (2) Is leader education associated with organisational readiness for AI transformation, and if so, through what mechanisms? (3) What patterns of success and failure can be identified in the transition from PoC to production deployment?

The article makes three original contributions: it presents one of the broadest empirical studies of AI transformation in Poland, integrating organisational, market, and project-level perspectives; it introduces the concept of the 'Awareness Paradox,' whereby leaders with higher competencies evaluate their organisations more critically despite reporting stronger, albeit self-reported, implementation outcomes; and it provides exploratory evidence of patterns consistent with a cascading effect of leader education.

Theoretical Background and Related Work

This section distinguishes the constructs of AI maturity and AI readiness, then reviews related work on maturity models, adoption barriers, Shadow AI, and leadership. Because peer-reviewed evidence lags practice in this fast-moving field, the conceptual framework is anchored in the academic literature, while industry reports are used strictly as sources of current market evidence.

AI Maturity and AI Readiness

Although often used interchangeably, the two constructs differ in temporal orientation. Maturity derives from the capability maturity tradition (Becker et al., 2009): it describes the current, evolutionarily achieved state of capabilities – retrospective and descriptive. Readiness is prospective: an organisation's capacity to undertake a specific change (Weiner, 2009) – the degree to which resources, structures, data, and attitudes enable effective adoption (Holmström, 2022; Jöhnk et al., 2021; Uren & Edwards, 2023). An organisation may thus be ready but immature, or display pockets of maturity without the readiness to progress – running advanced pilots while lacking the strategy, ownership, and change capacity needed for production deployment.

In this study, maturity is operationalised as an organisation's position on a five-stage model and on an implementation-quality ladder (see Methodology), whereas readiness is operationalised through the presence of organisational preconditions: a formal AI strategy, a designated transformation owner, employee access to AI training, and governance policies. This distinction structures the entire analysis: the study's central finding is precisely a readiness deficit underlying a maturity plateau.

Organisational AI Maturity

Organisational AI maturity models have evolved from stage-gate models to multidimensional frameworks encompassing strategy, data, talent, technology, and culture (Becker et al., 2009; Mikalef & Gupta, 2021). Enholm et al. (2022) show that value realisation depends on a chain of organisational enablers rather than the technology itself; Mikalef and Gupta (2021) link AI capability – tangible, human, and intangible resources – to creativity and performance. Sawang and Sornlertlamvanich (2026) propose an SME-grounded framework of eight dimensions and five levels, underscoring that AI maturity is nonlinear.

Market evidence confirms the discriminating power of maturity: 45% of high-maturity organisations keep AI projects operational for at least three years, versus 20% of low-maturity ones (Gartner, 2025); Apotheker et al. (2025) identified 5% 'future-built' firms, 35% scaling, and 60% failing to achieve measurable returns; Deloitte (2026) reports that only one-third of organisations use AI for deep transformation; and KPMG (2026) finds that technology ROI rises with maturity (200% on average, 450% among the most mature).

Individual Versus Organisational Adoption

The gap between individual and organisational adoption has clear theoretical anchors. At the individual level, technology acceptance research (Venkatesh et al., 2003) explains adoption through performance expectancy, effort expectancy, and social influence – dimensions on which generative AI assistants score exceptionally well. At the organisational level, the technology-organisation-environment framework (Tornatzky & Fleischer, 1990) makes adoption dependent on readiness factors such as top management support, resources, and absorptive capacity. When individual drivers race ahead of organisational enablers, theory predicts precisely the configuration documented here: mass bottom-up usage, organisational stagnation, and unsanctioned use (Shadow AI) as a coping mechanism (Dwivedi et al., 2021; Raisch & Krakowski, 2021).

Barriers to AI Transformation

Research on adoption barriers highlights the dominance of organisational factors. Jöhnk et al. (2021) identify strategic alignment, resources, knowledge, culture, and data as the five categories of readiness factors – none primarily technological. Uren and Edwards (2023) show that AI journeys stall at predictable points related to people and process readiness, and Davenport and Ronanki (2018) argue that successful adopters take an incremental, capability-building approach rather than a technology-first 'moon shot' approach.

