MECALUX | MIT Center for Transportation & Logistics | MIT Intelligent Logistics Systems Lab



The state of AI in warehousing

Global insights from supply chain leaders
on AI's economic and workforce impact – 2025

Contents

Introduction

Key findings

Theme 1: Current state of AI/ML adoption
AI adoption in warehousing reaches a new level of maturity
• The expanding footprint of AI in warehouse operations
• AI becomes part of the daily workflow
• A tool for operational complexity
• An enabler of high-impact value

Theme 2: AI/ML investment and ROI
AI investments move from pilot budgets to proven returns
• Budget allocation and ROI from AI
• AI investment drivers
• Payback periods reflect the scope of transformation

Theme 3: Current AI/ML implementation challenges and enablers
Overcoming challenges to accelerate AI adoption in warehouses
• Main barriers
• Internal capabilities for AI implementation
• Resources to speed up AI adoption

Theme 4: AI/ML impact on the workforce
People at the centre of warehouse transformation
• AI raises skills across the board
• AI creates new roles

Theme 5: Future AI/ML implementation outlook and priorities
The next wave: From prediction to decision
• Expanding capabilities and investment

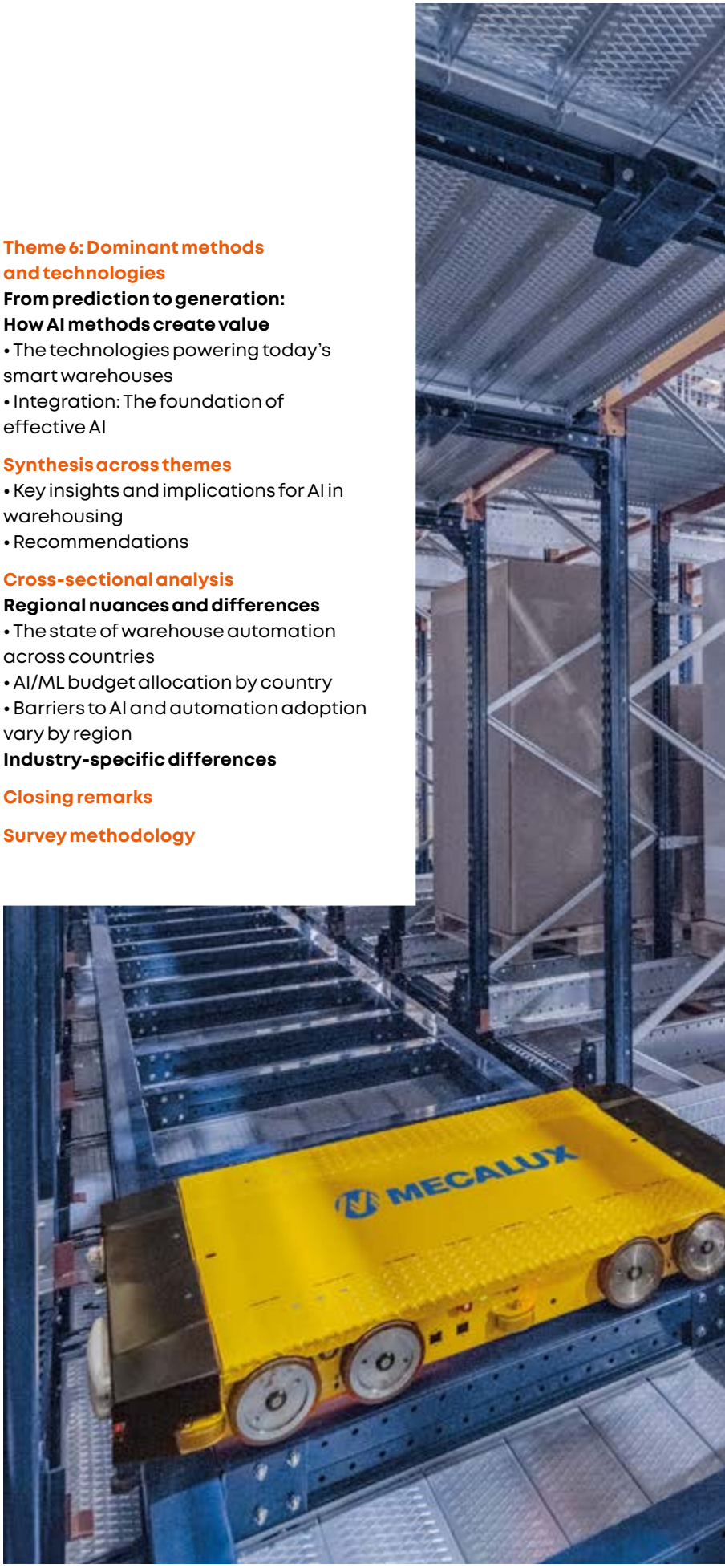
Theme 6: Dominant methods and technologies
From prediction to generation: How AI methods create value
• The technologies powering today's smart warehouses
• Integration: The foundation of effective AI

Synthesis across themes
• Key insights and implications for AI in warehousing
• Recommendations

Cross-sectional analysis
Regional nuances and differences
• The state of warehouse automation across countries
• AI/ML budget allocation by country
• Barriers to AI and automation adoption vary by region
Industry-specific differences

Closing remarks

Survey methodology





About the survey

Year: 2025

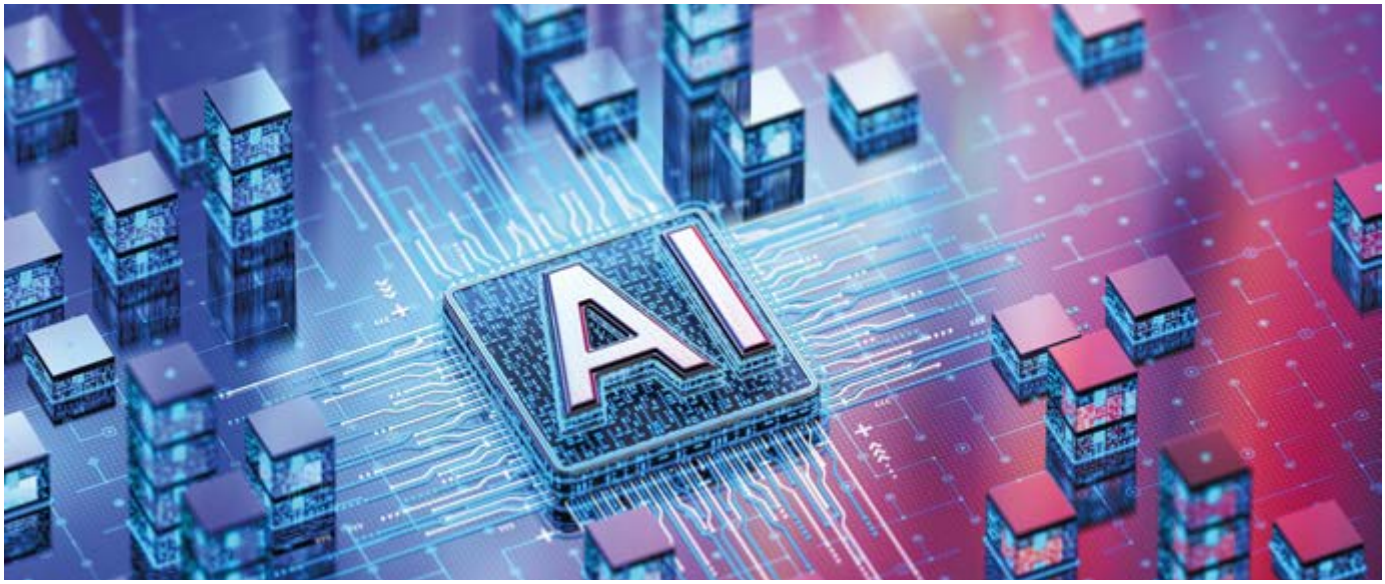
Participants: 2,000+ experienced supply chain and warehousing professionals.

Reach: 21 countries across Europe, North America, Asia-Pacific and Latin America.

Industry sectors: Agriculture, automotive, chemicals, construction, consumer goods, e-commerce & retail, energy, food & beverage, government, logistics, manufacturing, pharma, technology, textiles and transport.

Company size: Respondents represented companies ranging from 100 to over 5,000 employees, with the largest share coming from organisations with 1,000–4,999 employees.

Revenue: Most respondents (32%) represent companies with annual revenues between $251–999 million, followed by 26% in the $51–250 million range, 19% above $1 billion, 18% between $10–50 million, and 5% under $10 million.



Introduction

A data-driven view of AI adoption in warehouse operations

The MIT Intelligent Logistics Systems Lab and Mecalux jointly fielded a global survey of more than 2,000 experienced supply chain and warehousing professionals to assess the current state, investment patterns, challenges, workforce effects and outlook for artificial intelligence and machine learning (AI/ML) in warehouse operations. To ensure the findings reflected organisations with meaningful levels of warehouse activity and technology adoption, the survey focused on companies with at least 100 employees. Our aim was to establish a contemporary, evidence-based baseline for AI adoption in warehousing and logistics. The survey spanned six thematic blocks: current state of adoption; investment priorities and return on investment (ROI) considerations; implementation challenges; workforce impacts; future implementation outlook and priorities; and dominant methods and technologies, as well as questions about respondent demographics.

The data reveal a sector in transformation. More than four out of five organisations increased AI/ML use in the past year, and most expect budgets to rise further. The typical payback period — just two to three years — shows that AI is delivering tangible returns, not speculative value. Generative AI is emerging as the next frontier in logistics, speeding up process design, documentation and decision-making. The human side of automation is also evolving in positive ways: productivity and job satisfaction are rising together, driven by new roles, training and upskilling.

Warehousing is evolving from automation to intelligence, where data and algorithms complement human expertise. The next competitive edge will belong to those who treat AI not as a project, but as an embedded, measurable capability that turns insight into action faster.

Matthias Winkenbach
Director, MIT Intelligent Logistics Systems Lab

Key findings



Theme 1: Current state of AI/ML adoption

- **Nearly 9 out of 10** warehouses now operate at automation levels beyond basic processes.
- **57.5%** of organisations operate at advanced or full automation maturity; only **11.7%** remain largely manual.
- Full automation is most common among larger firms with higher revenue, more sites and more employees.



Theme 2: AI/ML investment and ROI

- Most companies dedicate **11–30%** of warehouse-tech budgets to AI/ML.
- Typical payback period: **2–3 years**.
- Main investment drivers: cost savings, customer needs, labour availability, quality, safety, sustainability and competitive pressure.



Theme 3: Current AI/ML implementation challenges and enablers

- Top adoption barriers: technical expertise (**48.6%**), system integration (**47.7%**), data quality (**46.2%**) and implementation cost (**46.1%**).
- Key enablers for faster adoption: better tools/platforms (**55.5%**), more internal expertise (**53.7%**), larger budgets (**51.9%**), clear roadmaps (**50%**) and external consultants (**43%**).



Theme 4: AI/ML impact on the workforce

- Positive workforce trends dominate: productivity up for **77.5%** of organisations, job satisfaction up for **75.4%**, training requirements up for **76.4%** and workforce size increased for **55.8%**.
- AI is creating — not replacing — jobs: AI/ML engineers (**60.1%**), automation specialists (**58%**), process-improvement experts (**51.9%**) and data scientists (**40%**).



Theme 5: Future AI/ML implementation outlook and priorities

- **92.1%** of firms are implementing or planning AI projects in the near term. Only **1.7%** have no plans; **6.2%** already have extensive implementations.
- **87%** expect to increase AI budgets in the next 2–3 years (**50.3%** slight, **36.7%** significant).
- Main investment goals: efficiency (**47.9%**) and innovation (**31.1%**), followed by cost reduction (**10.5%**) and competitive differentiation (**10%**).



Theme 6: Dominant methods and technologies

- Most valuable methods today: generative AI (**70.3%**), predictive ML (**58.4%**), computer vision (**49.8%**), reinforcement learning (**45.9%**) and NLP (**42.5%**).
- Top generative AI applications: automated documentation/ reporting (**55%**), layout optimisation (**53.6%**), process-flow design (**53.3%**) and code generation (**52.5%**).



Theme 1: Current state of AI/ML adoption

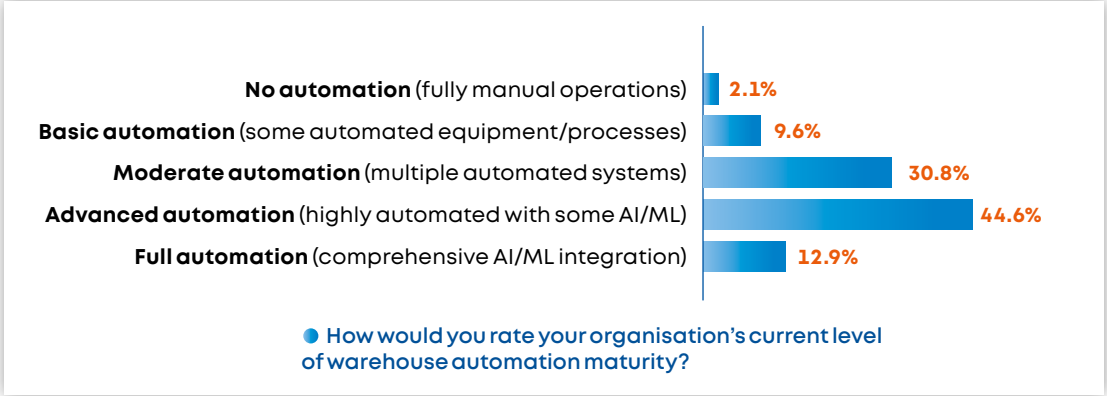
AI adoption in warehousing reaches a new level of maturity

The expanding footprint of AI in warehouse operations

Our results show that AI/ML adoption in warehousing is already well underway and expanding rapidly. Nearly 9 out of 10 warehouses now operate at automation levels beyond basic processes, while about 6 out of 10 report having implemented some form of AI or ML. A majority of respondents — 57.5% in total — describe their organisations as operating at advanced or full automation maturity (44.6% and 12.9%, respectively), with a further 30.8% reporting a moderate level of automation. Only 11.7% say their facilities remain at basic or fully manual operations (Figure 1).

Figure 1

Current level of warehouse automation maturity



Nearly 9 out of 10 warehouses now operate at automation levels beyond basic processes

AI becomes part of the daily workflow

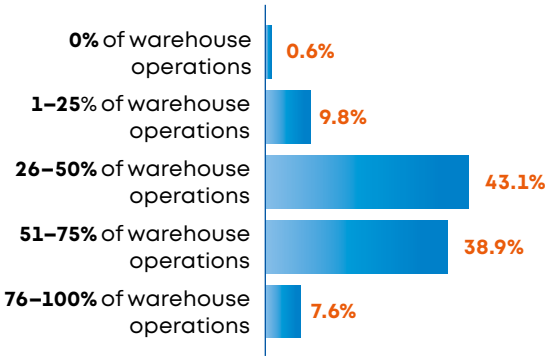
The operational footprint of artificial intelligence is similarly broad: 43.1% report that AI/ML supports between a quarter and half (26–50%) of their warehouse processes, and 38.9% say it covers more than half (51–75%) (Figure 2). This means that for most companies, AI is not confined to a single function — it is embedded across daily workflows such as order picking, inventory management, equipment maintenance and workforce scheduling.

Momentum continues to build: 83% of firms increased AI/ML use in the past year (Figure 3). The pace of adoption suggests that AI is becoming a standard tool for staying competitive rather than an optional innovation experiment.



Figure 2

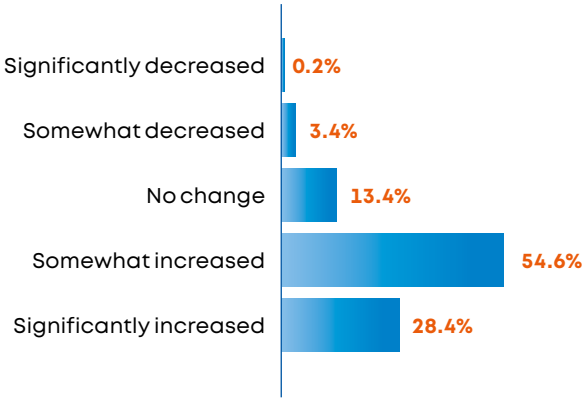
Warehouse operations utilising AI/ML technologies



What percentage of your warehouse operations currently utilise AI/ML technologies?

Figure 3

Change in AI/ML adoption over the last year (12 months)



Compared to one year ago, how has your organisation's use of AI/ML in warehouse operations changed?

