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Adoption of Artificial Intelligence and productivity growth in Kuwait's private sector

Enterprise perspectives and evidence

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Foreword

Artificial intelligence is moving rapidly from experimentation to real workplace use. For enterprises, the promise is clear: faster processes, better decisions and new ways to serve customers. Yet turning these possibilities into sustained productivity gains requires more than access to tools. It depends on practical enabling conditions: reliable data, appropriate governance, skilled people, and the ability to measure what works.

This report, led by the ILO Bureau for Employers' Activities (ACT/EMP) in collaboration with the ILO Regional Office for Arab States, the ILO Research Department and the Kuwait Chamber of Commerce and Industry, provides enterprise-level insights into how firms in Kuwait are adopting AI. Drawing on interviews and a validation dialogue with private-sector stakeholders, it highlights where AI is being applied along the firm value chain, what motivates adoption, and what constraints slow progress from pilots to scaled implementation.

The findings underscore a central message for employers and their organizations: productivity gains are most likely where adoption is accompanied by strengthened foundations that is data maturity, governance arrangements and workforce preparedness, as well as credible measurement practices that allow firms to verify results and scale investment with confidence. For smaller firms in particular, reducing the cost and complexity of these enabling conditions can be decisive.

ACT/EMP hopes this report will support employers, business membership organizations and policymakers in Kuwait and the wider region as they consider practical steps to foster responsible AI adoption and realize productivity improvements that strengthen competitiveness of firms and overall well-being in the region.

Deborah France Massin

Director, ILO Bureau for Employers' Activities

Acknowledgments

This report was produced under the leadership of the ILO Bureau for Employers' Activities (ACT/EMP), in collaboration with the ILO Regional Office for Arab States (ROAS), the ILO Research Department, and the Kuwait Chamber of Commerce and Industry (KCCI). The report was authored by José Manuel Medina Checa, Ekkehard Ernst and Daniel Samaan (International Labour Organization), together with Chaker Elmostafa (KCCI) and Hamad Elias (External Consultant to the ILO) , based on stakeholder interviews and a validation session led by Chaker Elmostafa and Hamad Elias. Hamad Elias also prepared an initial draft of the report.

The report is based on enterprise interviews and a validation dialogue convened with private-sector stakeholders in Kuwait. We are grateful to the Kuwait Chamber of Commerce and Industry (KCCI) and all participating firms and representatives for their time, insights and openness in sharing experience on AI adoption and productivity measurement. We also thank Caroline Fredrickson (Director of the ILO Research Department), and Claire Courteille (Director of ROAS) for their comments and suggestions. We thank PRODOC for their support, and Judy Rafferty (ILO Research) for her assistance.

Executive summary

This report examines how enterprises in Kuwait's private sector are adopting artificial intelligence (AI), where adoption is currently concentrated in the firm value chain, and to what extent productivity effects are being measured and verified. The analysis is based on enterprise interviews and a structured validation dialogue convened with the Kuwait Chamber of Commerce and Industry (KCCI). The findings should be read as **indicative practice-based patterns** among participating organizations rather than statistically representative estimates for the full private sector. Interviews were conducted in 2025 and findings were validated in October 2025; the report was finalized in January 2026 following analysis and report clearance processes.

What firms are doing with AI: use cases and adoption patterns

Across the sample, AI use is already present but remains uneven in depth. Most reported applications are concentrated in **support functions and operational workflows**, including document processing, customer interactions, forecasting, and anomaly detection. More integrated, enterprise-wide deployments are mainly found among larger and more digitally mature organizations.

Firms' use cases cluster around three broad domains: **(i) automating administrative tasks, (ii) analytical decision support, and (iii) customer-facing applications**, with advanced deployments still the exception rather than the norm.

A recurring pattern is that early-stage adopters often start with **stand-alone GenAI/LLM tools**, whereas more advanced firms build on existing analytics and optimization systems and "augment" them with machine learning and/or natural language processing connected to enterprise data environments (e.g., SQL systems and cloud platforms). This reinforces that moving from experimentation to higher-value use is largely conditioned by **data readiness and integration capability**, not simply access to tools.

Why firms adopt AI: strong economic motives, but uneven ability to scale

Enterprises most frequently describe AI as a pathway to reduce processing time, reduce errors, and increase efficiency. In the interview sample, **93 per cent** cite cost reduction and faster execution as a key motivation, while **78 per cent** cite strategic differentiation; competitive pressure and compliance-related motives are reported far less frequently.

Motivation is therefore high, but the ability to sustain investment and scale AI is often constrained by complementary capabilities, especially data systems, talent, governance, and measurement routines.

AI maturity in practice: a "two-speed" trajectory between large firms and SMEs

The evidence points to a clear size effect in adoption depth: larger firms are substantially more likely to move beyond pilots, supported by stronger data infrastructures, clearer governance structures, and access to specialized technical talent. SMEs are more likely to remain in exploratory and pilot stages, constrained by limited data maturity, governance gaps, and resource constraints.