Market evidence is consistent: McKinsey (2025) reports that 46% of leaders cite skill gaps as a major barrier and only about one-third of organisations have scaled AI; Deloitte (2026) identifies the skills gap as the single largest barrier. The OECD (2025a) argues that training supply is insufficient and that management, business-process, and social skills are the most in-demand competencies for high-AI-exposure occupations. In Poland, only 4.9% of SMEs utilised AI in 2024, against an EU-27 average of 12.6% (OECD, 2025b); yet over 70% of employees state that their organisations use AI tools, while only 30% report formal governance policies (KPMG, 2025c). This suggests a dual-track pattern – mass individual adoption, fragmented organisational adoption – precisely the gap this study investigates.

Shadow AI as a Governance Challenge

Shadow AI – employees' use of AI tools without official authorisation – has become one of the most pressing governance challenges of 2025–2026: 60% of IT teams lack confidence in their ability to identify unapproved AI tools (Cisco, 2025), and 45% of leaders confirmed or suspected sensitive data leaks tied to unauthorised third-party AI tools (KPMG, 2025b). The issue is urgent under the EU AI Act, whose key provisions on high-risk systems came into force in 2026. Yet prohibitive approaches appear counterproductive: Deloitte (2026) reports that enterprise-approved AI access expanded from under 40% to nearly 60% of workers, indicating that organisations increasingly formalise access rather than restrict it. Shadow AI thus appears to be a symptom of inadequate official solutions, not of employee ill will – a hypothesis this study's findings support.

The Role of Leader Competencies in AI Transformation

Academic and market literature converge on the critical role of leadership. Fountaine et al. (2019) argue that building an AI-powered organisation is primarily a matter of culture, structure, and ways of working, with leadership commitment as the decisive enabler; Kotter (2012) places leadership coalition-building at the centre of successful change; Weiner (2009) emphasises that readiness for change is a collective property irreducible to individual attitudes. Bedard and Beauchene (2026) estimate that only 10% of AI value derives from algorithms and 20% from technology – 70% depends on people, organisation, and culture. Leader education may therefore produce a multiplier effect, with a single trained decision-maker initiating changes across multiple organisational levels; Polish empirical studies examining this hypothesis remain scarce – a gap this article addresses.

Methodology

Research Design

The study adopts an exploratory, descriptive, mixed-methods design based on data source triangulation, combining three sources: (1) a structured survey of graduates of an AI leadership programme, (2) a structured survey of a market comparison group, and (3) a qualitative analysis of 539 AI projects. Triangulation mitigates the limitations inherent in any single data source.

Given the non-probability character of the sample, the design is explicitly not quasi-experimental. The graduate-Market contrast is treated as an exploratory, descriptive comparison of two structurally different populations and interpreted as a source of hypotheses, not evidence of causal effects. No inferential tests are applied, no statistical significance is claimed, and all reported percentages and means are descriptive.

Sampling Procedure and Recruitment

The study employed non-probability sampling: a convenience sample with purposive elements, targeting leaders involved in, or responsible for, AI-related decisions in Polish organisations. Respondents were recruited through two channels. The first group comprised graduates of the AI Managers programme (Editions 1 and 2), an intensive programme for senior management covering AI strategy, maturity frameworks, project canvases, and case studies; 102 completed the survey. The second group comprised participants of the AI Managers Conference 2026; 77 completed the survey, of whom 66 had not participated in the programme and constitute the market comparison group ('Market'). In total, the survey covered 179 respondents ($N = 179$); the remaining 11 conference respondents had completed the programme and are included in the combined sample but not in the two-group contrast (102 vs. 66). The unit of analysis is the individual leader reporting on his or her organisation; because responses were anonymous, it cannot be ruled out that more than one respondent described the same organisation. The third source – 539 AI projects developed by participants during the programme – comprised practical implementation concepts for participants' own organisations; one participant could submit more than one project, so the number of distinct participants and organisations is lower than the number of projects.

Participation was voluntary, unpaid, and anonymous (online questionnaire). Because membership in both groups results from self-selection (enrolment in a paid programme; conference attendance), the sample over-represents organisations already engaged with

AI; the implications are discussed in the Limitations section.