Figure 4

Share of AI/ML-enabled operations by company revenue

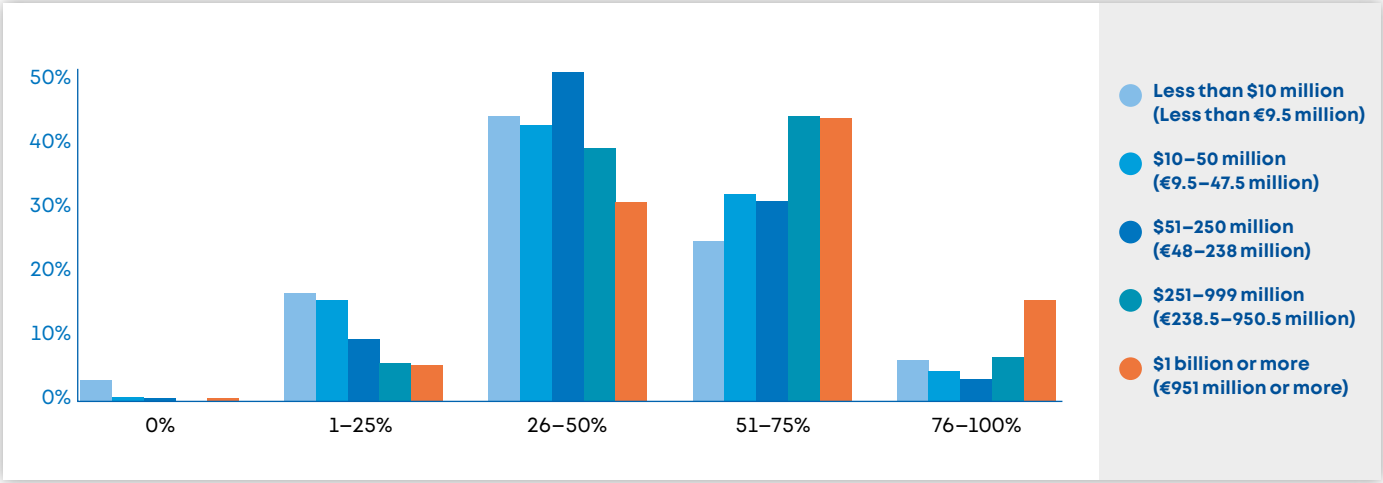


Figure 5

Share of AI/ML-enabled operations by company size

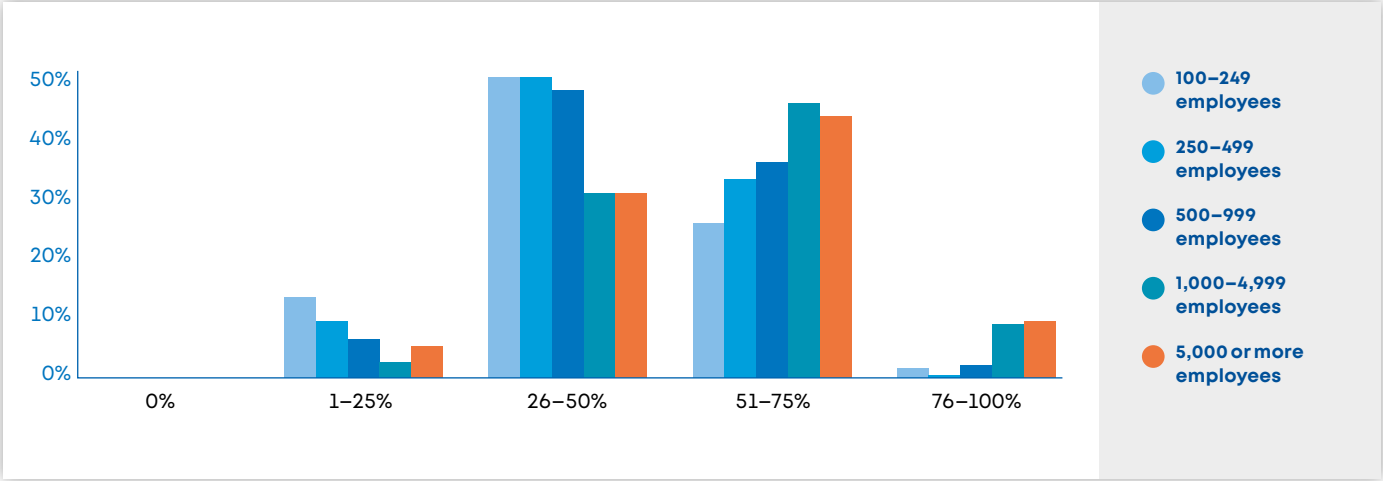
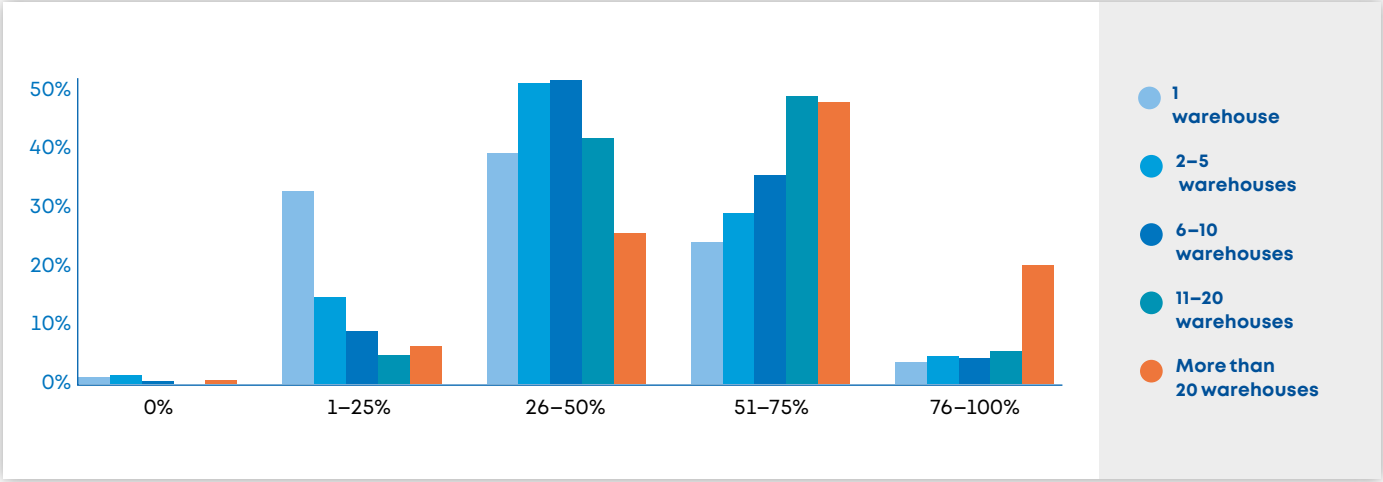


Figure 6

Share of AI/ML-enabled operations by number of warehouses



A tool for operational complexity

A company's level of AI/ML maturity — that is, the extent to which its operations have adopted automated systems and technologies — rises sharply with its scale and operational complexity. Our results indicate that full automation is more prevalent among firms with higher annual revenues, larger warehouse networks and larger individual facilities (Figures 4, 5 and 6). Smaller organisations, while less automated overall, represent the next frontier for adoption as AI becomes more accessible and scalable.



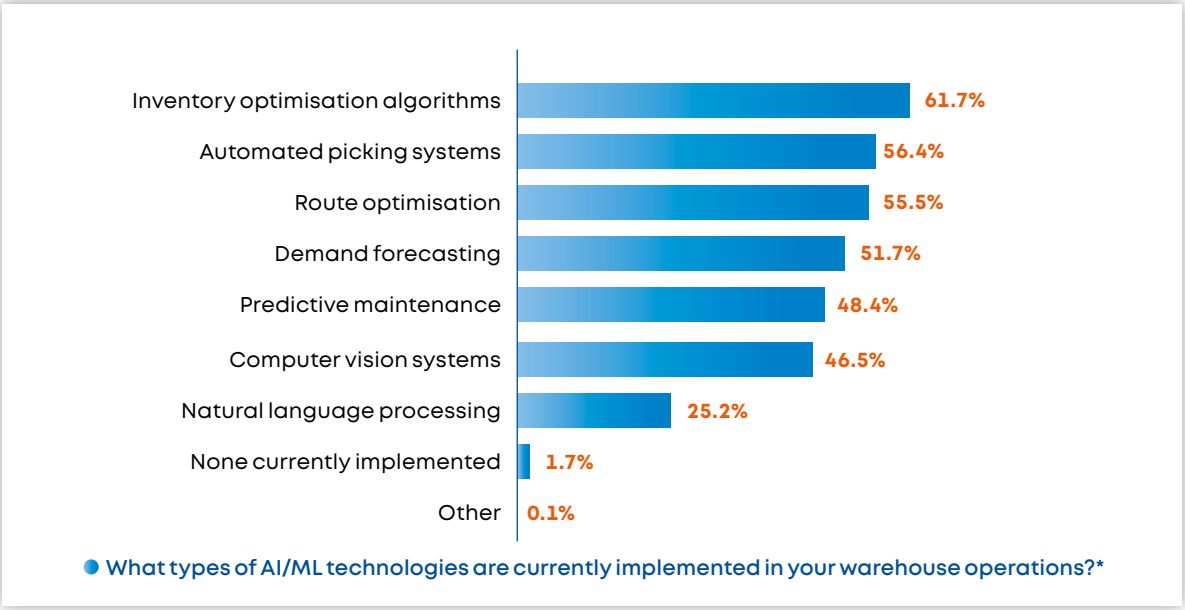
An enabler of high-impact value

Current AI/ML deployments concentrate on proven, high-impact capabilities with clear operational value: inventory optimisation algorithms (61.7%), automated picking systems (56.4%), route optimisation (55.5%), demand forecasting (51.7%), predictive maintenance (48.4%) and computer vision (46.5%). The adoption of natural language processing (NLP) technologies (25.2%) is still lagging (Figure 7).

Technology effectiveness improves with an organisation's automation maturity. Among fully automated sites, the share of respondents rating a technology as "very effective" rises to 56.5% for inventory optimisation, 57.1% for demand forecasting, 59.7% for route optimisation, 50.6% for predictive maintenance, 58.5% for automated picking and 68.4% for NLP. Mature users are not just using more AI — they are using it better.

Figure 7

AI/ML technologies implemented



*Multiple responses allowed; results do not add up to 100%



Theme 2: AI/ML investment and ROI

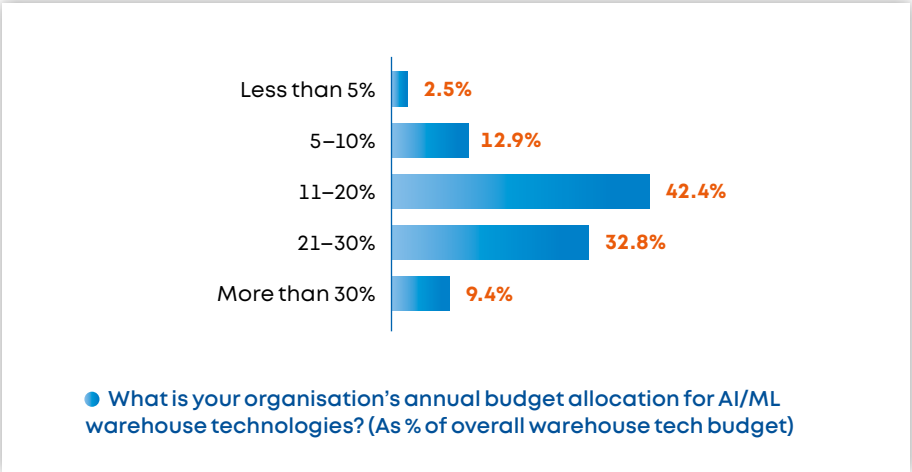
AI investments move from pilot budgets to proven returns

Budget allocation and ROI from AI

The overall approach to AI/ML investment in warehousing is pragmatic. Most organisations dedicate between 11% and 30% of their warehouse-technology budgets to AI and machine-learning initiatives (42.4% at 11–20% and 32.8% at 21–30%) (Figure 8).

Figure 8

Budget allocated to AI/ML technologies

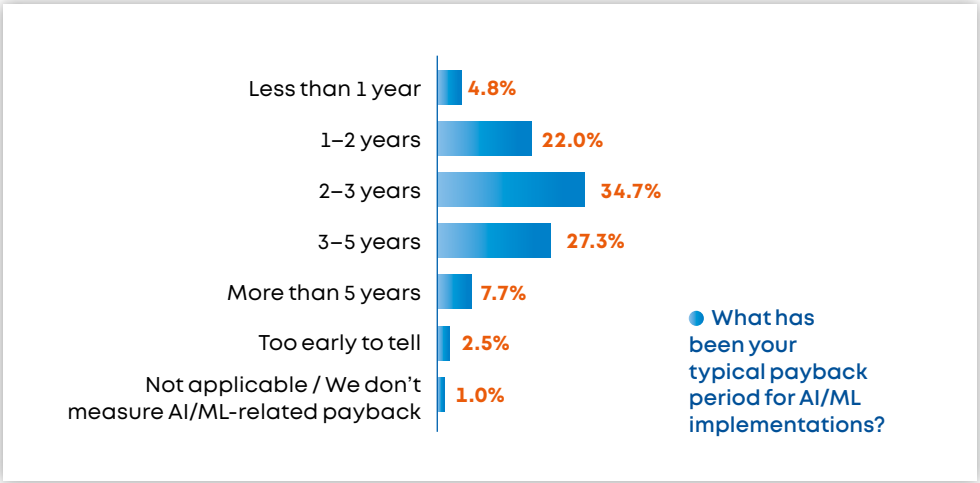


● What is your organisation's annual budget allocation for AI/ML warehouse technologies? (As % of overall warehouse tech budget)

Typical payback periods cluster around two to three years (34.7%), followed by three to five years (27.3%) and one to two years (22%) (Figure 9). This means that many companies are already seeing measurable returns within a single business cycle — a sign that AI is delivering real operational and financial value, not just long-term potential.

Figure 9

Payback period for AI/ML investments

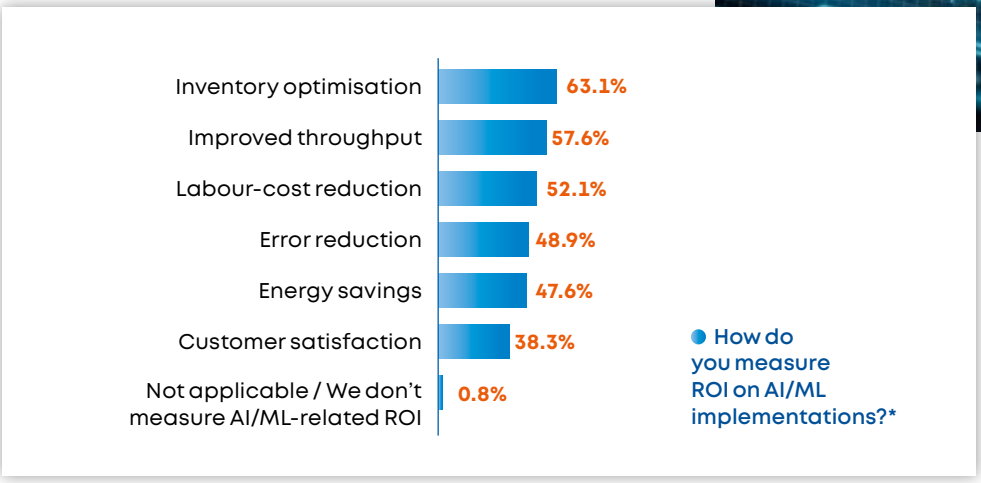


Return on investment is measured primarily through tangible, performance-driven outcomes such as inventory optimisation (63.1%), improved throughput (57.6%), labour-cost reduction (52.1%), error reduction (48.9%), energy savings (47.6%) and customer satisfaction (38.3%), which closely mirror the technologies deployed (Figure 10).



Figure 10

ROI metrics employed



*Multiple responses allowed; results do not add up to 100%

AI investment drivers

Common justifications for AI/ML investments appear to be multifactorial. Most respondents rate cost savings, customer requirements, labour availability, quality improvement, safety enhancement, sustainability goals and competitive pressure as very important or critical drivers in their decision-making. This mix of motivations underscores how AI adoption is shaped as much by productivity or cost efficiency as by workforce and sustainability goals.

Moreover, our results show statistically significant relationships between allocated budget levels and the perceived importance of several of these factors (Figures 11 and 12).

Figure 11

Budget allocation by perceived importance of competitive pressure as a driver of AI/ML investments

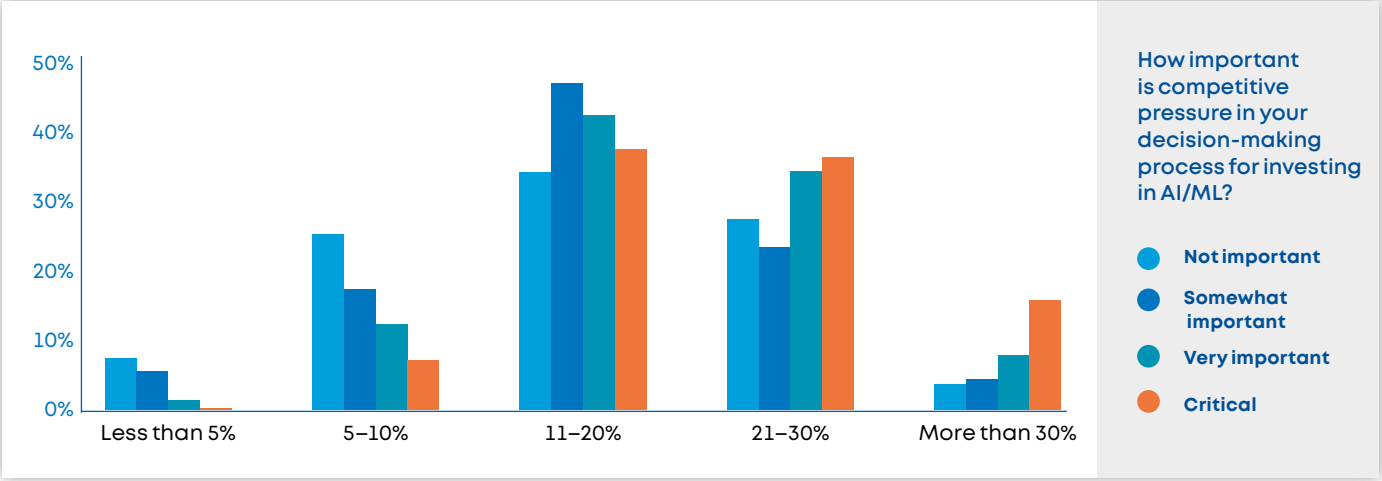
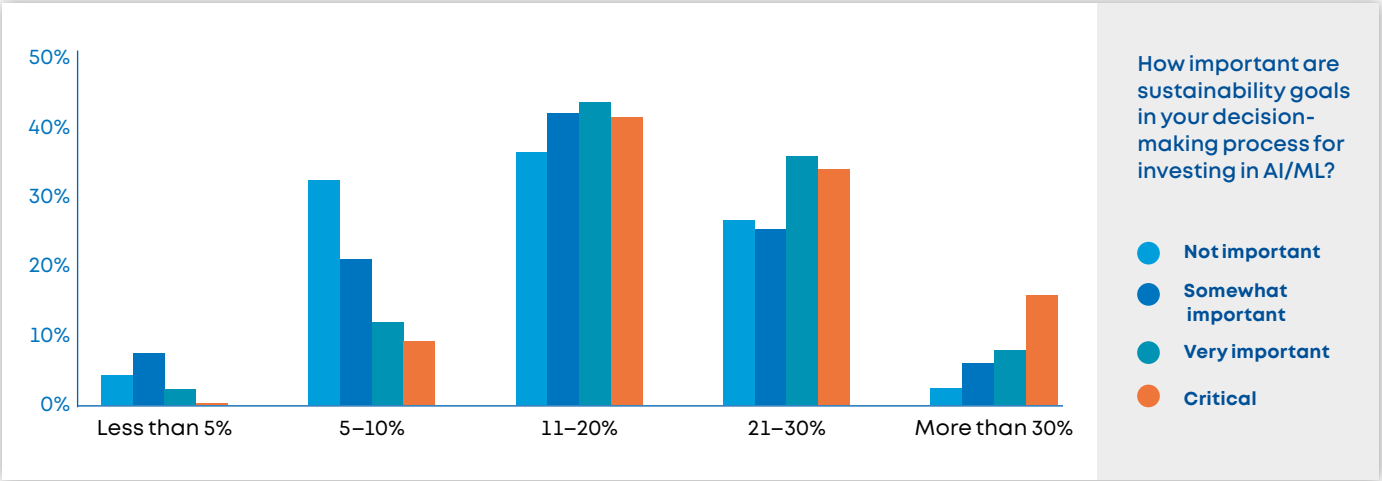


Figure 12

Budget allocation by perceived importance of sustainability goals as a driver of AI/ML investments





Payback periods reflect the scope of transformation

Expected investment payback periods vary by a company's AI/ML maturity level and other firm characteristics. Larger enterprises, higher budget commitments and multi-site warehouse networks tend to experience longer payback horizons, consistent with the greater complexity and integration scope of their transformations (Figures 13, 14, 15 and 16). For these organisations, AI is not a one-off investment. It is a long-term capability programme that requires more coordination but yields broader value once fully realised.