This "two-speed" dynamic is visible across readiness indicators. Formal AI policies and training are far more common among large firms than SMEs: in the interview sample, **AI policies are present in 45 per cent of large firms versus 14 per cent of SMEs,** and **training programmes in 65 per cent of large firms versus 29 per cent of SMEs**.

This matters because policy and training are not cosmetic additions: they shape whether firms can deploy AI responsibly, manage risks, and build the internal capability needed to scale.

Productivity effects: widely claimed, but rarely verified

A central contribution of the report is to distinguish between perceived productivity improvements and impacts supported by credible measurement. While many firms describe faster task execution and smoother workflows, only a minority have measurement approaches strong enough to verify attribution. In the sample, **26 per cent** of reported productivity impacts are classified as "verified" under the study's criteria, while 74 per cent remain "unverified."

Verified cases are concentrated among larger and more data-mature organizations, and SMEs reported no verified productivity gains.

Where verification exists, the reported effects can be substantial. Verified cases include sharp reductions in task time and document-processing costs in specific workflows, with some firms reporting **reductions of 60–98 per cent in task time** for targeted processes when measurement conditions were in place (named workflow, baseline, method tag, and at least one reporting cycle).

The key challenge emerging from the interviews is therefore often **not the absence of potential benefits**, but the lack of consistent baselines and measurement discipline required to move from pilots to scalable, demonstrable performance gains.

The binding constraint: data maturity and the "constraint flip" as firms progress

Data maturity emerges as the most consistent boundary condition determining how far firms can deploy AI and whether they can measure its impact. Across the interview sample, **32 per cent** of firms are at an initial stage of data maturity, **44 per cent** are developing, and **24 per cent** are advanced. The size gap is pronounced: **90 per cent of large firms** are at developing or advanced maturity, while **64 per cent of SMEs** are at the initial stage and none are classified as advanced in this sample.

Constraints also change character as firms mature. Across the sample, challenges are reported across three categories: **governance/strategic management frictions (38 per cent), external and policy-related factors (32 per cent), and internal capability/infrastructure (29 per cent).**

Early-stage firms are mainly constrained by data quality, legacy systems, and skills; more mature adopters increasingly report external "gates" such as approvals processes, data residency requirements, and vendor dependence that can limit flexibility and reversibility.

Implications for policy and practice in Kuwait

Taken together, the findings suggest that enabling productivity-enhancing AI adoption in Kuwait's private sector is less about awareness of AI's potential, which is already high, and more about strengthening the practical conditions that allow firms to **test, measure, and scale** AI safely and effectively. These conditions include stronger data foundations, skills and organizational capability (including governance), measurement routines and baselines, and greater clarity and confidence in the broader ecosystem environment (including supplier accountability and rules affecting data handling).

A core risk is that uneven readiness, e.g. between large firms and SMEs, could translate into a widening productivity gap. The results therefore point toward policy priorities that focus on enabling conditions (data foundations, practical skills, measurement templates, and governance guidance), while also reducing avoidable ecosystem frictions that become binding when firms seek to move from pilots to scale.

While this study focuses on enterprise adoption and productivity measurement, the organizational change associated with AI adoption highlights the role of social dialogue in supporting transparent implementation, skills development and effective governance.

Contents

1. Introduction

Artificial intelligence (AI) has become a general-purpose technology with the potential to reshape business models, production processes and the organization of work. Yet despite the speed of technological advances, particularly in Generative AI (GenAI), there remains substantial uncertainty about how AI will influence firms, workers and productivity (e.g. del Rio de Chanona et al., 2025). A central question for policymakers, researchers and business leaders alike is whether, and under what conditions, AI adoption can generate sizable productivity gains. This debate is especially relevant at a time when productivity growth has stagnated or even declined in many regions for prolonged periods (OECD, 2025, ILO, 2023). The OECD (2025) has emphasized that the expectations for AI to positively shape future productivity trends are high if the right policies are put in place. Nevertheless, national statistics do not yet show evidence of AI-induced productivity increases.

For the future, IMF researchers have estimated through simulations that medium-term productivity gains, for example in Europe, could total about 1% on the macroeconomic level, cumulatively over five years (Misch et al., 2025). The critical point, however, is not only to evaluate the theoretical capabilities of (Gen)AI, but to assess its adoption in real enterprise environments. Put plainly, the European Central Bank notes: 'Benefits can only materialize when firms actually use AI' (Bergeaud et al., 2025). Many organizations around the world are still determining how to integrate AI effectively and what prerequisites, for example with respect to data quality, workers' skills, or governance must be in place before adoption translates into measurable improvements in performance. McKinsey emphasizes that scaling productivity gains requires leadership, operating model changes, and workforce enablement, not just tool deployment (Mayer et al., 2025).