The sample reflected a decision-maker population: 78% held managerial positions or above (82% of graduates, 72% of the Market group), and 62% had real influence over AI decisions. The largest industries were IT/technology (31%), e-commerce/retail (15%), finance/banking (13%), and manufacturing (12%). The groups differed structurally: 45% of graduates represented international corporations and 42% organisations with 1,000+ employees, whereas the Market group featured predominantly Polish-owned firms (70%) and smaller organisations – a further reason the contrast is treated as exploratory. A detailed respondent profile is provided in Appendix A.

Data Quality Assessment

Several procedures safeguarded data quality: records were screened for completeness and duplicates, and incomplete questionnaires excluded; 'don't know' options were provided throughout to reduce forced guessing; technically demanding sections (e.g., cloud and data platforms) were optional and could be delegated to a technical colleague. The share of 'don't know' responses was retained as an indicator of organisational awareness. Open-ended responses and project descriptions were reviewed for substantive content before coding.

Research Instrument

The study employed a structured online questionnaire of 53 questions in eight thematic parts, combining single- and multiple-choice questions, five-point anchored rating scales, and optional open-ended questions; typical completion time was 15–20 minutes, and the instrument was administered in Polish and fielded across 2025 and 2026, spanning both recruitment channels. Its full structure, response formats, measurement dimensions, and key measurement items are presented in Appendix A.

Assessing AI Maturity

AI maturity was assessed through a triangulated self-placement procedure combining three components: (1) self-placement on a five-stage maturity model (Exploring, Experimenting, Scaling, Transforming, AI-Native), each stage defined by an operational criterion; (2) ratings of five capability areas on a five-point anchored scale (1 = no activity; 5 = scaled and optimised); and (3) placement of the most advanced deployments on the Value Ladder (Assist, Augment, Automate, Agentic). Responses were combined into a composite maturity score: each component was mapped onto a common 0–100 scale and combined with equal weights, with score bands defined as equal 20-point intervals (Exploring 0–20 through AI-Native 81–100); 'don't know' and omitted optional responses were not scored, and classification then relied on the completed components. Full operational definitions are provided in Appendix A. The procedure allowed cross-checking of stage self-placement against dimensional ratings and implementation quality, and underpins the Awareness Paradox analysis, which contrasts these (self-reported but verifiable) implementation indicators with purely evaluative declarations of benefit.

Analytical Methods

Data analysis was conducted across three layers: (1) combined data ($N = 179$), describing the overall state of AI transformation; (2) a descriptive contrast between the graduate and Market groups, interpreted as hypothesis-generating, not causal; and (3) analysis of discrepancies between subjective benefit declarations and implementation indicators (the Awareness Paradox). The 539 projects were analysed through qualitative thematic coding: operational problems were coded inductively, recurring patterns identified iteratively, and use cases categorised by business function. Design limitations are discussed in the Limitations and Future Research section.

Findings

AI Maturity of Polish Organisations

The vast majority of surveyed organisations remain at early stages: Exploring (no production deployments) accounts for 21%, Experimenting (pilots and PoCs) for 49%, Scaling for 26%, and Transforming or AI-Native for only 4%. The distribution between graduates and the Market was similar in the middle range (Experimenting: 49% vs. 48%), but diverges at the upper end: 7% of graduate organisations reached Transforming or AI-Native, compared to 0% in the Market group (Table 1).

These results are broadly consistent with global data – Apotheker et al. (2025) identified 5% 'future-built' firms, 35% scaling, and 60% failing to achieve measurable returns – despite Poland's lower starting point (4.9% of SMEs with AI in 2024; OECD, 2025b). The sample over-represents AI-engaged organisations, however, so the population-wide distribution is likely less favourable.

Table 1
AI Maturity Stages of Surveyed Organisations ($N = 179$)

Maturity stage	Poland ($N = 179$)	Graduates ($n = 102$)	Market ($n = 66$)
Exploring	21%	19%	25%
Experimenting	49%	49%	48%
Scaling	26%	26%	27%
Transforming + AI-Native	4%	7%	0%

Implementation quality (Value Ladder) deepens this picture: 48% of organisations are at Assist, 28% at Augment, 21% at Automate, and only 3% at Agentic. The association with maturity stage is pronounced: among Transforming and AI-Native organisations (n = 7) most deployments sit at Automate or Agentic, whereas among Exploring organisations 78% remain at Assist – consistent with the automation-augmentation tension (Raisch & Krakowski, 2021): genuine transformation requires qualitatively different deployments, not merely more pilots.