Smaller firms, by contrast, often benefit from faster returns because they can deploy AI solutions with less disruption.

Figure 13

Expected AI/ML investment payback periods by AI/ML maturity level

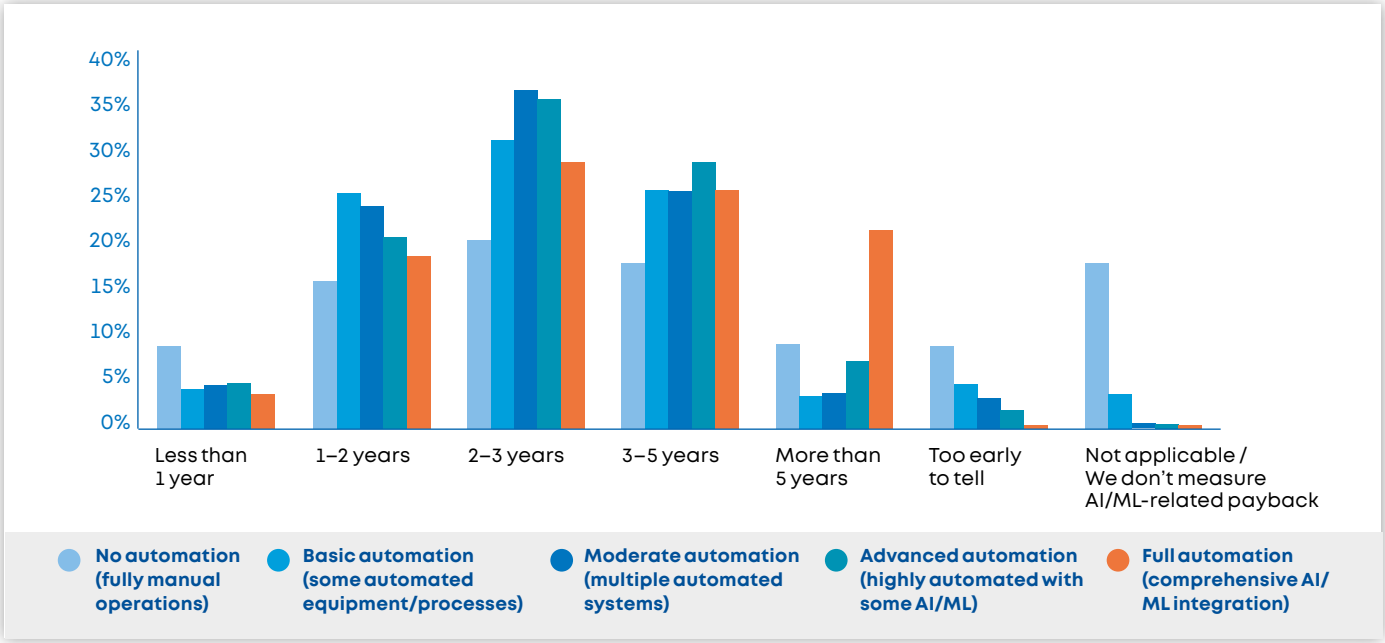


Figure 14

Expected AI/ML investment payback periods by company revenue

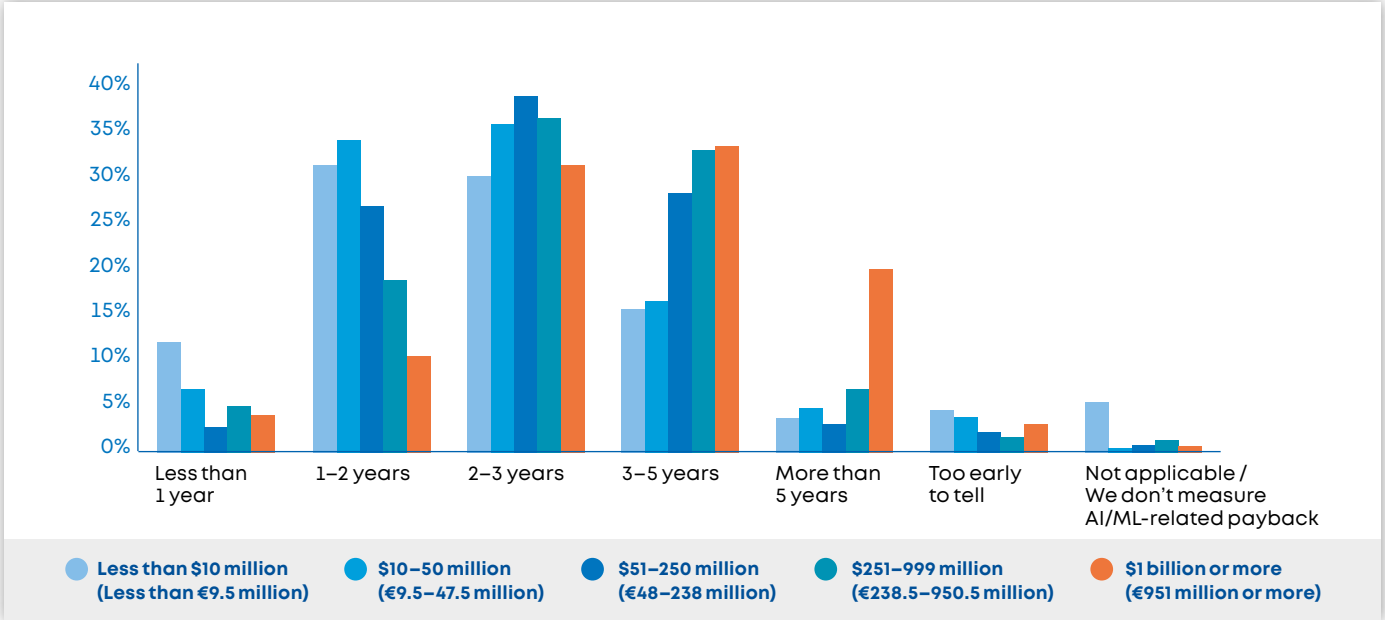
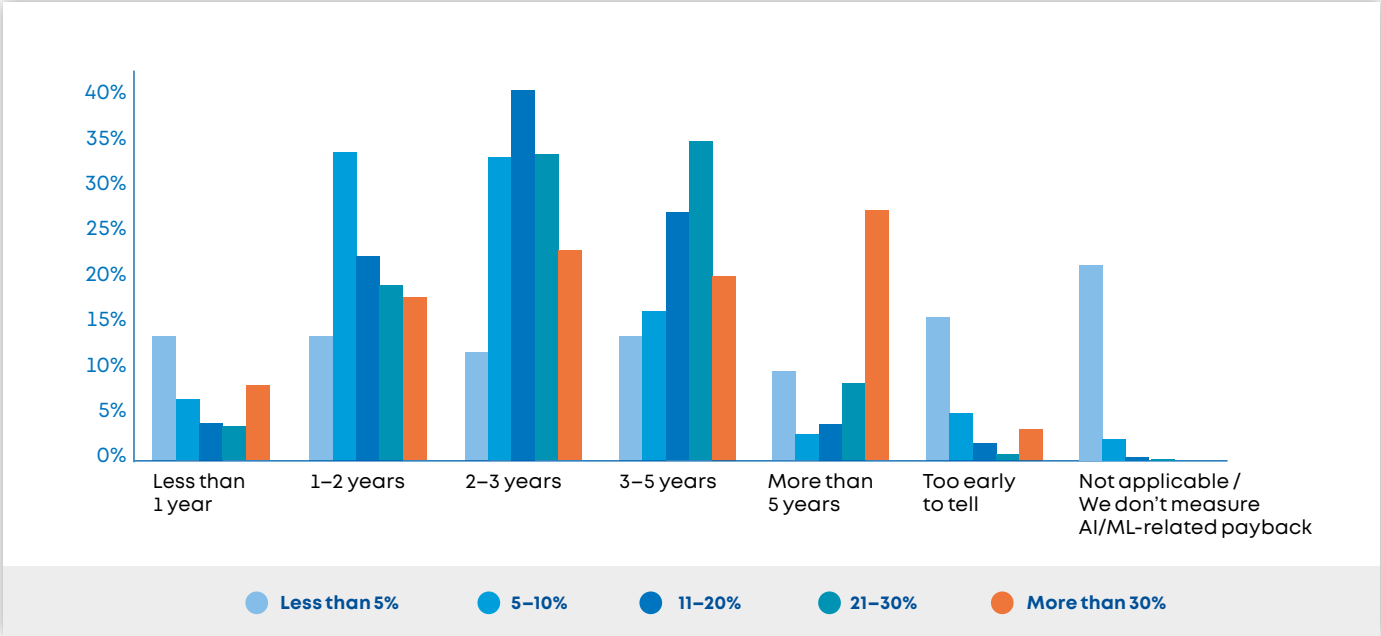


Figure 15

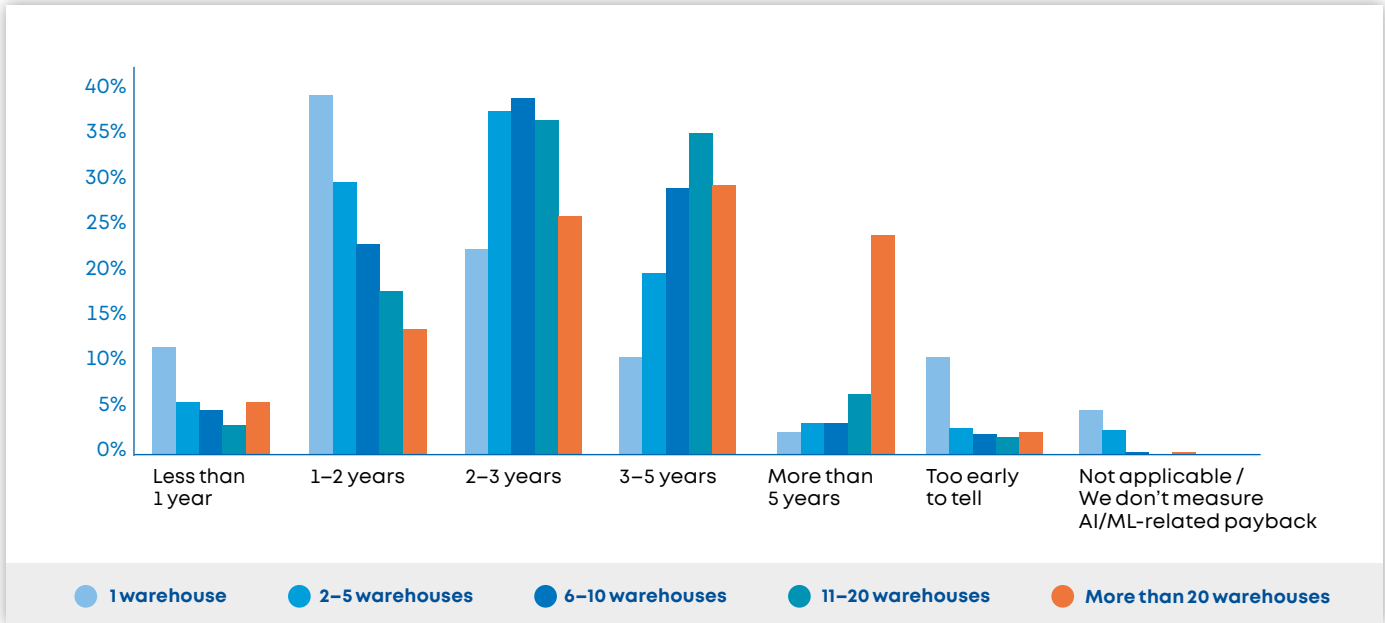
Expected AI/ML investment payback periods by AI/ML budget allocation



Smaller firms see returns sooner because AI deployment is simpler and disruption is lower

Figure 16

Expected AI/ML investment payback periods by number of warehouses in operation



Theme 3: Current AI/ML implementation challenges and enablers

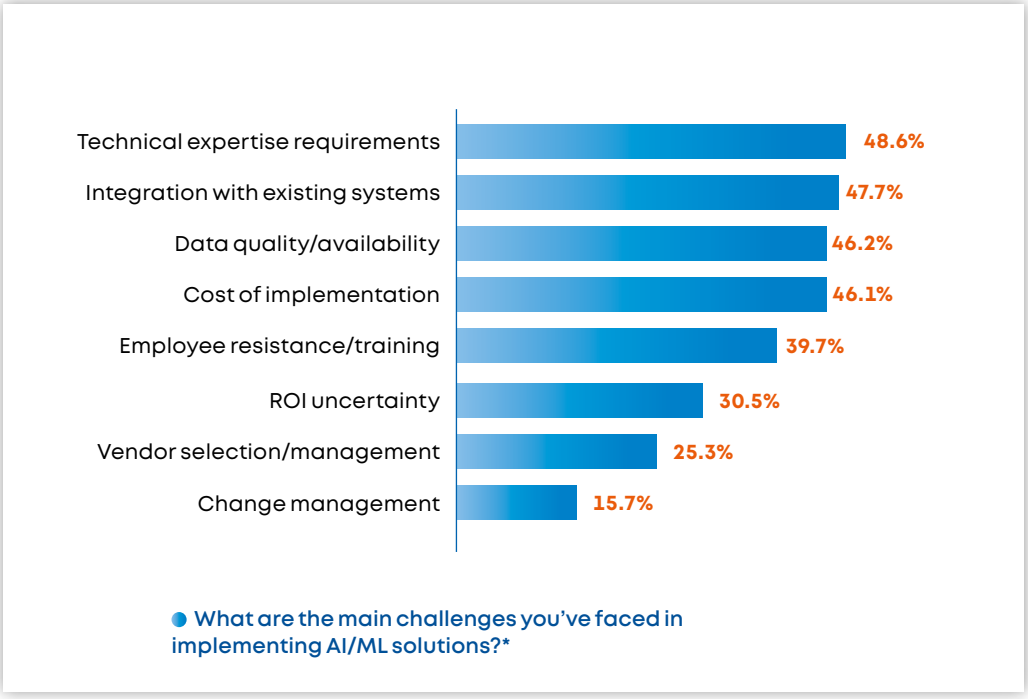
Overcoming challenges to accelerate AI adoption in warehouses

Main barriers

The main challenges to AI/ML adoption in warehouses are skills, system integration, data quality and cost — the core ingredients for any successful digital transformation. Nearly half of respondents selected technical expertise requirements (48.6%), integration with existing systems (47.7%), data quality and availability (46.2%) and cost of implementation (46.1%) among their top four challenges. These are followed by employee resistance and training (39.7%), ROI uncertainty (30.5%) and vendor selection or management issues (25.3%) (Figure 17). In simple terms, most organisations face the same problem set: connecting new tools to old systems, ensuring reliable data and developing the right in-house skills to make AI work.

Figure 17

Main barriers to AI/ML adoption



*Multiple responses allowed; results do not add up to 100%



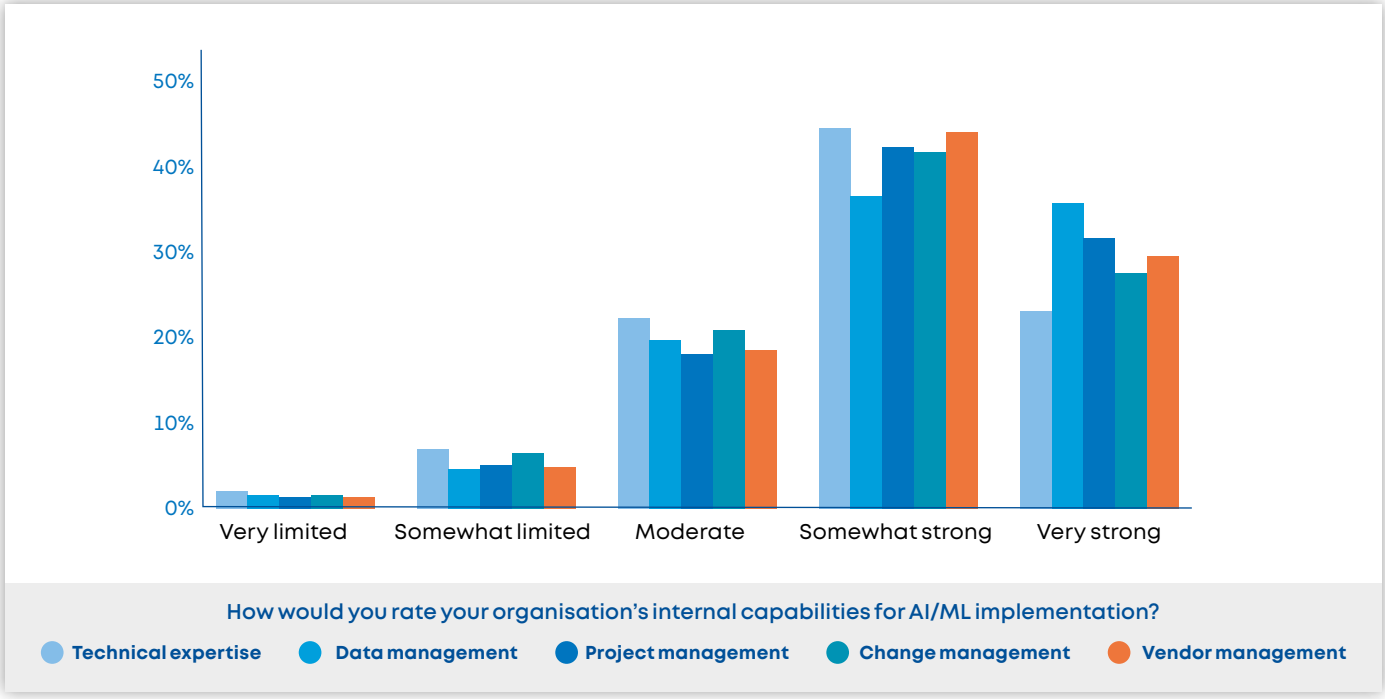
While technical depth may still be developing, companies already have solid foundations in organising projects and managing data

Internal capabilities for AI implementation

At the same time, many companies show encouraging signs of readiness. Across five internal capability areas — technical, data, project, vendor and change management — organisations report "somewhat strong" or "very strong", with "very strong" capabilities overall, and with very strong ratings in data management (36.4%) and project management (31.9%) (Figure 18). This suggests that while technical depth may still be developing, companies already have solid foundations in organising projects and managing data.