Experimental studies[1] on the use of GenAI demonstrate substantial productivity gains at the task level, often ranging between 20–60 per cent in controlled laboratory settings. In field experiments — conducted in real-world enterprise environments — the gains tend to be smaller but still significant, typically in the range of 15–30 per cent (del Rio de Chanona et al., 2025). These results are context-specific, depending on the study design, the complexity of working tasks to be carried out and other characteristics such as the skill level of the workers involved and the type of enterprise or organization using AI. It is also not evident at this stage whether these promising results can be generalized and hint at broader firm-level productivity improvements or could even predict future productivity growth at the macroeconomic level.

With a lack of secondary data available, a growing body of international research, both academic and policy-oriented, has turned to company interviews and surveys to gain better insights into the state of AI adoption across regions and enterprises (e.g., Lane et al., 2023; OECD/BCG/INSEAD, 2025). Results of these surveys indicate that that AI adoption within enterprises varies widely across countries, sectors and firm sizes. Skills shortages, insufficient data maturity and uncertainty about returns on investment consistently emerge as major barriers, while firms highlight the need for clearer guidance, stronger data infrastructures and targeted public-private collaboration to support effective use of AI. Even among firms already experimenting with AI, many still struggle to understand which applications are genuinely valuable and how to manage the organizational changes that AI entails.

1 Such experiments are carried out as randomized controlled trials (RCT).

In line with this, BCG finds that value capture from AI is increasingly uneven, with a widening gap between leading adopters and laggards, suggesting that productivity impacts are likely to remain highly heterogeneous across firms (Apotheker et al. 2025). Focusing on U.S. companies MIT/BCG (2025) similarly shows that adoption within firms is highly uneven: even within the same sector, some companies pilot only narrow use cases while others embed AI into core workflows. Differences in data quality, governance frameworks, internal skills and change-management capacity strongly shape these adoption trajectories. Survey and interview evidence across regions points to common challenges: the need for secure and well-structured data systems, clear accountability mechanisms, workforce preparedness, and robust safeguards for privacy, security and responsible use. Together, these findings underscore that AI adoption is not merely a technological upgrade but a complex organizational transition that depends heavily on strategy, capabilities and governance.

Recent survey evidence from the Middle East similarly suggests that, while interest in AI is high, many firms are still struggling to demonstrate and measure value creation from AI initiatives (Deloitte, 2025). Evidence points to a similar pattern of high ambition but constrained value realization. Deloitte's 2025 survey of business and technology leaders in Qatar, Saudi Arabia and the UAE reports strong pressure to adopt AI, widespread experimentation, and very high expectations that AI will raise productivity; yet implementation at scale remains uneven and many organizations struggle to define, measure, and communicate returns from AI initiatives. The same evidence highlights persistent readiness gaps, especially in talent, data foundations, and risk/governance arrangements, as well as concerns around data security and regulatory compliance, suggesting that productivity impacts are often constrained less by access to tools per se than by complementary capabilities and measurement discipline required to move from pilots to scalable, verifiable performance gains (Deloitte, 2025).

This complexity also applies to Kuwait, a high-income economy with a rapidly expanding digital foundation. Given its high GDP per capita ($PPP 46,137), Kuwait is seeking to translate its vast oil wealth into sustainable, productive growth driven by a diversified private sector. It aims to capitalize on its strong financial, retail, and logistics sectors - accounting for almost half of private-sector output - together with rapid digital growth and an evolving regulatory environment, to accelerate the adoption of emerging technologies. The Kuwait National AI Strategy 2025–2028, which is currently being finalized, places AI at the center of national ambitions for economic diversification, improved service delivery, and strengthened public trust. The upcoming strategy emphasizes responsible AI, clear accountability, privacy and security, strong data infrastructure, sector-specific pilots and cross-sector coordination. It aligns closely with Vision 2035, Kuwait's long-term national development strategy, and includes mechanisms for monitoring progress through defined indicators and regular evaluation. In parallel, the private sector in Kuwait, from finance and logistics to education and technology, has begun to introduce AI in areas such as customer service support, fraud detection, forecasting, and predictive maintenance. These initiatives demonstrate early task-level value, but the scale and depth of firm-level productivity gains remain largely unknown.

Against this backdrop, two evidence gaps are particularly important to address:

(1) the measurable impact of AI on productivity at the firm level across different stages of the value chain, and

(2) the organizational and enabling conditions that shape whether firms move from experimentation to scaled adoption, in particular data maturity, governance arrangements, skills and training, and the measurement practices needed to verify productivity impacts.