The Adoption Gap: Individual vs. Organisational

The study's central finding is the scale of the gap between individual adoption and organisational maturity. All respondents use at least one AI assistant, and 83% use AI daily; simultaneously, roughly 70% of their organisations (Exploring and Experimenting combined) lack sustained, systemic deployments. The most popular personal applications are research (63%), document analysis and summarisation (58%), writing and editing (55%), and brainstorming (48%); applications requiring integration with internal data remain marginal: decision support (32%), customer service (14%). Organisations deploy AI where it is easy, not where the potential is greatest.

Transformation Barriers

The analysis of barriers points to the dominance of human and organisational factors. Asked to rank their three most important barriers, respondents named the lack of an AI strategy most often (36%), followed by the absence of a transformation owner (32%) and insufficient competencies (32%). On the anchored 1–5 scale, change management received the lowest mean score ($M = 2.43$), marginally below strategy and governance ($M = 2.44$); data infrastructure was rated at 2.55, talent and competencies at 2.75, and technology stack at 2.77 (Table 2).

Graduates rate their organisations somewhat higher on strategy (+0.25), competencies (+0.27), and technology (+0.21), but the two groups converge exactly on change management (2.42 in both). Given the descriptive character of the comparison, we do not interpret these differences as programme effects; notable, however, is that the one dimension on which the groups do not differ at all is the organisation's capacity for change – suggesting a systemic barrier at the level of organisational culture (see Discussion).

Shadow AI, Governance, and the Regulatory Context

60% of surveyed organisations confirm the presence of Shadow AI: in 26% of cases 'widespread,' in 34% 'controlled but existing'; only 28% claim clear rules that eliminate the problem. The primary frustrations with official tools are lack of corporate context ('the tool doesn't know our company' – 25%) and poor output quality relative to free alternatives (24%). This produces what we term the 'Copilot Paradox': Microsoft 365 Copilot is the most frequently deployed enterprise AI tool (58%), but implemented without prior data clean-up, it amplifies chaos, and employees revert to free tools.

In the regulatory context, only 12% of respondents identify the EU AI Act as a significant risk, though 25% of the 539 projects fall within regulated domains (finance, HR, healthcare). Against EY (2025) data showing 71% of Polish firms working on AI Act compliance, transformation leaders paradoxically under-prioritise governance: it ranked second-to-last among planned 2026 initiatives (15%), trailing process automation (47%), training (44%), and chatbots (32%) – a significant risk in the year key AI Act provisions take effect.

The Valley of Death: From PoC to Production

Only 7% of organisations achieve high PoC-to-production effectiveness (>50% of projects deployed), 27% selective (10–50%), 20% experimental (<10%), 18% remain preparatory, and 28% cannot assess. Analysis of the 539 projects, read together with the survey data, identified five causes: lack of clear ownership for production deployment (35% of organisations have dispersed responsibility), data silos (70% of projects), no scaling budget (21% without a dedicated AI budget), expert resistance (45% of projects), and missing MLOps competencies (39% rely on individual specialists rather than teams).

The build-versus-buy analysis revealed a surprising pattern: organisations building internally report PoC effectiveness 3.7 times higher than those purchasing off-the-shelf SaaS (55% vs. 15%). This contrasts with the global dominance of purchased solutions (76% worldwide; Tully et al., 2025) – though that figure concerns prevalence, not effectiveness, and thus provides context rather than a direct benchmark. Explanations are elaborated in the Discussion. Notably, organisations using partners and integrators achieve the highest share of 4+ active deployments (44%), suggesting the optimal path may be 'building with a

Table 2
Self-Assessment of Organisational AI Capability Areas (Anchored 1–5 Scale, N = 179)

Capability area	Poland	Graduates	Market
Technology stack	2.77	2.83	2.62
Talent and competencies	2.75	2.85	2.58
Data infrastructure	2.55	2.60	2.40
Strategy and governance	2.44	2.51	2.26
Change management	2.43	2.42	2.42

domain-knowledgeable partner' rather than a binary build-or-buy choice.