Figure 18

Assessment of internal capabilities

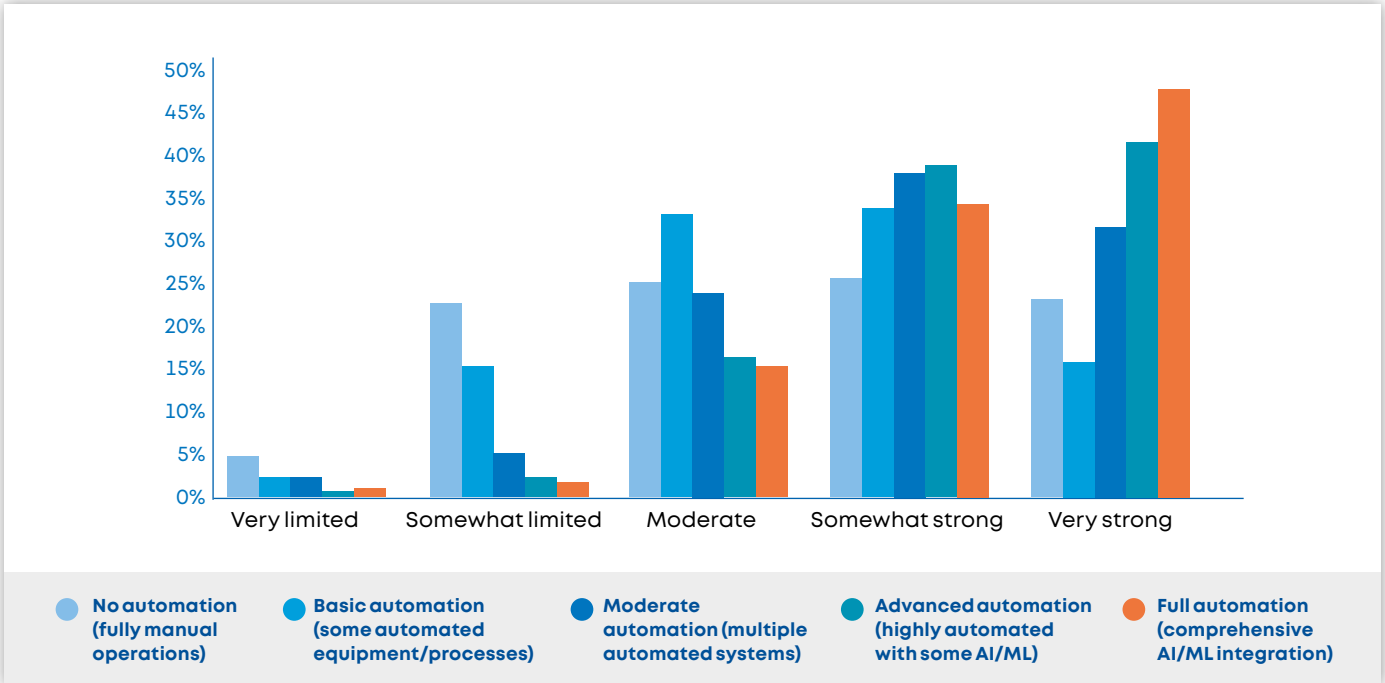




Crucially, each capability shows a statistically significant positive relationship with automation maturity, reinforcing what we call a capability-maturity flywheel (Figure 19). As businesses improve their skills and data practices, they deploy AI more effectively, and as AI deployments succeed, they strengthen internal expertise and confidence in return. For example, the share rating technical expertise as "very strong" rises from 7.5% among organisations with no automation to 35.7% among those with full automation, with similar upward trends for project, change, vendor and data management.

Figure 19

Assessment of internal capabilities by automation maturity level: technical expertise

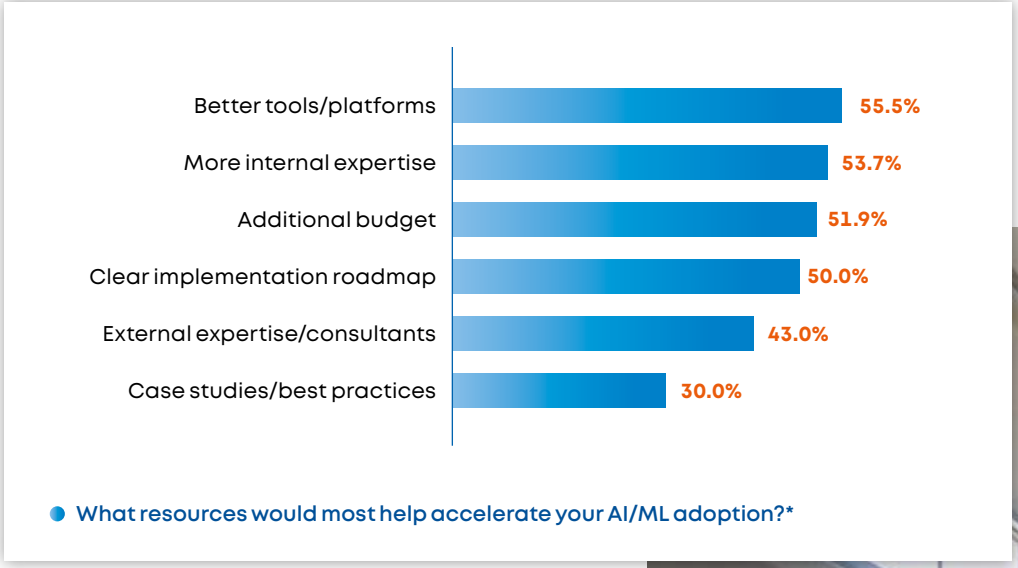


Resources to speed up AI adoption

When asked what would most accelerate adoption, respondents emphasised better tools and platforms (55.5%), more internal expertise (53.7%), additional budget (51.9%), a clear implementation roadmap (50%) and external expertise or consultants (43%) (Figure 20). These map directly to the leading obstacles and reveal a consistent playbook for progress: invest in people, simplify technology integration and plan for adoption as an ongoing process rather than a single project.

Figure 20

Enablers of accelerated adoption



*Multiple responses allowed; results do not add up to 100%

Accelerating adoption is about investing in people, simplifying systems and treating transformation as a continuous journey



Theme 4: AI/ML impact on the workforce

People at the centre of warehouse transformation

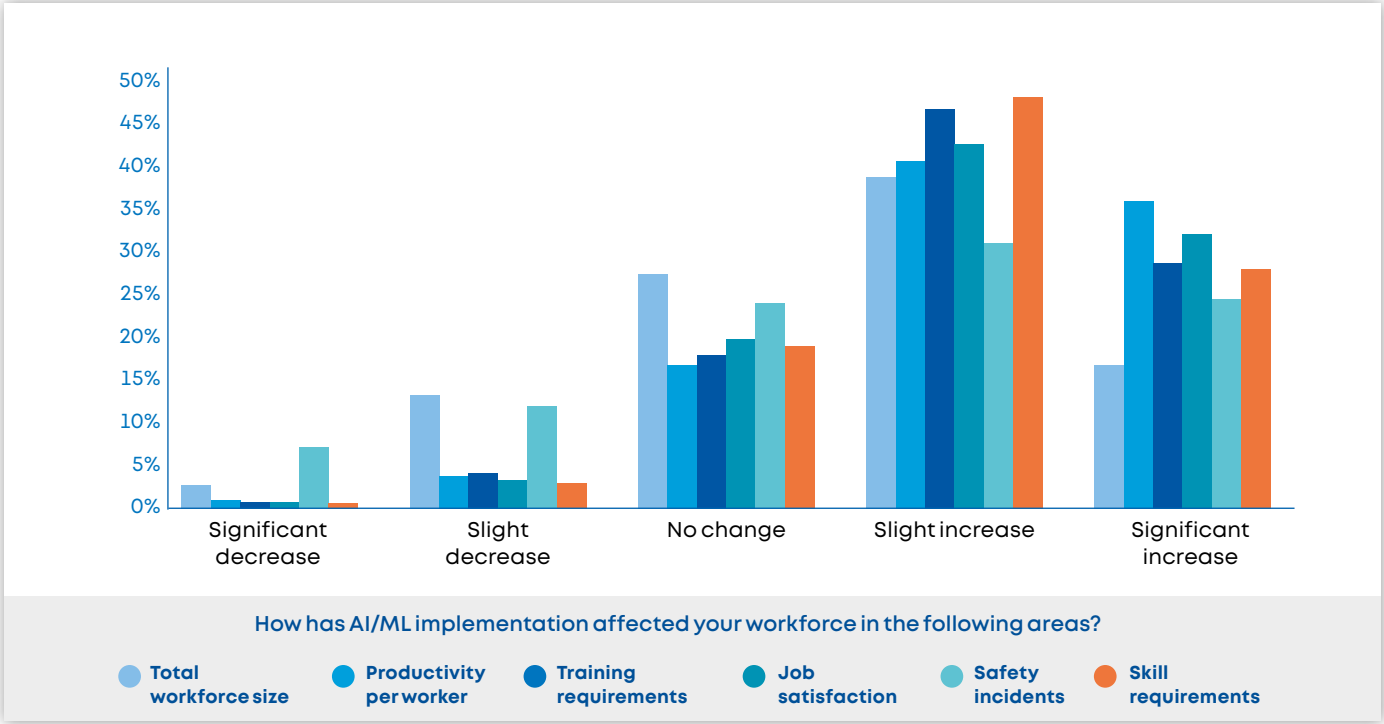
AI raises skills across the board

Organisations report mostly positive effects on their workforce from adopting AI and machine-learning technologies. Rather than reducing headcount, AI is helping employees become more productive, more satisfied and better trained. Increases outweigh decreases across all key measures, with productivity per worker up for 77.5% of companies (41% slight increase; 36.5% significant increase), job satisfaction rising for 75.4% (43% slight; 32.4% significant) and training requirements increasing for 76.4% (47.2% slight; 29.2% significant).

Even total workforce size trends upward, rising for 55.8% of businesses overall — 38.9% reporting a slight increase and 16.9% a significant one (Figure 21). These findings suggest that automation is creating complementary roles rather than displacing people, shifting human effort towards higher-value tasks that require judgement, coordination and technical oversight.

Figure 21

Workforce effects of AI/ML

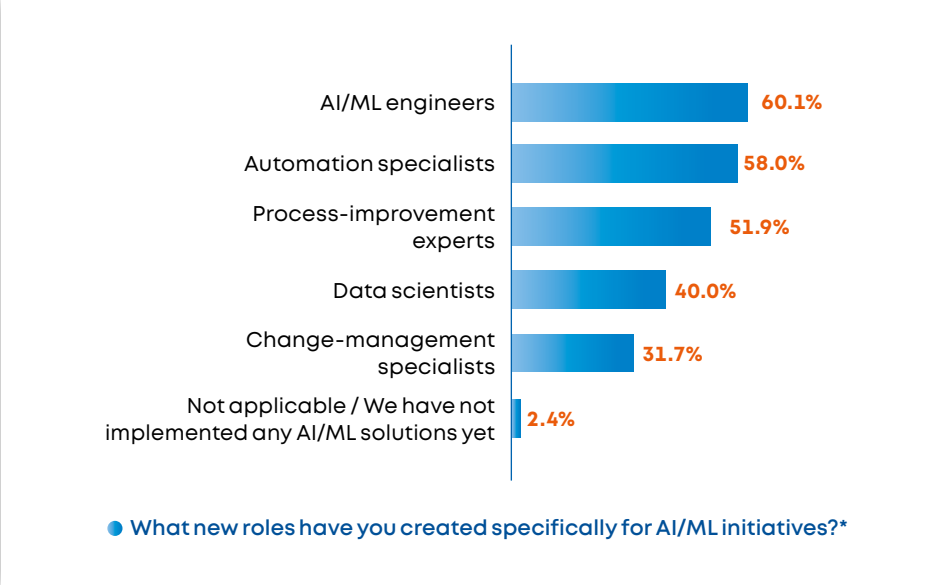


AI creates new roles

AI adoption is also reshaping job profiles inside the warehouse. As AI and machine-learning technologies become embedded in daily operations, new roles have emerged directly from this integration. Organisations most frequently created positions for AI/ML engineers (60.1%), automation specialists (58%), process-improvement experts (51.9%) and data scientists (40%) (Figure 22).

Figure 22

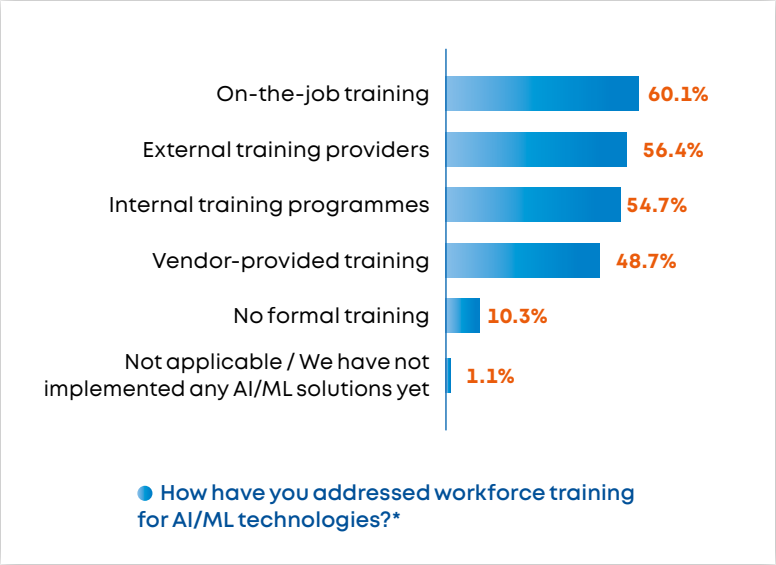
Emerging roles driven by AI/ML adoption



*Multiple responses allowed; results do not add up to 100%

Figure 23

Means of workforce training and upskilling



*Multiple responses allowed; results do not add up to 100%

Upskilling and training accompany this shift. Organisations invest actively in employee development, using a mix of on-the-job training (60.1%), external providers (56.4%), internal training programmes (54.7%) and vendor-provided training (48.7%). Only 10.3% report no formal training (Figure 23). This blended approach shows that continuous learning has become part of the warehouse operating model, helping workers adapt to automation while advancing their careers in a more data-driven environment.

Theme 5: Future AI/ML implementation outlook and priorities

The next wave: From prediction to decision

Expanding capabilities and investment

Looking ahead to the next phase of AI and machine-learning adoption, the focus is shifting from automating tasks to enabling intelligent decision-making and generative capabilities. Implementation timelines are short and active, signalling a sector that continues to evolve at high speed.

Of 2,000-plus respondents, 25.2% are currently implementing AI/ML solutions, 22.8% plan to do so within six months, 27.5% within one year and 16.6% within two years. This means that 92.1% of organisations are either deploying or preparing to deploy new AI initiatives in the near term. Only 1.7% report no current plans, while 6.2% already have extensive implementations (Figure 24).

This widespread activity is a clear indication that warehouse intelligence is becoming a strategic priority rather than a pilot programme.

Figure 24

Future timeline for AI/ML implementation

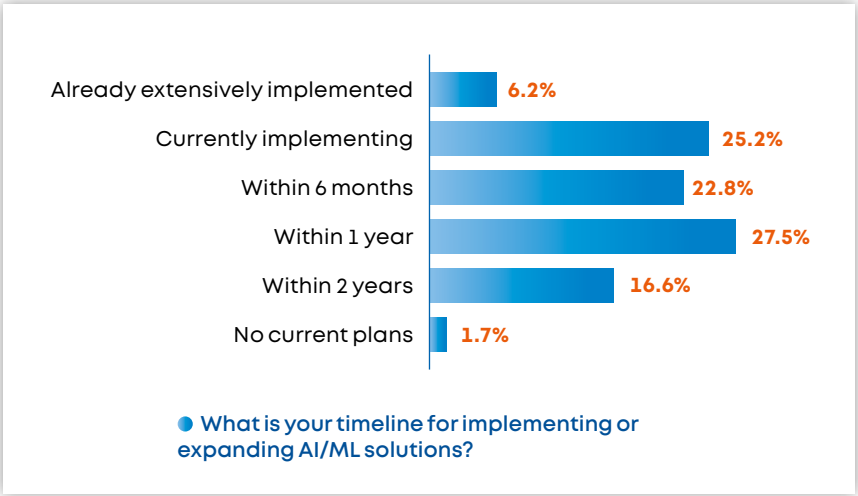
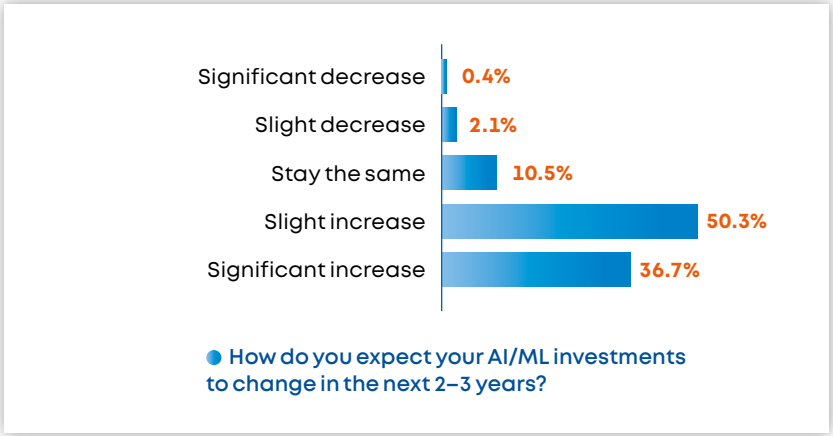


Figure 25

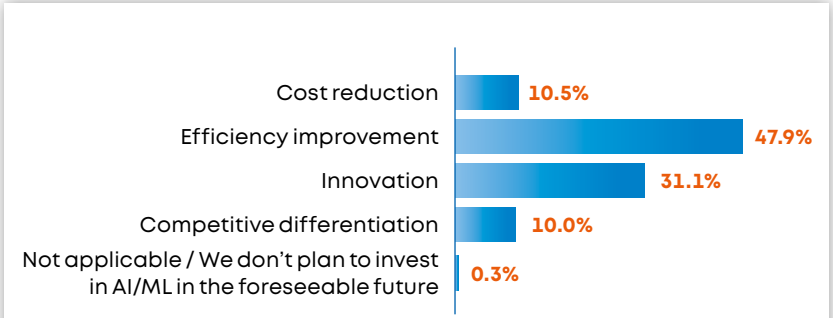
Expected change in AI/ML investments



How do you expect your AI/ML investments to change in the next 2–3 years?