This report contributes to filling these gaps by providing new insights based on interviews with enterprises carried out jointly by the ILO and the Kuwait Chamber of Commerce and Industry. The study explores how firms in Kuwait understand, experiment with and implement AI tools; what motivates adoption; and what barriers slow or prevent wider deployment. By focusing on Kuwaiti firms, the report provides country-specific evidence on how these dynamics play out across sectors and functions in Kuwait's private sector. At the same time, it contributes to the broader international discussion on enterprise AI adoption by documenting early use cases, organizational prerequisites, and the conditions under which task-level gains may (or may not) translate into measurable firm-level productivity improvements. Understanding these dynamics is essential for designing effective policies on skills development, regulation, digital infrastructure, responsible innovation and social dialogue among enterprises, workers and the government.

A validation meeting with private-sector representatives helped refine and contextualize the findings to ensure they reflect the realities faced by Kuwaiti enterprises.

The remainder of the report is structured as follows. Section 2 describes the methodological approach, including sample selection and the interview process. Section 3 presents findings on AI adoption drivers, use cases and challenges. Section 4 summarizes the validation session and reflects on the findings. Section 5 provides policy considerations to support effective and responsible AI adoption in Kuwait's private sector.

2. Methodological approach, scope and sample

2.1 Scope of the report

This report was prepared jointly by the Kuwait Chamber of Commerce and Industry, the ILO Bureau for Employers' Activities, and the ILO Research Department. Its purpose is to provide an evidence-based assessment of how enterprises in Kuwait understand, experiment with and adopt artificial intelligence, and how these processes relate to productivity outcomes and organizational change. The report contributes to the growing international research literature that uses firm-level interviews to complement limited secondary data on AI adoption.

The analysis draws on 34 semi-structured interviews with senior representatives from enterprises across multiple sectors and firm sizes in Kuwait. These interviews provide qualitative insights on the current state of AI use, perceived opportunities, emerging productivity effects, and the barriers that shape adoption trajectories.

A key focus of the study is to distinguish between task-level experimentation, which is where many firms are currently situated, and deeper forms of organizational integration that may be required for sustained productivity gains.

The findings are descriptive rather than representative, and they reflect the perspectives of interviewed companies at their current stage of adoption. Nonetheless, they offer a valuable baseline for understanding how AI is being approached in Kuwait's private sector, what conditions support or impede progress, and where policy makers may consider targeted measures to advance skills development, data readiness, responsible governance, and productive use of AI.

2.2 Interview design and questionnaire

The report provides and synthesizes the results of semi-structured interviews, which combine a set of predefined guiding questions with the flexibility to explore issues that emerge organically during the conversation. This approach is widely used in research when the objective is to uncover patterns across cases while still capturing the contextual nuances that standardized surveys miss[2]. It is particularly suitable for examining AI adoption, where practices, terminology and organizational readiness vary substantially across firms. Semi-structured interviews allow respondents to explain their experiences in their own words while ensuring that all participants are asked about the same core themes. Interviews were conducted in either Arabic or English, depending on the interviewee's preference, with detailed notes recorded and later synthesized to preserve accuracy and comparability across cases.

The questionnaire used in this study is organized around several thematic blocks that reflect the key issues identified in the introduction: the motivations that drive firms to experiment with AI; the types of tools and types of workflows in which AI is currently used; how companies measure, or attempt to measure, productivity effects; the challenges they face related to skills, data quality, governance and organizational change; and finally, their expectations for future adoption. While the structure provides a consistent analytical framework, the semi-structured format ensures that firms are able to discuss additional issues relevant to their specific sector, business model or technological maturity. The thematic blocks are summarized in this section, and the full questionnaire is provided in the Appendix.

Before conducting the interviews, the research team reviewed and refined the interview guide to ensure clarity and alignment with the report's analytical objectives. The structure of the questionnaire and the underlying concepts were further validated during a consultation with private-sector representatives, confirming that the themes addressed were both relevant and appropriate for the Kuwaiti context.

2.3 Sampling and recruitment of enterprises

The recruitment of enterprises for this study was carried out in close collaboration with the Kuwait Chamber of Commerce and Industry (KCCI), which facilitated access to firms and supported outreach efforts. The Chamber played a central role in identifying potential participants and encouraging engagement across different

2 A survey was considered, but at the current stage of knowledge it was deemed too restrictive for respondents and less suitable for uncovering new insights and context-specific details. Semi-structured interviews were therefore chosen as the primary method. Based on the findings from this phase, a survey could be developed for follow-up work.

sectors of Kuwait's economy. This partnership was essential for securing interviews with senior representatives who had direct knowledge of their organizations' digital strategies and AI-related initiatives.