The Awareness Paradox

The Awareness Paradox emerges from contrasting two classes of indicators. The first is subjective-evaluative: declarations of benefits achieved and of AI's impact. The second is factual-implementational: reports of verifiable organisational facts – whether a documented AI strategy exists, what share of PoCs reached production, whether employees have training access, how many solutions are in active use. Both are self-reported, but the second refers to observable states of affairs rather than evaluations; 'paradox' is used as a descriptive label for the reversal of orderings documented below, not as a claim about an established cognitive mechanism.

On the subjective-evaluative indicators, the Market group consistently declares higher benefits: productivity (62% vs. 38%), faster decisions (48% vs. 26%), faster product deployment (30% vs. 17%), new revenue (13% vs. 3%). On the factual-implementational indicators, the ordering reverses: graduates report more formal strategies (33% vs. 21%), higher selective PoC effectiveness (30% vs. 20%), broader training access (67% vs. 51%), and more active deployments (32% vs. 23% with 4+). Higher declared benefits thus do not necessarily signal higher maturity; leaders with greater competencies may simply possess more precise evaluation frameworks and judge their organisations more strictly (see Discussion).

Education-Related Differences

The descriptive contrast between the graduate and Market groups reveals systematic differences across readiness indicators (Table 3).

Graduates show consistently higher readiness indicators and lower 'don't know' rates across all infrastructure and strategy questions – a pattern consistent with a cascading-effect hypothesis: a trained decision-maker formalises strategy, initiates team training, raises infrastructural awareness, and selects projects more effectively. Two alternative explanations must be stated: self-selection (participants may come from organisations already more advanced) and structural composition (more corporations and large organisations among graduates). The present design cannot adjudicate between them; a longitudinal design could. The consistency of the pattern across seven indicators – and its complete absence in exactly one dimension, change management (2.42 = 2.42) – nonetheless makes the hypothesis a productive candidate for further testing.

The Impact of AI on Team Structures

Projections of AI's impact on team structures over 12 months reveal moderate optimism: stability is the most common expectation (42%), 17% of leaders see AI as a growth driver, 8% forecast competency structure changes, 7% plan workforce reductions, and 26% are unable to forecast. Sectoral variation is notable: in telecommunications/media no respondents expect team structures to remain stable (60% are uncertain), healthcare has the highest share of optimists (30%), while finance and e-commerce report the highest planned reductions (8–9%).

Discussion

The findings align with and extend existing research; in line with the exploratory design, the interpretations below are evidence-based hypotheses rather than demonstrated causal claims.

The Adoption Gap Is Bottom-Up in Shape

The adoption gap (83% daily individual adoption vs. roughly 70% of organisations at early stages) is consistent with global observations of divergence between technology availability and organisational readiness (Deloitte, 2026; McKinsey, 2025), and with the prediction that individual acceptance drivers (Venkatesh et al., 2003) can outpace organisational enablers (Tornatzky & Fleischer, 1990). Poland has among the lowest SME-level AI adoption in the EU (OECD, 2025b), yet leaders' individual adoption approaches global averages: Polish AI transformation

Table 3
Education-Related Differences in Organisational Readiness Indicators (Descriptive Contrast)

Dimension	Graduates	Market	Difference
Formal AI strategy	33%	21%	+12 pp.
AI training available	67%	51%	+16 pp.
Selective PoC effectiveness	30%	20%	+10 pp.
4+ active deployments	32%	23%	+9 pp.
'Don't know': cloud provider	11%	26%	-15 pp.
'Don't know': build vs. buy	20%	33%	-13 pp.
'Don't know': data/ML team	4%	11%	-7 pp.
Change management (1–5)	2.42	2.42	0

Note. Differences are descriptive; given the non-probability sample and structural differences between groups, they should not be interpreted as causal effects of the programme.

is fundamentally 'bottom-up', generating distinctive governance challenges, including Shadow AI.