Figure 26

Primary objectives of AI/ML implementation



What is your primary objective for AI/ML implementation in the next 2–3 years?

Investment levels are also set to rise. Over the next two to three years, a total of 87% of organisations plan to increase their AI/ML funding — 50.3% anticipating a slight rise and 36.7% a significant one.

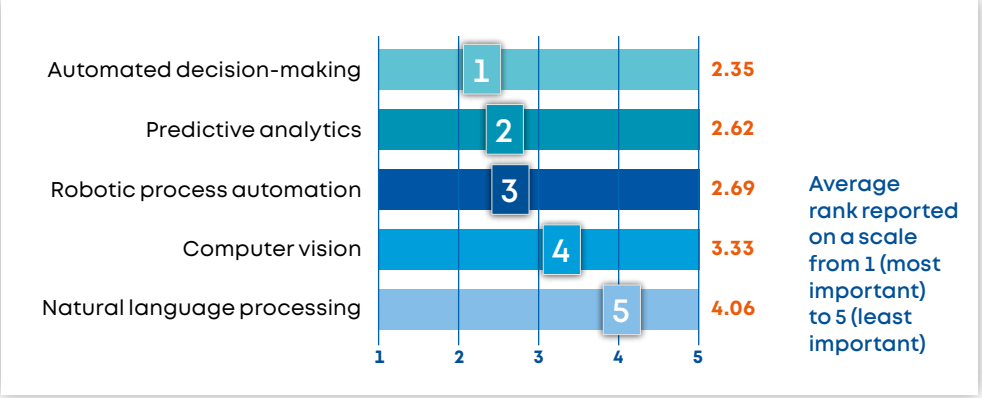
Another 10.5% expect budgets to remain steady, and only 2.5% foresee decreases (Figure 25). This strong upward trend confirms that companies are moving beyond experimentation and into long-term capability building.

The primary objective for these future investments is efficiency improvement (47.9%), followed by innovation (31.1%), with cost reduction (10.5%) and competitive differentiation (10%) as secondary aims (Figure 26). In other words, companies see AI not just as a tool for saving money but as a foundation for innovation and sustained competitiveness.

When asked which AI capabilities will have the greatest future impact, respondents ranked automated decision-making first (average rank 2.35), followed by predictive analytics (2.62), robotic process automation (2.69), computer vision (3.33) and natural language processing (4.06) (Figure 27). This ranking reflects a maturing industry focus: organisations are now looking to empower systems that can learn, recommend and even decide autonomously within controlled parameters.

Figure 27

Importance ranking of AI/ML capabilities



Theme 6: Dominant methods and technologies

From prediction to generation: How AI methods create value

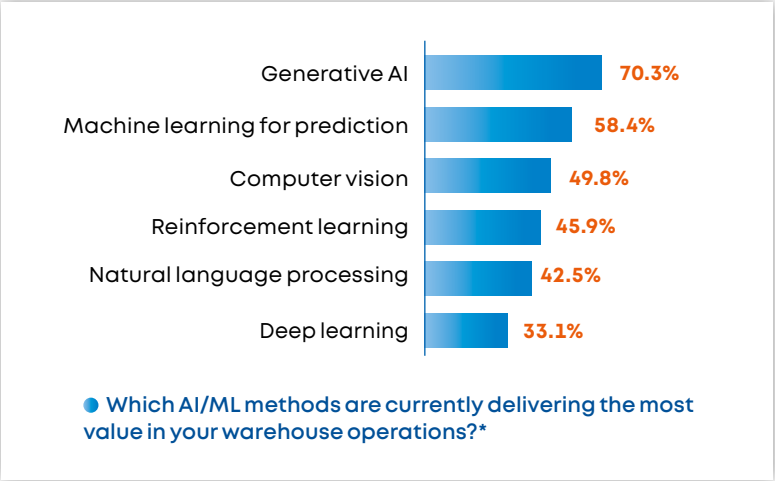
The technologies powering today's smart warehouses

Warehouses are now powered by a diverse ecosystem of AI and machine-learning methods, each serving a distinct purpose in optimising performance. Respondents identify several AI/ML techniques as delivering the greatest value today. Generative AI stands out as the leading source of impact (70.3% selected it among their top three), followed by machine learning for prediction (58.4%), computer vision (49.8%), reinforcement learning (45.9%), natural language processing (42.5%) and deep learning (33.1%) (Figure 28).

When focusing on generative AI, respondents see a wide range of promising uses that directly connect to warehouse operations. The most promising applications according to our respondents are automated documentation and reporting (55%), warehouse-layout optimisation (53.6%), process-flow design (53.3%), code generation for automation systems (52.5%), natural language interfaces (39.3%) and scenario planning and simulation (32.3%) (Figure 29). These results show that generative tools are not limited to creative tasks — they are already helping engineers and managers streamline complex processes, reduce administrative workload and accelerate system configuration.

Figure 28

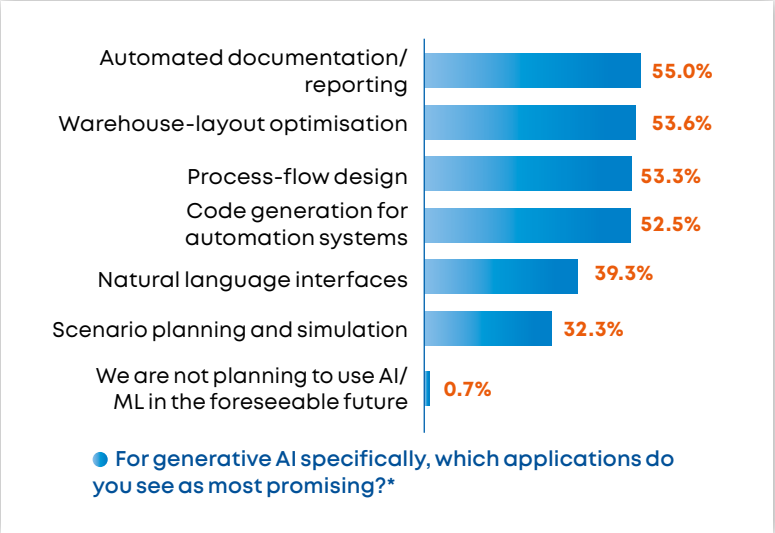
Current perceived value by AI/ML technology



*Each respondent could choose three answers

Figure 29

High-impact applications of generative AI



*Multiple responses allowed; results do not add up to 100%

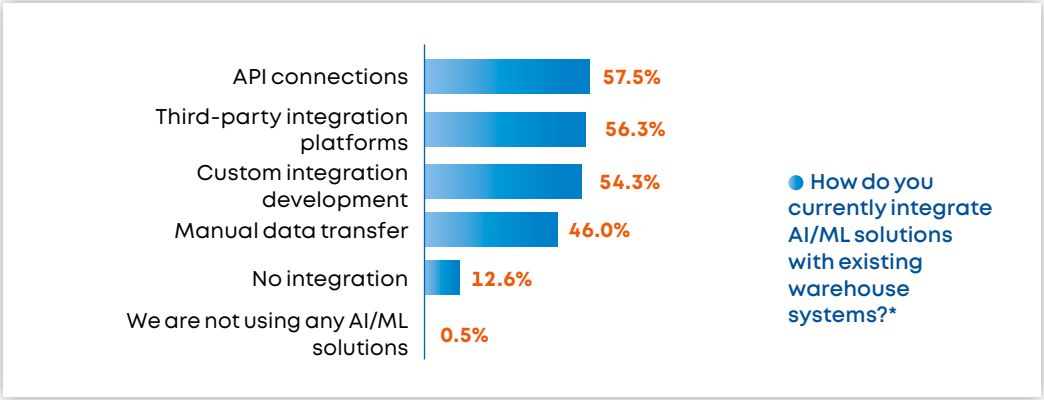
Integration: The foundation of effective AI

Integration and data foundations are critical for realising the full potential of these technologies. Most organisations rely on API connections (57.5%), third-party integration platforms (56.3%) and custom development (54.3%) to connect AI tools with existing systems. Yet nearly half (46%) still depend on manual data transfers, and 12.6% report no integration at all, showing that many companies are still bridging the gap between advanced algorithms and legacy infrastructure (Figure 30).

On the data side, the warehouse management system (WMS) remains the primary source of information (67.7%), followed by enterprise resource planning (ERP) systems (61.2%) and IoT sensors (51.8%). Manual data entry (39.1%) and third-party data sources (25.5%) are also common (Figure 31). This mix underlines both the progress and the challenge: AI needs consistent, high-quality data flows to perform at its best, and many organisations are still in the process of modernising those pipelines.

Figure 30

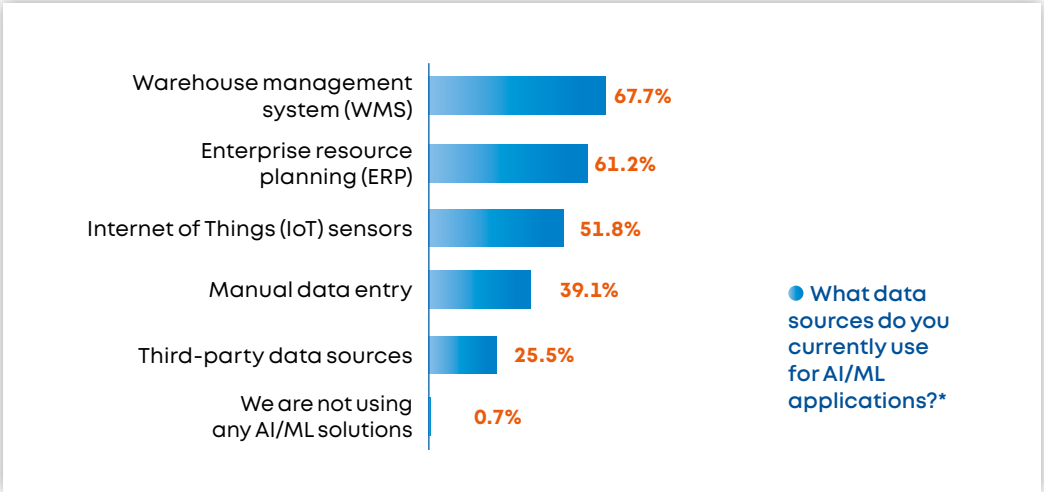
AI/ML integration with existing software



*Multiple responses allowed; results do not add up to 100%

Figure 31

AI/ML data sources



*Multiple responses allowed; results do not add up to 100%

Synthesis across themes

Key insights and implications for AI in warehousing



A closed loop between deployment, measurement, effectiveness and payback

What organisations choose to deploy is precisely what they measure — and where they see returns. The most widely implemented capabilities — inventory optimisation (61.7%), automated picking (56.4%), route optimisation (55.5%), demand forecasting (51.7%), predictive maintenance (48.4%) and computer vision (46.5%) — line up almost one-for-one with the top ROI metrics tracked: inventory optimisation (63.1%), improved throughput (57.6%), labour-cost reduction (52.1%), error reduction (48.9%) and energy savings (47.6%) (Theme 1, Figure 7; Theme 2, Figure 10).

At higher automation maturity, respondents are more likely to rate these technologies "very effective" (e.g. 56.5% for inventory optimisation; 59.7% for route optimisation). This, in turn, explains why payback periods cluster at two to three years (34.7%), with the bulk of remaining cases at one to two (22%) and three to five years (27.3%) (Theme 2, Figure 9). Put differently: the sector invests in operational workhorses, measures the outcomes those workhorses improve, sees strong effectiveness at advanced maturity and realises paybacks on a cadence consistent with that performance.

Scale is an amplifier — and a challenge

Larger firms and multi-site networks are over-represented among respondents reporting full automation and high AI/ML penetration across processes (Theme 1, Figures 4, 5 and 6). The same scale, however, tends to lengthen time-to-value: longer payback windows are more common among organisations with larger budgets directed to AI/ML, higher revenues, more sites or higher maturity (Theme 2, Figures 13, 14, 15 and 16).

This reflects the real challenge of connecting AI and automation systems to warehouse management, ERP and control platforms across multiple sites, as well as the added complexity of managing change at that scale. In practice, scale increases both the potential rewards and the complexity. Larger operations can capture more value by automating more processes, but they also face tougher coordination and governance challenges, which is reflected in longer payback periods.

As teams build skills, projects run smoother — and every success fuels the next round of investment



Capabilities drive maturity, which drives effectiveness: The flywheel dynamic

Organisations rating their technical, data, project, vendor and change-management capabilities as strong are also the ones furthest along the maturity curve (Theme 3, Figures 18 and 19). For example, the share of organisations rating their technical expertise as "very strong" climbs sharply from those with no automation to those operating at full automation.

These same organisations also report higher technology effectiveness (Theme 1), which in turn supports shorter payback periods (Theme 2). The pattern works like a flywheel: as teams build skills, deployments run more smoothly; smoother deployments drive stronger performance; and stronger performance leads to more confidence and budget for the next wave. That leaders most often call for "better tools and platforms", "more internal expertise" and "a clear roadmap" (Theme 3, Figure 20) simply makes the causal levers explicit: capability building is the flywheel's first gear.



Generative AI is already practical because it shortens the path from intent to action

Respondents rank automated decision-making first and predictive analytics second for expected future impact (average ranks 2.35 and 2.62), while also placing generative AI at the top of "most valuable methods today" (selected by 70.3%) (Theme 5, Figure 27; Theme 6, Figure 28). The specific GenAI use cases viewed as most promising — automated documentation and reporting (55%), warehouse-layout optimisation (53.6%), process-flow design (53.3%) and code generation (52.5%) — sit at the core of daily operations, where configuration and change management often slow the pace of value realisation (Theme 6, Figure 29).

Combined with the sector's dominant integration patterns (APIs 57.5%, iPaaS 56.3%, custom development 54.3%) and a solid data backbone (WMS 67.7%, ERP 61.2%, IoT 51.8%), GenAI acts as an accelerant on top of predictive systems, reducing the latency between a performance insight and a safe, automated decision (Theme 6, Figures 30 and 31; Theme 5, Figure 27).

People strategy is the hinge between intent and outcomes

The workforce data challenge the idea that automation simply replaces people. Increases in productivity per worker (77.5% overall), job satisfaction (75.4%) and training activity (76.4%) occur alongside workforce growth (55.8%) (Theme 4, Figure 21). Rather than reducing headcount, AI adoption appears to be creating new opportunities and higher-skill work.

Organisations are staffing to match their ambition, creating new roles such as AI/ML engineers (60.1%), automation specialists (58%) and process-improvement experts (51.9%), and supporting them through a mix of blended training (on-the-job 60.1%, external 56.4%, internal 54.7% and vendor 48.7%) (Theme 4, Figures 22 and 23). The implication is straightforward: companies getting the most from AI/ML are those that treat talent development as a core element of their AI strategy, not as an afterthought.



Momentum is durable — and near-term

AI adoption in warehousing continues to accelerate, and the pace shows no signs of slowing. Eighty-three percent of respondents increased AI/ML usage over the past year (Theme 1, Figure 3). Looking ahead, 25.2% are currently implementing new solutions, 22.8% plan to do so within six months and 27.5% within one year; only 1.7% report no current plans, while 6.2% already have extensive implementations (Theme 5, Figure 24).

Investment intent reinforces this trajectory: 87% of organisations expect to increase AI/ML budgets over the next two to three years — 50.3% slightly and 36.7% significantly (Theme 5, Figure 25). This alignment between recent momentum, active projects and planned funding suggests that adoption will continue to accelerate — especially as stronger internal capabilities and faster configuration through generative AI reduce the effort required to scale.

Implications for programme design

For single-site operations or smaller networks, the data point to starting with near-term wins — areas where effectiveness is already high — such as inventory optimisation and route or pick automation. These efforts should be paired with clear performance tracking around inventory accuracy, throughput, labour efficiency and quality — the same metrics most organisations already use (Theme 1, Figure 7; Theme 2, Figure 10).

For larger, multi-site enterprises, it pays to design for integration at scale from the beginning and to plan for longer payback periods. The data show that complexity extends the timeline for returns, but it also broadens the overall value potential (Theme 2, Figures 13, 14, 15 and 16).

In all cases, build internal capability as a core workstream (Theme 3), combine predictive and optimisation tools with generative AI to speed up change cycles (Themes 5–6) and keep investing in people and training that convert technology potential into operational performance (Theme 4).

Recommendations



Use generative AI where it eliminates time-consuming tasks

Grounded in our cross-theme findings — what organisations deploy, how they measure value and where they see effectiveness — the following recommendations focus on actions most likely to accelerate impact in real warehouse settings.

1. Focus your next 3–6 months on what already works

Start with the value drivers the data consistently support: inventory accuracy and availability, throughput, labour efficiency, first-time-right quality and energy use. These are the metrics most widely tracked and directly tied to the most effective AI capabilities (Theme 1 – Q2/Q3/Q4; Theme 2 – Q2/Q3).

Plan for a two- to three-year payback, with 6–9-month checkpoints to verify progress and build confidence across teams.