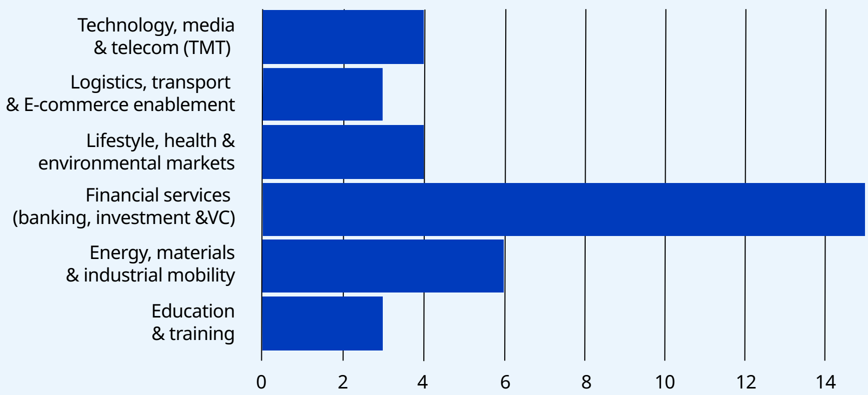
The final sample consisted of 34 enterprises, covering a broad spectrum of economic activities, including finance, logistics, manufacturing, education, retail, hospitality, and information technology. Both large companies and small and medium-sized enterprises (SMEs) were represented, ensuring that the study captured perspectives from firms with varying levels of resources, digital infrastructure, and organizational complexity. While the sample includes a diverse set of firms, it is not statistically representative of Kuwait's private sector as a whole. Rather, it offers indicative insights into the experiences of firms that expressed interest in participating and had sufficient internal knowledge to discuss AI-related developments.

A non-probability, convenience sampling approach was used, reflecting the exploratory nature of the research and the objective of generating qualitative insights into AI adoption. This method allowed the study to prioritize the depth of information from knowledgeable respondents rather than the breadth of coverage. Participating enterprises were selected based on their willingness to engage and their ability to provide informed accounts of AI experiments, implementation challenges, and anticipated workforce implications. Consequently, the findings should be interpreted as descriptive and illustrative, offering important signals about emerging patterns of AI adoption in Kuwait, rather than generalizable estimates for the wider economy.

2.4 Characteristics of the participating firms

The study draws on interviews with 34 enterprises operating in Kuwait's private sector. The sample covers organizations of different sizes and levels of digital maturity, reflecting the heterogeneity of the country's economic landscape. Firms included both large enterprises with established data infrastructures and smaller businesses at earlier stages of digital transformation. This diversity enables an initial understanding of how AI adoption is unfolding across different operational environments, without yet drawing conclusions about outcomes or effects.

▶ **Figure 1: Sample Distribution by Industry Sector**



Source: Authors' calculations.

Notes: Figure 1 shows the six sectors from which the interviewed companies were drawn. About half of the companies are from the financial services sector.

Sectoral representation, illustrated in Figure 1, spans six broad industries. The largest share of participating firms comes from Financial Services (approximately 44 per cent), including commercial banks, investment companies and venture capital entities. These organizations typically possess more advanced digital systems and dedicated innovation budgets, which may facilitate early engagement with AI technologies. Their strong presence in the sample provides valuable insight into AI uptake in digitally mature environments, while also introducing a sectoral bias that should be kept in mind when interpreting the overall sample. Firms in Technology, Media and Telecommunications (TMT) constitute roughly 15 per cent of the sample. These companies often operate at the technological frontier and may act as both developers and users of AI solutions. Their participation helps capture perspectives from organizations with advanced technical capability.

Approximately 18 per cent of the sample consists of enterprises in Energy, Materials and Industrial Mobility, sectors undergoing progressive digitalization of physical operations. Their inclusion offers a view into how AI is being considered within asset-heavy industries and field-based workflows. The remaining sectors, Logistics and Transport, E-commerce Enablement, Lifestyle, Health and Environmental Markets, and Education and Training, account for around 9 per cent each. Although these industries are underrepresented relative to their weight in the national economy, they provide valuable perspectives from service-oriented, consumer-facing and knowledge-intensive activities. Across sectors, participating firms reported engagement with a wide range of potential AI applications, from customer-facing tools to operational and analytical functions. At this stage of the report, these use cases are referenced only to illustrate sample diversity; detailed findings on adoption patterns, barriers and drivers are presented in Section 3.