Organisational Barriers Dominate

The dominance of organisational barriers is consistent with the readiness literature (Jöhnk et al., 2021; Uren & Edwards, 2023) and McKinsey's (2025) skill-gap findings. The three most frequently named barriers – lack of strategy (36%), owner (32%), and competencies (32%) – reinforce the pattern of readiness lagging behind technology. Linking barriers to outcomes, change management as the lowest-rated dimension ($M = 2.43$) coincides with 93% of organisations not reporting high PoC-to-production effectiveness – consistent with Bedard and Beauchene's (2026) thesis that 70% of AI value depends on people and organisations, not technology.

The Awareness Paradox Challenges Self-Report Methodology

The Awareness Paradox contributes to the discourse on AI maturity measurement. The point is not that two groups disagree, but that the group scoring higher on subjective-evaluative indicators scores lower on factual-implementational ones – and vice versa: the Market group, which declares markedly higher productivity gains (62% vs. 38%), does not outperform the more critical graduates on any implementation indicator. The phenomenon bears a cautious analogy to the miscalibration described by Kruger and Dunning (1999); the analogy remains tentative, as respondents' actual knowledge and self-assessment accuracy were not directly measured. The implication is that maturity studies relying solely on evaluative self-assessment may overstate the maturity of less advanced organisations and understate that of more advanced ones; future research should pair evaluative declarations with factual implementation metrics.

Leader Education and the Cascading-Effect Hypothesis

The education-related differences in Table 3 align with the consensus that executive commitment is among the strongest predictors of implementation success (Bedard & Beauchene, 2026; Fountaine et al., 2019; McKinsey, 2025), and with Deloitte's (2026) finding that transformation-stage organisations are 3–4 times more likely to have dedicated governance and upskilling programmes. The observed differences may, however, be partially or wholly explained by selection and group composition. The appropriate conclusion is conditional: the pattern is consistent with a cascading effect of leader education and justifies longitudinal verification, but does not prove such an effect.

The Build-Versus-Buy Inversion

The inverted build-versus-buy pattern contrasts with a global market in which purchased solutions dominate in prevalence (Tully et al., 2025). Four complementary mechanisms may make the inversion market-specific. First, data-infrastructure immaturity: Polish organisations carry substantial 'data debt' (70% of analysed projects reported data silos); off-the-shelf SaaS presupposes integration-ready data, whereas internal builds engage with integration from day one. Second, a localisation gap: many global SaaS products offer limited support for Polish-language content, local document standards, and regulatory specifics. Third, relative factor costs: competitively priced Polish engineering talent versus SaaS priced in dollars or euros shifts the calculus towards building. Fourth – a caveat rather than a mechanism – sample composition: IT/technology firms (31%) are over-represented, which may inflate the observed effectiveness of building. The inversion is therefore framed as a plausible, multi-causal, market-specific pattern requiring verification on a representative sample; its practical reading is the sequence articulated by respondents themselves: data → processes → AI, whether an organisation builds or buys.

Change Management as a Systemic Barrier

Perhaps the most consequential – and most easily misread – finding is the exact convergence of the two groups on change management ($2.42 = 2.42$), against graduate advantages on every other indicator. This must not be read as evidence that education does not work: the data cannot show what education causes. The pattern indicates something narrower: whatever is associated with leader education across strategy, training, and infrastructure awareness does not extend to the organisation's capacity for change. This is theoretically coherent – readiness for change is a collective property (Weiner, 2009), and successful change requires structural mechanisms no single trained individual can supply (Kotter, 2012). Training decision-makers moves many levers, but change management requires whole-organisation intervention – culture, incentives, structures – alongside individual competency development.

Conclusions

The survey of 179 leaders and the analysis of 539 AI projects yield a coherent picture of AI transformation in the studied sample of Polish organisations: strong individual foundations (83% daily AI adoption among leaders) coexist with weak organisational foundations (roughly 70% at the pilot stage, 32% naming the absence of a transformation owner as a main barrier, only 28% reporting clear AI-use policies). Closing this gap is the central challenge of 2026–2027. Five conclusions follow.