2. Treat data and system connections as core work, not an afterthought

Data quality and integration remain among the top barriers to AI success (Theme 6 – Q3/Q4; Theme 3 – Q1).

Most warehouse AI relies on data from WMS, ERP and sensors, typically connected through APIs or integration platforms. Make that data "plumbing" simple and consistent:

- Agree on shared definitions (SKU, location, order, task, equipment).
- Standardise event feeds across sites.
- Replace manual file drops with automated feeds.
- Set clear rules for each feed (frequency, handling duplicates/changes, who approves updates).
- Keep a basic dashboard that shows whether data is timely and complete.

3. Build the "capability flywheel" on purpose

The data show that stronger internal capabilities lead to higher maturity and higher effectiveness, and organisations explicitly ask for better tools, more expertise and clear roadmaps to accelerate adoption (Theme 3 – Q2/Q3).

Set up a small, cross-functional core team (operations lead + data/ML engineer + WMS/WES specialist + change manager).

Define a few clear roles (automation specialist, process-improvement lead) and blend vendor enablement with hands-on training on the warehouse floor.

Baseline each site's current skill level and invest in people development alongside technology deployment.

4. Use generative AI where it speeds up set-up and change

Generative AI is already proving highly valuable in warehouse operations. Its top use cases include documentation, layout and process design and code generation, while leaders identify automated decision-making as the next major frontier — turning insight into action faster (Theme 6 – Q1/Q2; Theme 5 – Q2/Q4).

Use GenAI where it eliminates time-consuming tasks: drafting SOPs and reports, suggesting warehouse-layout or slotting improvements, mapping processes or generating small bits of code or configuration for WMS/WES integrations. Connect it to existing analytics so forecasts and exception patterns automatically generate ready-to-review drafts, always with a person approving before anything goes live.





Put basic safeguards in from day one: ground responses in your documents/data, keep an audit trail, require approvals and check outputs against safety, labour and service-level rules.

5. Sequence by footprint and complexity

Larger or multi-site operations typically show higher penetration and maturity but also face longer payback periods, mainly due to the complexity of integration and the broader scope of change. Most organisations, however, still plan implementations within 6–12 months, showing that near-term action and long-term planning can coexist (Themes 1–2 – maturity/effectiveness/payback; Theme 5 – Q1).

For multi-site enterprises, design for scale from the start (with shared data standards, reusable integrations and repeatable deployment playbooks) and expect longer returns in exchange for broader impact.

For single-site or smaller networks, focus on fast-cycle wins such as inventory optimisation, routing and picking improvements or targeted computer vision pilots. Capture early savings, demonstrate success and reinvest to build capability for the next phase.

Cross-sectional analysis

Regional nuances and differences

The state of warehouse automation across countries

The cross-country results show a global market that is already well beyond the pilot stage and into everyday use, but at different speeds. Most respondents report advanced automation, meaning that many warehouses have already adopted a broad range of automated systems in their daily work. A smaller but visible group have reached full automation, where technology is deeply embedded across all processes. Several countries lead the way with high maturity and strong AI integration, while others are making steady progress or facing specific barriers to scaling up.

AI/ML maturity and adoption levels

Country	AI/ML maturity score (1–5)	Degree of AI/ML adoption			Share of AI/ML penetration
		Advanced	Full	Advanced or full adoption	
Leaders					
Brazil	3.86	46%	19%	65%	51%
Sweden	3.82	**82%***	0%	82%	57%
Canada	3.82	42%	17%	60%	44%
UK	3.74	46%	15%	61%	48%
China	3.71	50%	13%	63%	53%
Israel	3.67	56%	11%	67%	49%
Strong followers					
Mexico	3.73	33%	19%	52%	47%
Germany	3.68	39%	18%	57%	47%
France	3.55	41%	12%	53%	50%
Italy	3.52	**52%***	5%	57%	42%
Czech Republic	3.44	**55%***	0%	55%	39%
Mid-pack					
Poland	3.71	**31%***	8%	39%	49%
US	3.50	37%	12%	49%	47%
Australia	3.41	**41%***	3%	44%	41%
Netherlands	3.24	**46%***	0%	46%	43%
Low end					
Spain	3.42	26%	11%	37%	42%
Argentina	3.37	26%	11%	37%	46%
Belgium	3.22	32%	5%	37%	38%
Romania	3.05	12%	2%	14%	35%
Japan	2.91	24%	7%	30%	41%
Portugal	2.86	10%	0%	10%	40%

*** Plateauing at advanced automation**

Leaders and close followers

Several countries are past pilots and running advanced automation at scale. Brazil leads, posting the highest average warehouse automation maturity score (3.86 on a 1–5 scale), with roughly 65% of sites at advanced or full automation and about 19% already fully automated. Israel on the other hand reports 67% of advanced or full automation (11% Full), while its warehouse automation maturity score is slightly lower at 3.67. China (3.71; 63% Advanced or full; 13% Full), the UK (3.74; 61%; 15% Full) and Canada (3.82; 60%; 17% Full) exhibit a similar profile: broad adoption of advanced systems and a meaningful share of operations already using AI and machine learning with a non-trivial full-integration tail.

A strong second tier includes Germany (3.68; 57%; 18% Full), Italy (3.52; 57%; 5% Full), the Czech Republic (3.44; 55%; 0% Full), France (3.55; 53%; 12% Full) and Mexico (3.73; 52%; 19% Full).

The US (3.50; 49%; 12% Full) — one of the largest national samples — shows many highly automated sites, but a large group of moderately automated facilities brings down the average despite strong adoption overall.

Similarly, the Netherlands (3.24; 46%; 0% Full) sits mid-pack, followed by Australia (3.41; 44%; 3% Full). Poland (3.71; 39%; 8% Full) is mid-lower despite its relatively high maturity score.



Plateau at advanced automation

A distinct set of markets appears to be capped at advanced rather than full automation. Most notably, Sweden (82% Advanced; 0% Full), the Czech Republic (55%; 0%) and the Netherlands (46%; 0%) each report a significant share of advanced automation, but have not crossed into fully integrated, end-to-end decisioning.

Similarly, markets such as Poland, Italy and Australia report disproportionally small shares of full automation compared to their combined share of advanced and full automation. This plateau points to limitations beyond technology-specific point capabilities or equipment. The key constraint appears to be the tougher task of connecting data and decisions across processes so AI/ML can operate coherently across receiving, storage, picking and dispatch. Where organisations have not yet industrialised integration and governance, they remain highly automated in parts of the operation without reaching end-to-end intelligence.

Lower maturity

At the lower end of the distribution, Spain (3.42; 37%; 11% Full), Argentina (3.37; 37%; 11% Full) and Belgium (3.22; 37%; 5% Full) show mixed adoption, while Japan (2.91; 30%; 7% Full), Romania (3.05; 14%; 2% Full) and Portugal (2.86; 10%; 0% Full) show thicker basic/none tails and a heavier moderate automation middle.

Mexico (52%; 19% Full) and Argentina (37%; 11% Full) illustrate Latin America's breadth: Mexico resembles the leaders with a substantial full automation tail, while Argentina is more bimodal, with sizeable advanced and even full automation segments and basic/none segments coexisting. Spain exhibits a similarly bimodal structure.

In Japan's case, healthy moderate and advanced shares paired with a comparatively large basic/none segment point to uneven diffusion across facilities rather than a lack of technical capability per se.



Key takeaways

Two notes to keep in mind when interpreting the results for decision-making:

• **Country sample sizes vary and were weighted in proportion to each country's gross domestic product (GDP)**. China (n=660) and the US (n=542) provide stable estimates, while several smaller markets with n≈20–35 show results that should be viewed as directional rather than precise indicators (e.g. Sweden).

• **The differences between countries point to a shared transition challenge**: moving from advanced to fully integrated automation is less about adding more machines and more about connecting data, systems and people effectively.

Countries that appear to have plateaued at the advanced automation level are likely wrestling with systems integration, data quality/readiness and workforce enablement — the prerequisites needed to scale AI/ML beyond isolated use cases.

In practical terms, the fastest path up the curve is to strengthen digital connections (APIs/iPaaS into WMS/ERP/WES), standardise data around core warehouses and build processes that keep humans in the loop. When these foundations are strong, full automation rises; when they are not, adoption levels flatten at advanced despite solid technology in place.

Taken together, the outlook is encouraging for the next planning cycle. Leaders already operate with high levels of automation and a growing full segment (Brazil, China, UK, Canada, Germany, Mexico, France, US). The mid-pack countries have substantial "advanced" penetration and a clear path forward once integration and data constraints are addressed. Markets showing an advanced ceiling (Sweden, Czech Republic, Netherlands) should focus on building integration and data readiness to reach the next stage to Full. Countries in the lower tier (Japan, Portugal, Romania) should first reduce variability across sites and strengthen core integration, data quality and change-management capabilities that will support step-changes in maturity over the next two to three years.

For portfolio prioritisation, this argues for differentiated plays:

Full-ready leaders	Last mile to full	Mid-pack with uneven depth	Foundations first
Scale and saturate	**Advanced ceiling**	**Raise penetration and consistency**	**Reduce variability, build capability**
Focus: • Convert large advanced automation footprints into full automation by standardising WMS/ERP/WES orchestration, hardening APIs/iPaaS and scaling proven AI/ML applications (e.g. forecasting, slotting, orchestration) across sites. • Prioritise network-wide playbooks, shared data products and human-in-the-loop governance to push facilities from the 51–75% penetration band to 76–100%.	**Focus:** • Move from individual automated processes to coordinated, end-to-end decision-making. Rationalise vendors, close integration gaps between automation islands, uplift data quality/observability and formalise change controls. • Target outcome: lift Full by 10–15 points without materially increasing hardware footprint.	**Focus:** • Move sites from 26–50% to 51–75% penetration via API-first integrations to WMS/ERP, master-data clean-up and targeted capability building (ops engineering, data ops). • Use lighthouse sites to codify reusable SOPs and accelerate replication.	**Focus:** • Shrink basic/none tails and establish the integration/data baseline (device connectivity, telemetry standards, canonical data models, identity/permissions). • Pair with workforce enablement and a sequenced pilot roadmap that proves ROI, then ramp budgets towards the 11–20% and 21–30% bands as wins accrue.

The leap to full automation depends less on hardware and more on how well data, systems and people work together

How to operationalise this across portfolios

Start with integration and data foundations (short-term value), then expand into AI-driven decision orchestration (scaling phase) and finally focus on governance and continuous improvement (long-term sustainability).

Where full automation is already gaining traction (e.g. Brazil, Mexico, Germany, Canada, UK, China, France, US, Israel), emphasise rapid rollout and cross-site standardisation.

Where advanced automation has plateaued (e.g. Czech Republic, Netherlands, Australia, Sweden), prioritise integration and data cohesion.

Where foundations are weakest (e.g. Japan, Romania, Portugal), focus first on reducing variability and strengthening core capabilities before scaling AI/ML further.

How widely AI is used tracks closely with overall automation

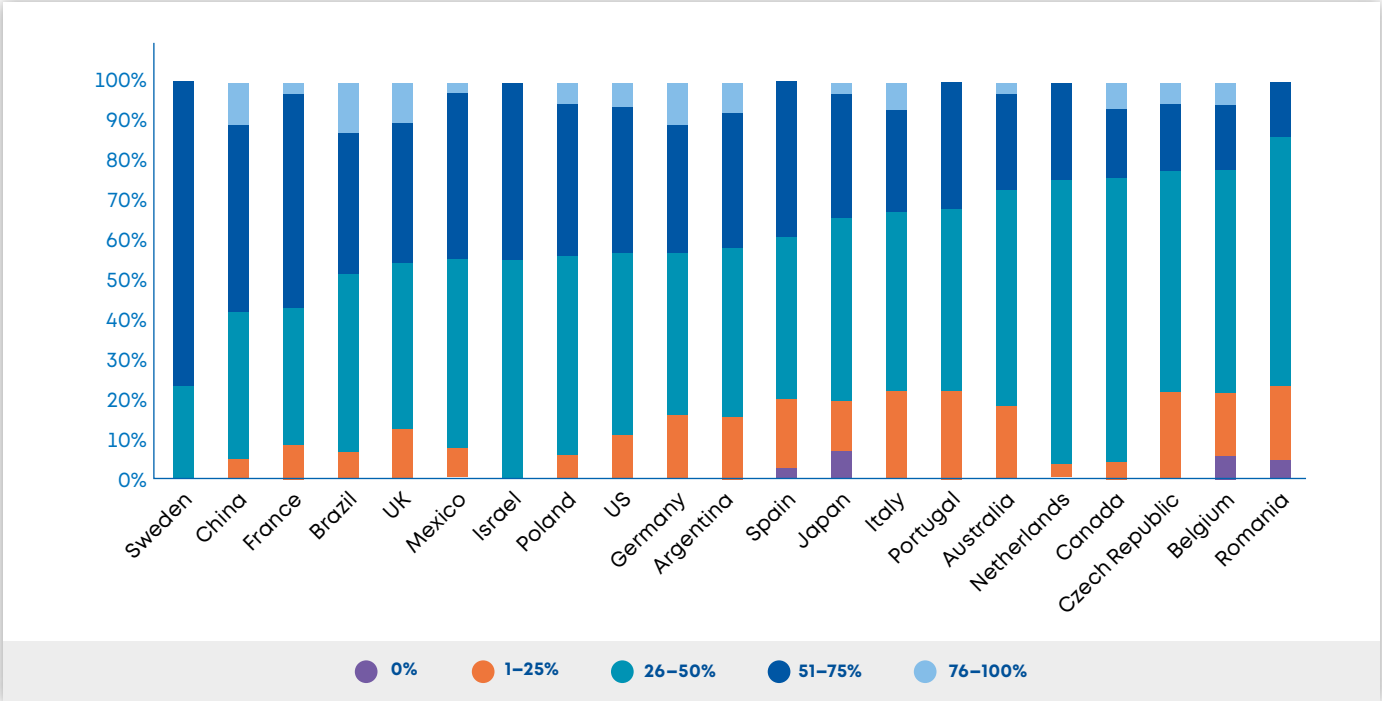
Beyond overall automation levels, the data also show a clear connection between how automated warehouses are and how extensively they use AI and machine-learning technologies in day-to-day operations (Figures 32 and 33).

China, Brazil, the UK, Canada, Germany and France lead in AI adoption, mirroring their positions among the most automated countries. Portugal, Romania and Japan form a lower tier, with Spain, Belgium and Argentina also below the median; Australia and the Netherlands are mid-range, and the Czech Republic is advanced but not yet fully automated.

The pattern is revealing: in most countries, the majority of warehouses use AI in roughly one-quarter to three-quarters of their processes (26–75%), with only a small number reporting near-total use (76–100%). In short, AI is now part of many warehouse workflows, but full integration across all operations remains uncommon — matching the "advanced-but-not-full" stage seen in the maturity data.

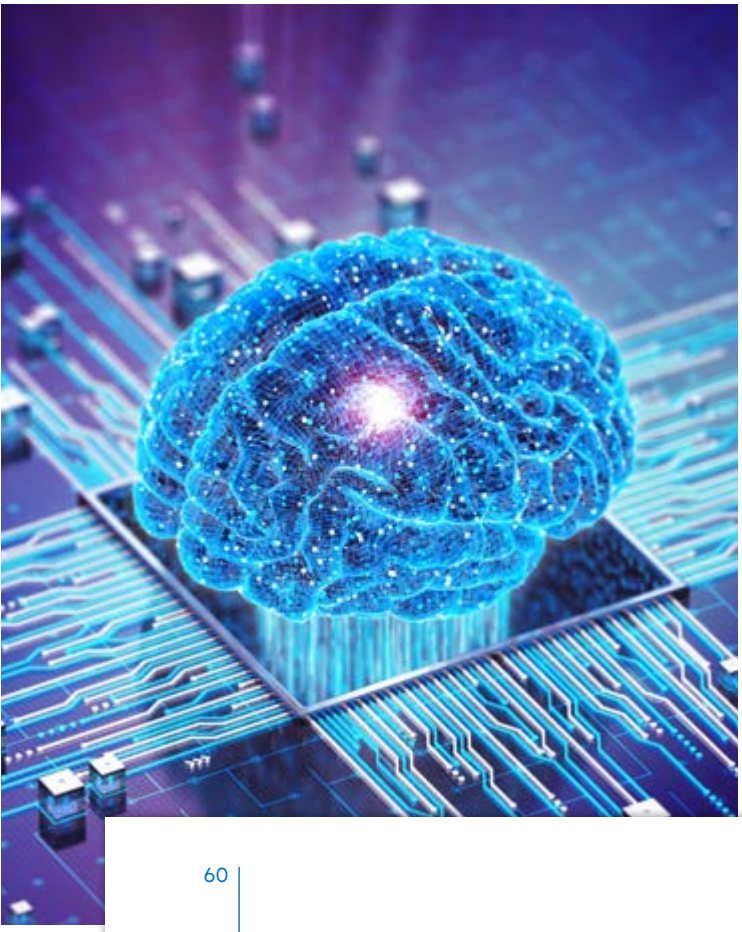
Figure 32

AI/ML penetration by country



The differences between countries are especially useful for action. Canada and Italy perform better than expected for their current level of AI use, suggesting they are getting strong results thanks to solid mechanisation, process discipline and well-coordinated operations even before AI is fully deployed (Figure 33). The Czech Republic shows an advanced-but-not-full plateau — strong point solutions that have not yet translated into end-to-end integration.

By contrast, Japan, Portugal and Argentina are progressing more slowly, showing lower automation maturity for how much AI they use. This points to integration and change-management barriers: many have AI pilots or mid-scale projects that are not yet producing consistent, system-wide impact.