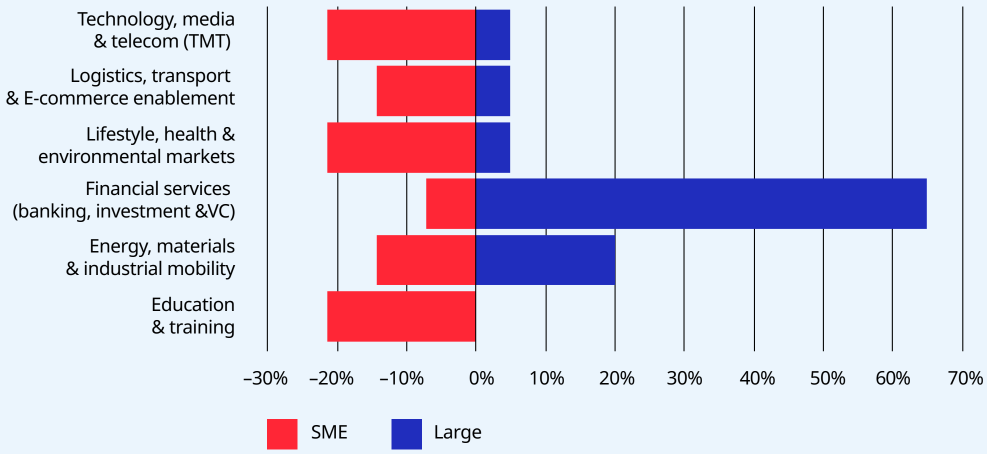
The sectoral composition of the sample offers both strengths and limitations. The inclusion of firms from six different industries provides a broad cross-section of perspectives and helps avoid an overly narrow sector-specific interpretation of AI adoption. At the same time, the heavy concentration of Financial Services organizations means that aggregate patterns in the sample may reflect conditions typical of large, digitally mature financial institutions more than those found in other parts of the economy. Smaller firms in sectors such as lifestyle services, education or consumer markets may confront markedly different operational constraints, levels of digital readiness and adoption incentives than those implied by the aggregate findings.

Firm size is another important characteristic of the sample. Large enterprises represent 59 per cent of participating firms (20 organizations), while small and medium-sized enterprises (SMEs) account for 41 per cent (14 organizations).[3] Larger firms typically possess more formalized IT structures, larger budgets, greater access to specialized technical talent and more established data systems - all factors that influence how AI initiatives are evaluated, tested and scaled. By contrast, SMEs often operate with more limited resources, smaller data environments and more informal decision-making processes, yet may be able to experiment with new ideas more quickly due to fewer procedural constraints.

3 Firm size classification follows a multi-criterion approach. Firms were classified as large if they met any of the following: (i) publicly listed or holding a licensed banking charter; (ii) employing ≥250 staff (consistent with common OECD/European Commission thresholds); or (iii) operating across two or more countries. Firms not meeting any criterion were classified as SMEs.

The interaction between firm size and sector composition further shapes the analytical interpretation of the sample. Approximately two-thirds of large enterprises in this study operate within the Financial Services sector, creating a dual concentration by both sector and size. This suggests that certain insights, in particular those related to data infrastructure, governance maturity or resource availability, may be more reflective of conditions within large financial institutions than of the broader economy.

▶ **Figure 2: Sample Distribution by Industry Sector and Firm Size**



Source: Authors' calculations.

Notes: Figure 2 shows the distribution of firm sizes by sector, distinguishing between large firms and SMEs. In total, 20 firms (59 per cent of the sample) were classified as large, while 14 firms (41 per cent) were SMEs.

In addition to firm-level characteristics, the profile of interview participants also influences the type of insights obtained. Executives and senior leaders made up approximately 63 per cent of interviewees. These individuals typically hold responsibility for strategic direction, budget allocation and approval of AI initiatives, and therefore provided perspectives on organizational intent, priorities and perceived value. The remaining 37 per cent of interviewees were managers and technical specialists with hands-on responsibility for implementation, data systems or operational workflows. Their contributions grounded the findings in the day-to-day realities of integrating AI tools, addressing data constraints and supporting user adoption. The combination of strategic and operational viewpoints helped ensure that the evidence reflects both organizational vision and practical execution challenges.

2.5 Analytical approach

The analysis followed a qualitative research design grounded in thematic coding and cross-case synthesis. In qualitative studies, coding refers to the systematic process of labelling segments of interview material according to predefined themes. This approach makes it possible to distil comparable insights across diverse organizations while still preserving the contextual detail that is often essential in early-stage technology research. Semi-structured interviews are well suited for this purpose, as they generate rich, open-ended information while ensuring that all participants address the same core topics.

All interview notes were coded using a structured framework reflecting the five thematic blocks covered in the questionnaire:

(1) Motivation for using AI tools;

(2) Use and adoption of AI tools;

(3) Measuring and gauging productivity;

(4) Challenges and governance;

(5) The future of AI

The coding process involved two steps: an initial pass to assign thematic labels to relevant excerpts, followed by a consistency review across all interviews. This ensured that similar concepts, such as data maturity, readiness levels, or types of use case, were interpreted in the same way across firms. Only evidence tied to a concrete workflow or practice was retained for analysis; general statements without operational detail were recorded but treated cautiously. This selective approach, adapted from the consultant's detailed coding scheme, helped maintain analytical discipline while keeping the process appropriate for a policy report.