First, the barriers are human and organisational, not technological: effective transformation requires change management competencies, decision structures, and an innovation-friendly culture (cf. Bedard & Beauchene, 2026; McKinsey, 2025).

Second, the data reveal a pattern consistent with a cascading effect of leader education (+12 pp. strategy formalisation, +16 pp. training access, +10 pp. PoC effectiveness among graduates); subject to the selection caveats above, AI competency programmes should target senior management, not only technical teams.

Third, the Awareness Paradox challenges the reliability of maturity studies based solely on evaluative self-assessment; maturity measurement should combine declarative data with factual implementation metrics (deployments, PoC effectiveness, strategy formality).

Fourth, the inverted build-versus-buy pattern shows that global recommendations cannot be transposed uncritically to markets with lower data maturity; data and process clean-up precedes AI deployment regardless of the build or buy model.

Fifth, change management emerges as a systemic barrier – the only dimension where the groups do not differ – so building change capacity requires whole-organisation intervention (culture, incentives, communication structures), not individual development alone.

Limitations and Future Research

The findings must be read against the design's limitations. First, the sample is a non-probability convenience sample of AI-engaged leaders: it is not representative of Polish organisations, and reported maturity levels likely overestimate market-wide reality. Second, the graduate-Market contrast is affected by self-selection and structural differences between the groups; it was therefore reported as descriptive and hypothesis-generating, with no inferential statistics applied. Third, all data are self-reported; verifiable facts were not independently audited. Fourth, the cross-sectional design precludes tracing causal pathways over time.

Future research should pursue longitudinal designs following organisations before and after leader education, representative samples of Polish enterprises, in-depth case studies of the change management barrier, and comparisons with other Central and Eastern European countries to test the proposed market-specific explanation of the build-versus-buy inversion.

The appendices are available in the online version of the journal.

References

Apotheker, J., Beauchene, V., de Bellefonds, N., Forth, P., Franke, M. R., Grebe, M., Kataeva, N., Kirvelä, S., Kleine, D., de Laubier, R., Lukic, V., Luther, A., Martin, M., Walters, J., & Schweizer, C. (2025). *The widening AI value gap: Build for the future 2025*. Boston Consulting Group. https://media-publications.bcg.com/The-Widening-AI-Value-Gap-Sept-2025.pdf

Becker, J., Knackstedt, R., & Pöppelbuß, J. (2009). Developing maturity models for IT management: A procedure model and its application. *Business & Information Systems Engineering, 1*(3), 213–222. https://doi.org/10.1007/s12599-009-0044-5

Bedard, J., & Beauchene, V. (2026). *AI transformation is a workforce transformation*. Boston Consulting Group. https://web-assets.bcg.com/pdf-src/prod-live/ai-transformation-is-a-workforce-transformation.pdf

Cisco. (2025). *2025 Cisco cybersecurity readiness index*. Cisco. https://newsroom.cisco.com/c/dam/r/newsroom/en/us/interactive/cybersecurity-readiness-index/2025/documents/2025_Cisco_Cybersecurity_Readiness_Index.pdf

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

Deloitte. (2026). *State of AI in the enterprise 2026*. Deloitte Global. https://www.deloitte.com/content/dam/assets-shared/docs/about/2025/state-of-ai-2026-global.pdf

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., ... Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management, 57*, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial intelligence and business value: A literature review. *Information Systems Frontiers, 24*(5), 1709–1734. https://doi.org/10.1007/s10796-021-10186-w

EY. (2025). *Jak polskie firmy wdrażają AI: Analiza zmian rok do roku* (edycja 2) [How Polish companies are implementing AI: A year-on-year analysis of changes (2nd ed.)]. Ernst & Young. https://www.ey.com/content/dam/ey-unified-site/ey-com/pl-pl/noindex/ey-raport-ai-final.pdf

Fountaine, T., McCarthy, B., & Saleh, T. (2019). Building the AI-powered organization. *Harvard Business Review, 97*(4), 62–73.