Practically, the playbook is country-specific:

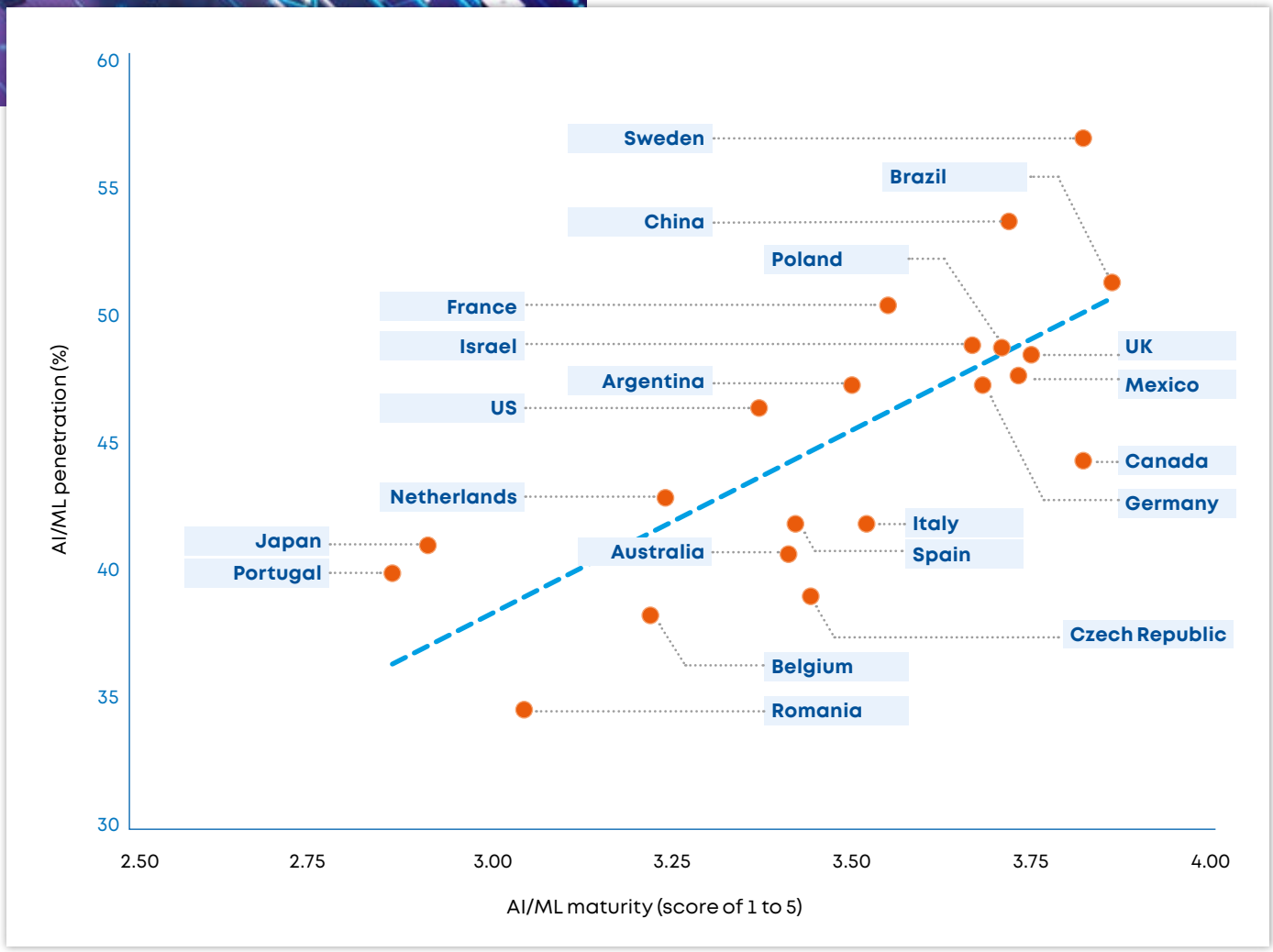
• **High-AI users** such as China, Brazil, the UK, Canada, Germany and France should focus on taking warehouses that use AI in roughly half of their processes (51–75%) and bringing them closer to full integration (76–100%) by strengthening WMS/WES integrations and standardising data.

• **Mid-range markets** (US, Mexico, Australia, Netherlands, Spain, Poland, Argentina, Belgium), where about 26–50% of warehouse processes already use AI, can move forward by improving data quality, expanding integration across sites and applying consistent governance to reach the 51–75% range.

• **Lower-performing markets** (Portugal, Romania, Japan) should work on reducing variability between sites so that current AI efforts translate into higher overall maturity.

Figure 33

AI/ML penetration vs. AI/ML maturity by country



AI/ML budget allocation by country

The budget view reinforces the adoption trends and gives a clearer picture of momentum. China dedicates the largest share of its annual warehouse budget to AI and machine learning, averaging about 23% (Figures 34 and 35). Nearly all respondents there (96%) invest at least 11%, and more than half (58%) invest over 21%; around 14% already spend above 30%.

Brazil follows closely, averaging 22%, but with a slightly "hotter" tail: 17% of sites already commit more than 30%, suggesting many programmes have moved beyond pilots and are now scaling up. A second tier, including Poland (19%) and Mexico (19%), also shows strong commitment, with roughly half of sites (47% and 41%) allocating at least 21%, respectively.

Among core Western markets, such as Canada (19%), Germany (19%), France (18%) and the US (18%), around one-third of respondents (31–37%) dedicate 21% or more of their warehouse budget to AI/ML, and roughly 6–11% spend above 30%. This pattern points to steady, ongoing programmes rather than isolated pilots.



Figure 34

Distribution of budget allocation to AI/ML by country

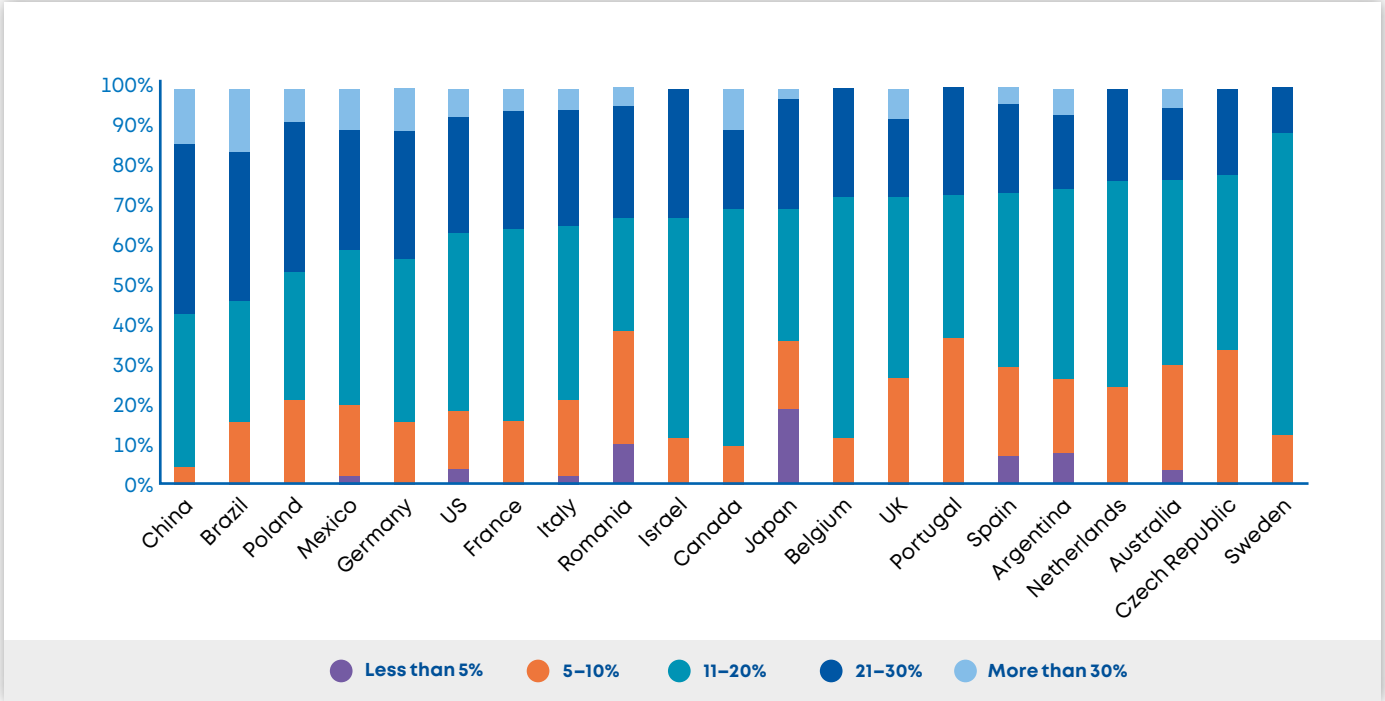
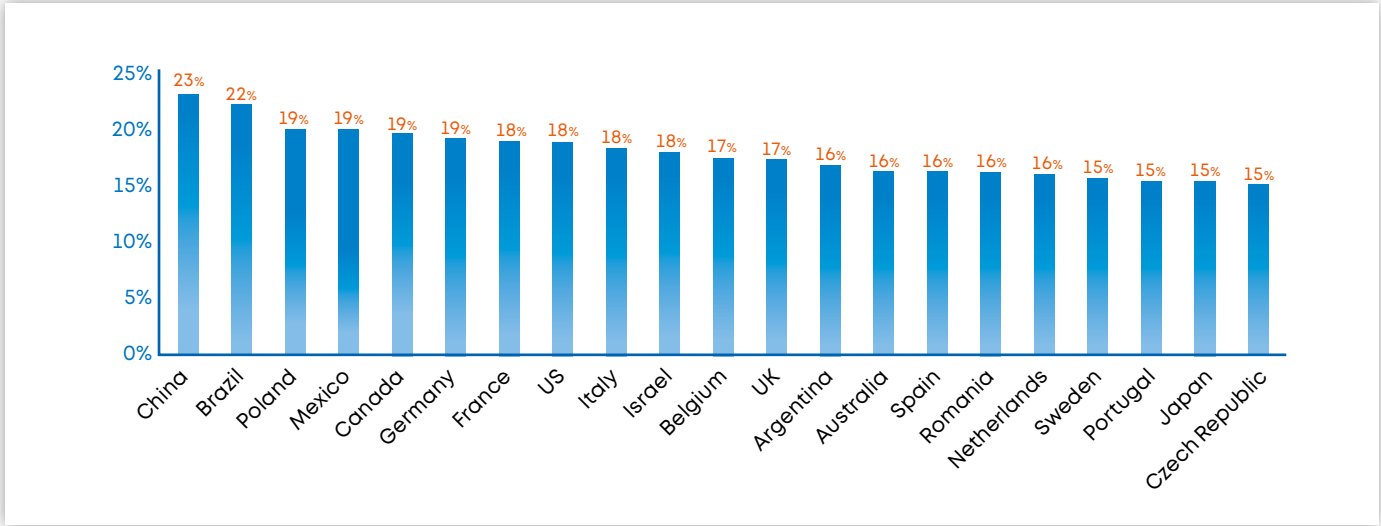


Figure 35

AI/ML share of annual budget by country (average)



At the other end, lower-spend countries average 15–16% of their warehouse budgets for AI/ML. The Netherlands (16%) and Spain (16%) show virtually no respondents above 30%, with Portugal (15%), Japan (15%) and the Czech Republic (15%) taking a similarly conservative approach despite healthy adoption elsewhere.

This lower investment aligns with the "advanced-but-not-full" stage seen in capability data: many companies have introduced AI/ML but have not yet committed significant funding to the data integration and system work needed for full, end-to-end impact.

Regionally, Asia-Pacific's average is boosted by China, even as Japan remains cautious; Latin America benefits from Brazil and Mexico's strong growth, while Europe shows a split, with Poland outpacing peers as the Netherlands and Portugal lag.

Looking ahead, budget shares above 21% are a strong sign of faster progress towards full automation in the next cycle. By contrast, countries clustered around 15–16% will likely need to increase investments — especially in integration, engineering talent and data quality — to turn existing adoption into broad performance gains.

Barriers to AI and automation adoption vary by region

In the Americas, the main obstacles are people and change.
Employee resistance and the need for training are the most common top-ranked barriers, especially in Argentina (57.7%), Canada (62.2%) and Mexico (55.6%). Brazil and the US break this pattern, where the cost of implementation is the leading issue (about 54% and 50%, respectively). This suggests many sites are already convinced of AI's value and are now working through budget approval and scaling challenges rather than basic adoption concerns.

In Europe, the main hurdles are technical — system integration and skills.
France (56.2%), Italy (65.7%) and Portugal (72.7%) name integration with existing systems as their biggest issue, while the Czech Republic (72.2%) and the UK (55.3%) highlight shortages of technical expertise. Germany stands out, with data quality and availability (51.9%) taking the top spot.

Some European markets — the Netherlands (64%), Romania (60%) and Spain (54.5%) — still put employee resistance and training first, showing that change management remains essential even where technology is already advanced.

In Asia-Pacific, most barriers are also technical, but they vary by country.
Australia points to integration (61.8%), China to technical skills (53%) and Japan to cost (57.3%) as their top challenges. In short, even in markets with advanced adoption, the final step towards full automation depends on improving systems fit, deepening technical expertise and managing budgets effectively — not on overcoming scepticism.

Looking across all countries, the same five issues keep organisations from moving beyond advanced automation:

- Integration with existing systems (78% of countries)
- Lack of technical expertise (67%)
- Cost of implementation (61%)
- Data quality and availability (50%)
- Employee resistance or lack of training (44%)

These mirror the earlier findings: where AI is used in multiple workflows but not across entire warehouses, integration, talent and data quality are the bottlenecks. Where mechanisation is strong but AI use is uneven, workforce readiness and training become more important.

Budgets tell the same story.
Markets that already spend 21% or more of their annual warehouse budgets on AI/ML (such as China, Brazil, Poland and Mexico) tend to cite integration and skills as their next challenge. Meanwhile, countries spending closer to 15–16% — like the Netherlands, Portugal, Japan and the Czech Republic — more often point to cost and change management as their biggest barriers.

What is next:

• In the Americas, focus on training and change management to turn proven successes into standard practice.

• In Europe, accelerate API-led integration, WMS/ERP/WES orchestration and engineering capacity. At the same time, manage change where resistance is elevated.

• In Asia-Pacific, adapt locally — close integration gaps in Australia, build skills depth in China and address total cost of ownership in Japan — so that current progress translates into complete, end-to-end operations.



Industry-specific differences

How business models shape AI adoption in warehousing

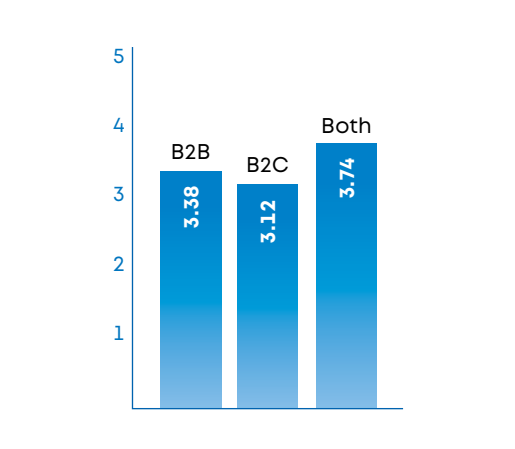
The results show clear differences in how companies adopt and use AI depending on their business model.

Omnichannel leads the way

Omnichannel operators (both B2B and B2C) are well ahead in automation, AI adoption and supporting capabilities. They report the highest automation maturity (3.74 out of 5) compared with B2B (3.38) and B2C (3.12) companies (Figure 36). About 64% of omnichannel warehouses fall into the advanced or full automation category (vs. 52% for B2B and 37% for B2C), and very few remain mostly manual (6% vs. 18% and 25%).

Figure 36

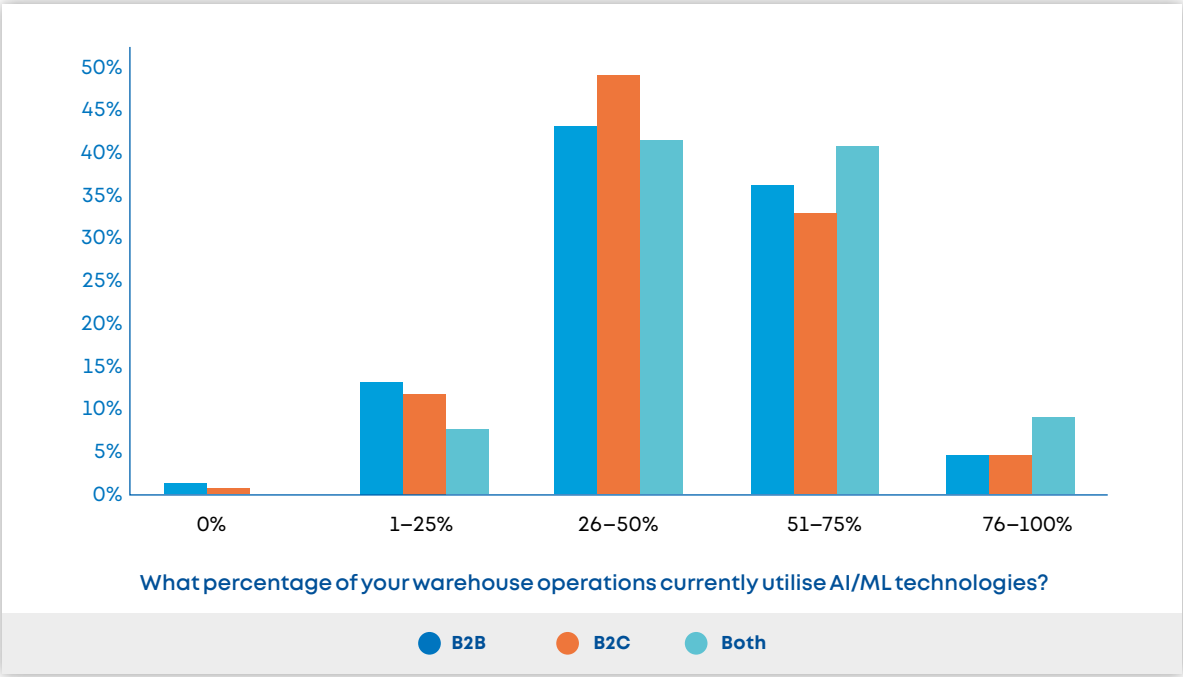
Warehouse automation maturity by business model



Their AI use is also broader and deeper on average (0.504 on a 0–1 index): half of omnichannel sites use AI in more than half of their processes (51–100%), compared with 41% for B2B and 38% for B2C. Almost none report zero AI use (0.1%).