Following coding, a cross-case synthesis was conducted to identify patterns that appeared across sectors, company sizes and levels of digital maturity. Rather than treating each interview as an isolated case, the analysis compared similarities and divergences to determine which factors were consistently associated with higher readiness, clearer adoption strategies, or reported productivity gains. Sector–size interactions, in particular the concentration of large, digitally mature financial firms, were examined carefully to avoid overgeneralization.

Finally, the emerging insights were validated through an internal review and a dedicated consultation meeting (validation meeting) with representatives from Kuwait's private sector. This meeting provided an opportunity to verify the plausibility of findings, clarify contextual factors and ensure that the interpretation reflected the realities faced by enterprises in Kuwait.

2.6 Limitations

This study is based on a convenience sample of 34 enterprises recruited through the Kuwait Chamber of Commerce and Industry (KCCI). As participation was voluntary and not randomly selected, the findings should be interpreted as indicative patterns rather than statistically representative estimates for all private-sector firms in Kuwait. The sample is also concentrated in large organizations and in the Financial Services sector, which amplifies the perspectives of digitally mature, well-resourced firms. Insights from SMEs and underrepresented service sectors should therefore be treated as directional.

Semi-structured interviews rely on participants' perceptions and self-reported information, which may not always capture operational realities. The predominance of senior executives among interviewees further introduces the possibility that strategic aspirations are emphasized more strongly than day-to-day implementation challenges. Time constraints in the interview format also limited the depth of discussion on certain technical issues such as data governance and measurement practices.

To support analytical consistency, the same coding rules were applied across all interviews, self-reported figures are clearly indicated, and confidentiality and informed-consent procedures were followed. While the qualitative approach provides rich, contextual insights into AI adoption in Kuwait, follow-up research—potentially including surveys or detailed workflow studies—will be important to validate and extend the findings.

▶ 3. AI adoption in Kuwait's private sector

This section presents the main findings from interviews with 34 enterprises, organized according to the five thematic areas of the interview questionnaire. While the experiences of participating firms cannot be generalized to all companies in Kuwait, the results offer indicative patterns that shed light on how AI adoption is unfolding in practice. Each subsection synthesizes enterprise perspectives while highlighting differences by sector, firm size and levels of digital maturity. The analysis also integrates evidence from thematic coding to identify recurring motives, adoption pathways, measurement practices, governance challenges and expectations for the future. Together, these findings provide a grounded view of how Kuwaiti firms are currently engaging with AI technologies and the conditions that shape their capacity to translate adoption into productivity gains.

Section 3 is organized around the five thematic domains used in the interview questionnaire (see Annex), covering motivations for using AI, patterns of adoption, productivity impacts, challenges and governance, and future plans.

3.1 Motivation for using AI

Across interviewed enterprises, cost efficiency stands out as the dominant motivation for adopting AI tools. Firms consistently emphasized expectations of reducing operational costs, accelerating workflows, and improving accuracy. Strategic differentiation also plays a role, although to a lesser degree, and is largely concentrated among digitally mature firms.

Main motivations reported by firms:

- **Cost efficiency - Reduce cost and time (92.6 per cent):**
  "The work you did in 6 hours became 5 minutes."
- **Strategic differentiation - Create new value and edge (77.8 per cent):**
  "We aim to be the first AI-driven bank in Kuwait."
- **Competitive pressure - Defend share and keep pace (14.8 per cent):**
  "We need to have a one-up against competition."
- **Compliance and policy mandate - Meet rules and controls (7.4 per cent):**
  "We aspire to integrate AI into the curriculum."
- **Client or peer pressure - Respond to client pull and signals (3.7 per cent):**
  "We should do it because we see others doing that."

The dominance of cost motivations reflects the structure of many participating organizations, especially those with high volumes of repetitive, data-intensive tasks where AI can rapidly enhance throughput. Several executives described substantial time reductions in routine processes.

Differences also emerged by work intensity and firm size.

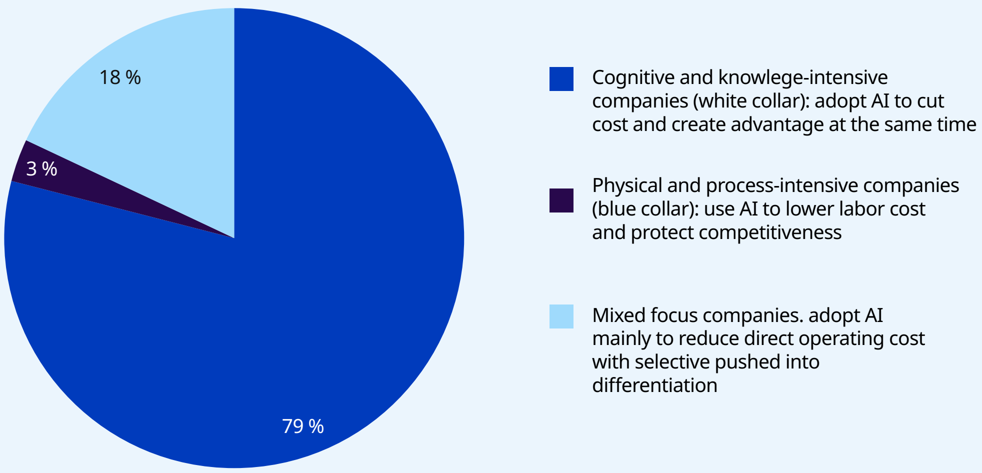
- **White-collar and mixed-workforce firms** often pursue both efficiency and differentiation, using AI for customer-facing services, analytics, and decision support.
- **Blue-collar firms** cited competitive pressure more strongly, emphasizing cost survival rather than innovation.