Gartner. (2025, June 30). *Gartner survey finds 45% of organizations with high AI maturity keep AI projects operational for at least three years* [Press release]. https://www.gartner.com/en/newsroom/press-releases/2025-06-30-gartner-survey-finds-forty-five-percent-of-organizations-with-high-artificial-intelligence-maturity-keep-artificial-intelligence-projects-operational-for-at-least-three-years

Holmström, J. (2022). From AI to digital transformation: The AI readiness framework. *Business Horizons, 65*(3), 329–339. https://doi.org/10.1016/j.bushor.2021.03.006

Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or not, AI comes – An interview study of organizational AI readiness factors. *Business & Information Systems Engineering, 63*(1), 5–20. https://doi.org/10.1007/s12599-020-00676-7

Kotter, J. P. (2012). *Leading change*. Harvard Business Review Press.

KPMG. (2025a). *Monitor transformacji cyfrowej biznesu. Edycja 2025* [Business digital transformation monitor: 2025 edition]. https://kpmg.com/pl/pl/wiedza/technologia/monitor-transformacji-cyfrowej-biznesu-edycja-2025.html

KPMG. (2025b). *Shadow AI is already here: Take control, reduce risk, unleash innovation*. https://kpmg.com/kpmg-us/content/dam/kpmg/pdf/2025/shadow-ai-already-here-take-control-reduce-risk-unleash-innovation.pdf

KPMG. (2025c). *Sztuczna inteligencja w Polsce: Krajobraz pełen paradoksów* [Artificial intelligence in Poland: A landscape full of paradoxes]. https://assets.kpmg.com/content/dam/kpmgsites/pl/pdf/2025/07/pl-Raport-KPMG-w-Polsce-KPMG-AI-Trust-2025-web.pdf.coredownload.inline.pdf

KPMG. (2026). *KPMG Global tech report 2026: Leading in the intelligence age*. https://assets.kpmg.com/content/dam/kpmgsites/xx/pdf/2026/01/global-tech-report.pdf

Kruger, J., & Dunning, D. (1999). Unskilled and unaware of it: How difficulties in recognizing one's own incompetence lead to inflated self-assessments. *Journal of Personality and Social Psychology, 77*(6), 1121–1134. https://doi.org/10.1037/0022-3514.77.6.1121

McKinsey & Company. (2025). *The state of AI in 2025: Agents, innovation, and transformation*. https://www.mckinsey.com/~/media/mckinsey/business%20functions/quantumblack/our%20insights/the%20state%20of%20ai/the-state-of-ai-in-2025-vf.pdf

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management, 58*(3), 103434. https://doi.org/10.1016/j.im.2021.103434

OECD. (2025a). *Bridging the AI skills gap: Is training keeping up?* OECD Publishing. https://www.oecd.org/content/dam/oecd/en/publications/reports/2025/04/bridging-the-ai-skills-gap_b43c7c4a/66d0702e-en.pdf

OECD. (2025b). *Progress in implementing the European Union coordinated plan on artificial intelligence (Volume 1): Poland*. OECD Publishing. https://www.oecd.org/content/dam/oecd/en/publications/reports/2025/10/progress-in-implementing-the-european-union-coordinated-plan-on-artificial-intelligence-volume-1-country-notes_b0385317/poland_c78d9cfe/518e8a57-en.pdf

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

Sawang, S., & Sornlertlamvanich, V. (2026). *Artificial intelligence (AI) maturity in small and medium-sized enterprises: A framework of internalized and ecosystem-embedded capabilities* (arXiv:2603.08728). arXiv. https://arxiv.org/abs/2603.08728

Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation*. Lexington Books.

Tully, T., Redfern, J., Das, D., & Xiao, D. (2025). *2025: The state of generative AI in the enterprise*. Menlo Ventures. https://menlovc.com/wp-content/uploads/2025/12/menlo_ventures_enterprise_ai_report-2025-123125.pdf

Uren, V., & Edwards, J. S. (2023). Technology readiness and the organizational journey towards AI adoption: An empirical study. *International Journal of Information Management, 68*, 102588. https://doi.org/10.1016/j.ijinfomgt.2022.102588

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

Weiner, B. J. (2009). A theory of organizational readiness for change. *Implementation Science, 4*, 67. https://doi.org/10.1186/1748-5908-4-67

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