Figure 37

AI/ML penetration by business model

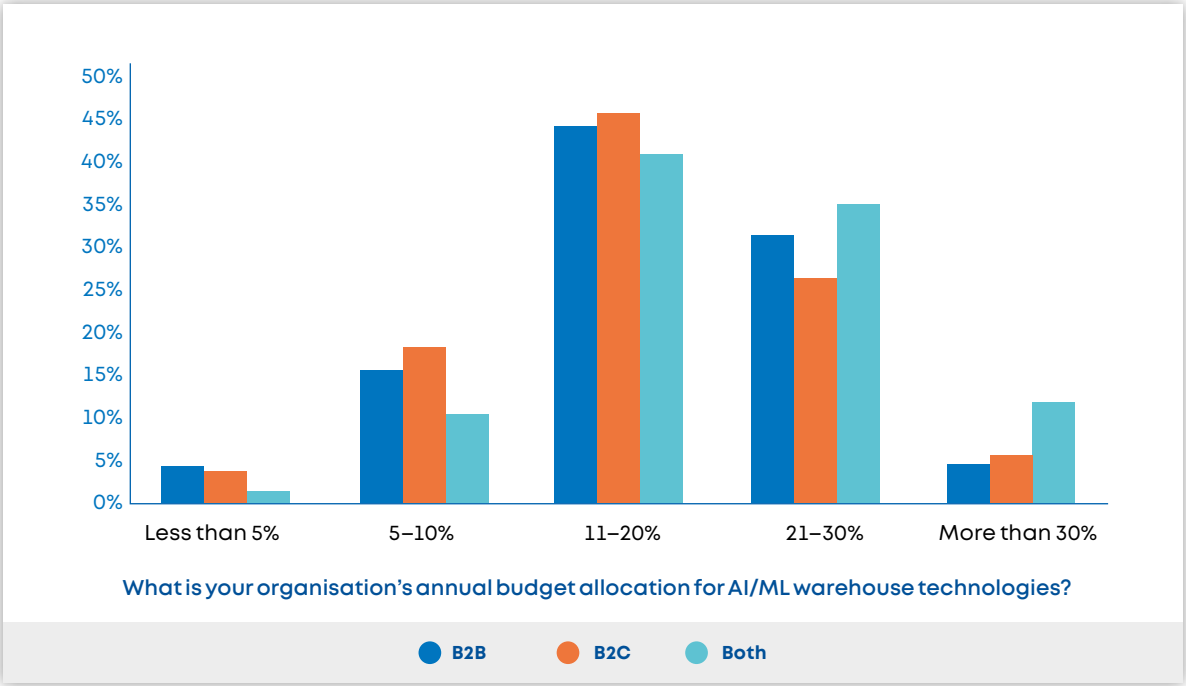




Omnichannel players allocate the largest share of their warehouse spending to AI/ML (20.9% on average), with nearly half — 46.9% — spending at least 21%, and 12.1% already devoting more than 30%. By comparison, B2B and B2C operators spend around 18% on average, with about one-third (35.7% and 32%) allocating more than 21%, and only 4.5% and 5.7% exceeding 30%.

Figure 38

AI/ML budget allocation by business model



Omnichannel companies also lead in the capabilities needed to turn technology into results. Roughly three out of four omnichannel respondents rate their change management (76.5%), technical expertise (75%) and vendor management (79.8%) as strong. That is well ahead of B2B (61.9%, 58.5% and 68.3%) and B2C (55.9%, 54.2% and 61.7%), respectively.

B2B outperforms B2C
Between single-channel models, B2B generally outperforms B2C across most dimensions.

B2B operations have higher automation maturity (3.38 vs. 3.12) and greater advanced adoption (52% vs. 37%), with fewer still operating manually (18% vs. 25%). Their AI penetration is also slightly deeper (41% vs. 38% using AI in over half their operations).

Budgets are similar on average (17.9% B2B; 17.5% B2C), but B2C companies show a slightly larger share spending above 30% (5.7% vs. 4.5%), suggesting some consumer-focused networks are investing more heavily in automation to handle peak demand.

The capability scores make the gap clear: B2B companies are consistently stronger than B2C ones in managing change, technical skills and coordinating with vendors. This suggests that some of B2C's investments are not yet fully converting into maturity and penetration gains.

The big picture
Taken together, these results point to clear priorities for planning:

- **Omnichannel firms should focus on scaling** what already works — standardising integrations and expanding AI coverage from 51–75% of operations to full (76–100%).

- **B2B companies should extend their strongest practices** across sites and strengthen data and system integration to move from advanced to full automation.

- **B2C companies should prioritise building internal capabilities** — closing gaps in change management, technical skills and vendor coordination — so investments deliver broader results rather than isolated pockets of excellence.

This sequencing reflects the broader survey trend: when organisations have strong internal capabilities, higher budgets lead to deeper AI adoption and greater automation maturity. Where those foundations are weaker, returns on investment remain limited until those gaps are addressed.

Closing remarks

Overall, the evidence in this report shows that AI and machine learning are moving from pilot projects to large-scale use across a majority of organisations. Most operations now use AI in roughly one-quarter to three-quarters (26–75%) of their warehouse processes, with budgets continuing to rise and a typical payback period of just two to three years.

The value story is consistent: reducing costs, increasing throughput and improving service levels are the main goals. Predictive and optimisation tools continue to drive most of the impact, while generative AI is speeding up everyday tasks like creating documentation, designing layouts and configuring processes or code, especially when combined with those core predictive systems.

At the same time, the main barrier is not the algorithms themselves but the underlying infrastructure. Data quality, system integration and disconnected workflows still hold many organisations back from full, end-to-end automation — the "last 25%" where most competitive advantages now appear.

The impact on people has been largely positive. Productivity and job satisfaction are rising together, though transitions do bring some challenges, such as increased training needs and some reported incident upticks during transitions. This highlights the importance of designing for safety, introducing phased rollouts and maintaining clear operating guardrails.

Differences between organisations also matter. Omnichannel operators (both B2B and B2C) continue to lead in automation maturity and investment. Regional variations reflect a mix of cost pressures, skills gaps and change-management challenges.

Governance and performance tracking are maturing, with ROI measurement now widespread and several relationships in the data statistically significant. However, successful execution still depends on the fundamentals: solid data infrastructure, skilled people and disciplined change management.

The near-term playbook is clear: complete system and data connections to eliminate gaps, turn insights into action automatically through better process feedback loops, invest in skills and safety to support adoption and evolve from multiple AI use cases to coordinated, end-to-end operations.

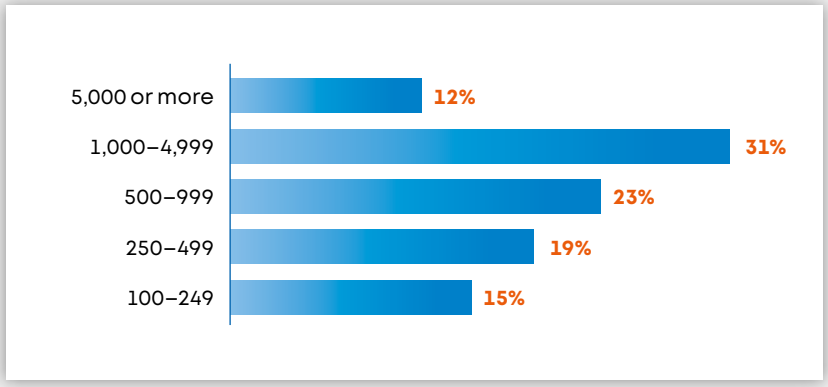
Survey methodology



This report draws on a global survey conducted in 2025, collecting insights from more than 2,000 experienced supply chain and warehousing professionals across 21 countries in Europe, North America, Asia-Pacific and Latin America. The study captures a representative picture of automation maturity and AI/ML adoption across industries and regions. Sample sizes were set proportionally to each country's gross domestic product (GDP).

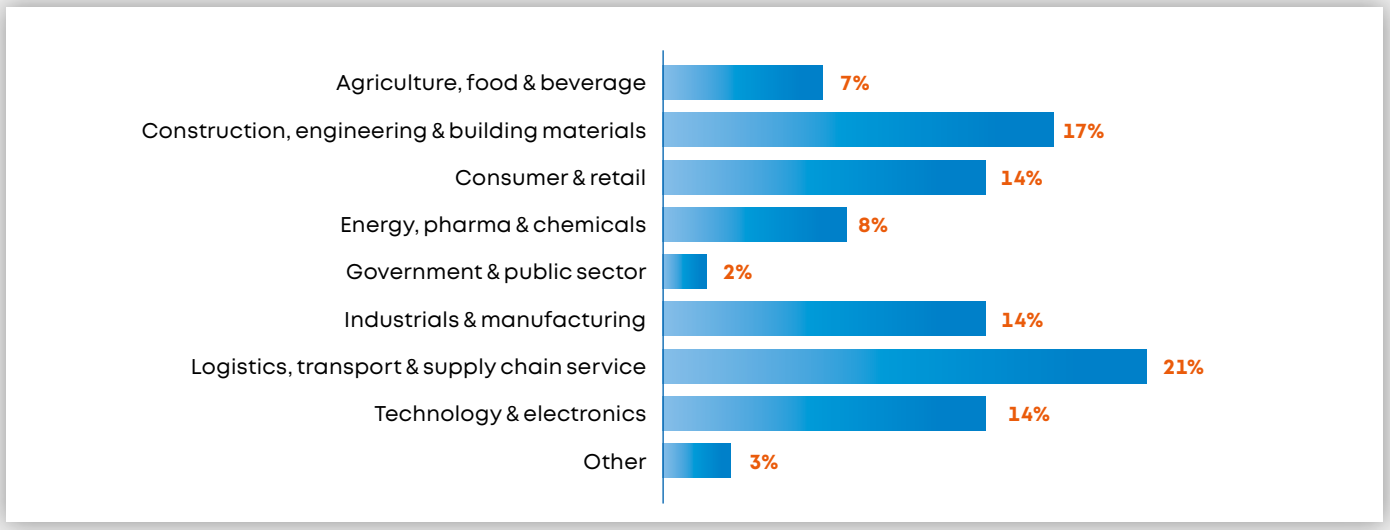
To ensure the analysis focused on organisations with meaningful levels of warehouse activity and technological adoption, participation was limited to companies with at least 100 employees. The sample includes firms of various sizes, with the majority representing mid- to large-sized organisations (1,000–4,999 employees).

Company size (employees)



Respondents represented a wide range of industries, including agriculture, automotive, chemicals, construction, consumer goods, e-commerce and retail, energy, food and beverage, government, logistics, manufacturing, pharmaceuticals, technology, textiles and transport.

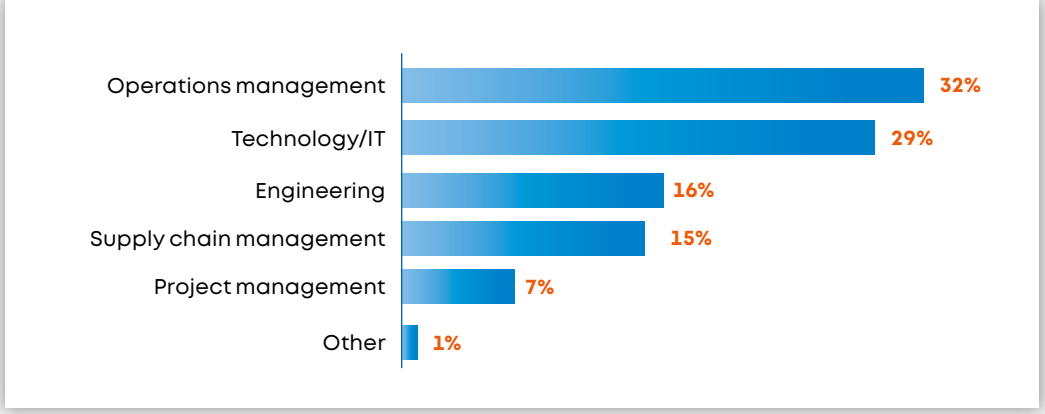
Industry sector





The survey drew responses from professionals across key warehouse and supply chain functions. Most work in operations management or technology and IT, reflecting the growing role of automation and digital systems. Engineering and supply chain management also feature prominently, underscoring the technical and logistical focus of modern warehouse operations.

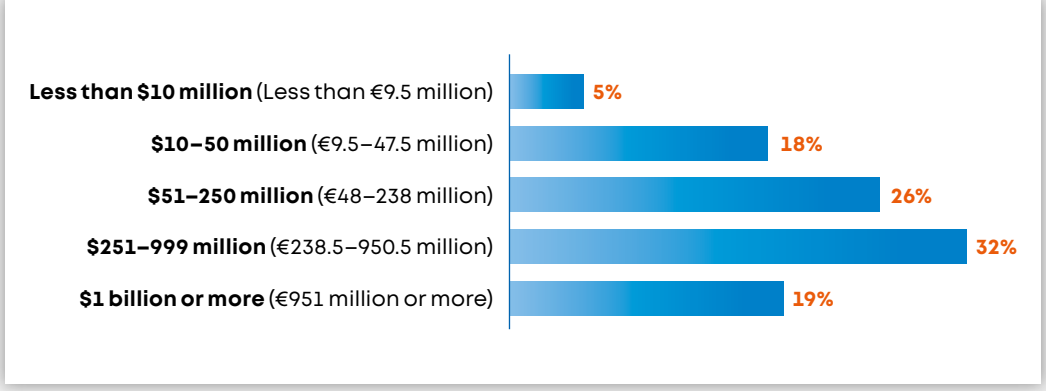
Area of expertise



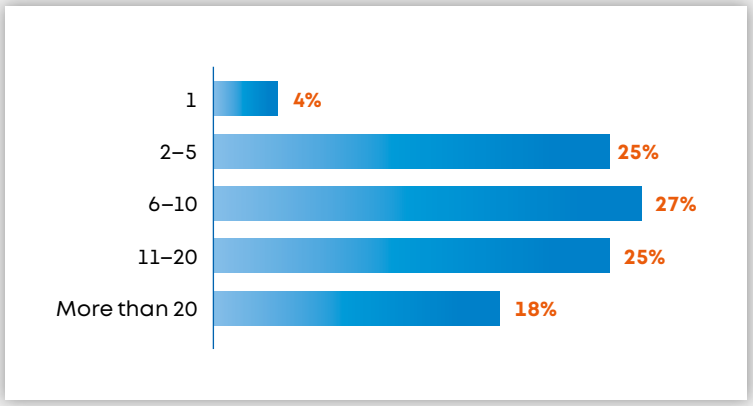
The study captures a representative picture of automation maturity and AI/ML adoption across industries and regions

In terms of annual revenue, the survey sample is weighted towards mid- to large-sized companies. The largest share of respondents comes from organisations earning between $251 million and $999 million (€238.5–950.5 million), followed by a strong representation of both upper-mid-market and billion-dollar enterprises. Smaller firms make up a limited portion of the sample, ensuring the results reflect organisations with substantial warehouse operations and investment capacity.

Annual revenue



Number of warehouses operated

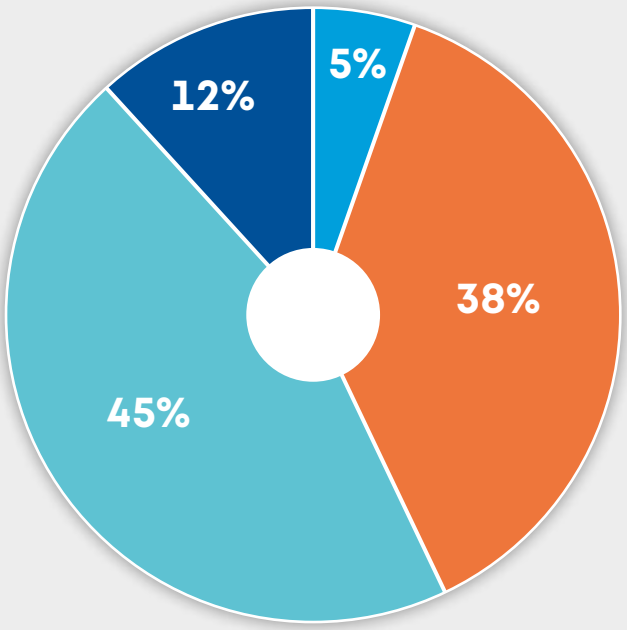


Most companies in the sample operate multiple warehouse sites. Over two-thirds manage between 2 and 20 warehouses, while nearly one in five operate more than 20, reflecting the scale and complexity typical of businesses investing in advanced automation.

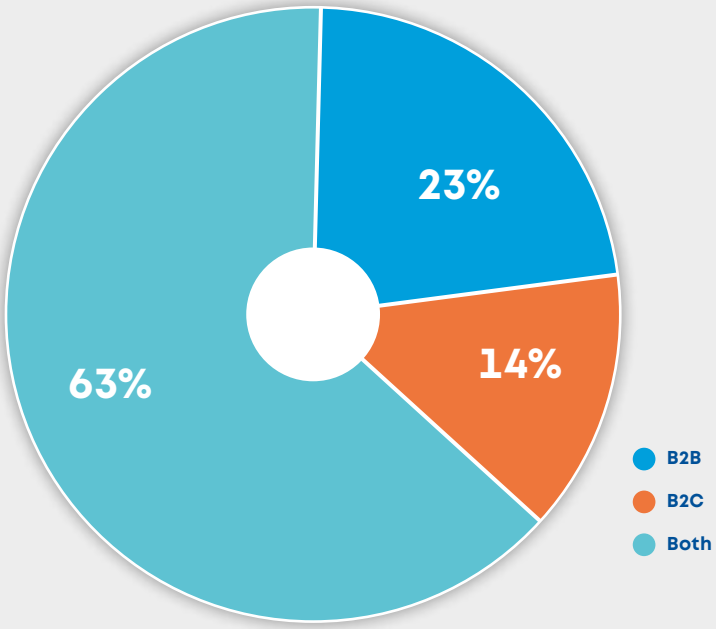
Most warehouses in the sample fall in the mid-size range, typically between 15,000 and 100,000 ft² (1,393–9,290 m²). The majority operate facilities in the 50,000–100,000 ft² (4,645–9,290 m²) range, while only a small share run very small or exceptionally large sites. This reflects a focus on medium and large facilities, typical of companies with mature logistics operations.

Nearly two-thirds of the companies surveyed (63%) operate in both B2B and B2C channels, reflecting the growing integration of consumer and business markets. About one in four (23%) focus solely on B2B, while 14% serve only B2C customers. This mix underscores that most warehouse operations today are designed to handle the complexity of omnichannel distribution.

Average size per warehouse



Business model




6
7
MECALUX

MIT–Mecalux research collaboration

The MIT Intelligent Logistics Systems Lab's five key research streams



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