Large enterprises expressed a more ambitious dual motive—efficiency and differentiation—supported by stronger governance systems, broader talent pools, and more mature data environments. SMEs, while equally motivated by efficiency, showed more cautious and selective adoption intent.

Overall, the findings indicate that AI adoption in Kuwait is primarily economically driven, with firms viewing AI as a tool to reduce costs and increase operational throughput. Strategic aspirations emerge mainly where digital infrastructures and internal capabilities already provide a foundation for more sophisticated applications.

Beyond the concrete operational motives, interviews revealed a strong underlying optimism toward artificial intelligence. Across the sample, nearly nine out of ten enterprises expressed a positive outlook on the potential of AI to enhance their operations, even when internal capabilities or data maturity were still developing.

Figure 3: Motivation to use AI by type of work



Source: Authors' calculations.

Notes: Figure 3 classifies interviewed firms into three broad profiles based on how they frame the main rationale for adopting AI: Cognitive and knowledge-intensive firms, physical and process-intensive firms and mixed-focus firms.

This sentiment does not replace cost- and efficiency-driven motivations, but it reinforces them by creating a favorable climate for experimentation and early adoption.

In several firms, this optimism was described as a belief that AI represents an inevitable step in modernization, pushing leaders to explore opportunities even before formal business cases or governance structures are fully established.

3.2 Use and adoption of AI tools

This subsection corresponds to the interview theme on firms' current AI use cases and adoption maturity. Key patterns emerging from the interviews include:

- Use cases cluster around three domains:
  1. **Automation of administrative tasks,**
  2. **Analytical decision support,**
  3. **Customer-facing applications.**
- Adoption depth varies sharply by firm size: large enterprises advance further along the implementation path, while SMEs remain in early pilot phases.
- Data maturity is the primary boundary for adoption: firms deploy AI only as far as their data quality, integration and governance allow.
- Constraints evolve with maturity: early adopters face internal capability limits; more advanced firms confront regulatory, data residency and vendor-dependence issues.
- Optimism is high but investment is conditional: confidence rises with maturity, yet firms scale only when data, governance and regulatory clarity are in place.

▶ Box 1: AI tools used by firms, by adoption stage.

Early-stage adoption. Firms in the early stages of AI adoption mainly use readily accessible Generative AI tools and LLMs, often as stand-alone applications rather than tools integrated into core systems.

More advanced adoption. Firms with stronger data infrastructure and resources tend to build on pre-existing business optimization and analytics tools, which are then "augmented with AI" (typically machine learning and/or natural language processing) applied to enterprise data environments (e.g. SQL-based systems and cloud data platforms) to support analysis and decision-making.

Implication. This pattern suggests that progressing from experimentation to higher-value use depends largely on data readiness and integration capabilities.

Patterns of AI use in Kuwait's private sector reflect a broad spectrum of maturity, ranging from early experimentation to more structured deployments embedded in core business processes. Across the sample, firms reported introducing AI primarily in support functions and operational workflows, such as document processing, customer interaction, forecasting or anomaly detection, while more advanced or enterprise-wide deployments remain concentrated among larger, digitally mature organizations. Although the range of tools mentioned varied, use cases generally fell into three categories: automating repetitive administrative tasks, enhancing decision-making through analytical models, and improving service delivery through conversational or predictive applications.

A clear size effect is visible in adoption depth. Larger firms are significantly more likely to have moved beyond pilots and early trials, supported by stronger data infrastructures, clearer governance structures and access to specialized technical talent. Many of these organizations described a progression from small-scale experiments toward more stable operational systems, often situated in operational units, customer-facing channels or compliance-related functions. SMEs, by contrast, tend to remain in exploratory or pilot stages, constrained by limited data maturity, the absence of formal governance mechanisms and resource constraints. As a result, while interest in AI is high across firms of all sizes, the ability to operationalize tools at scale remains uneven.

Five AI adoption phases (based on interviews):

1. **Prospect:**
   No ongoing AI projects (personal, unbudgeted, unmanaged); per centage of enterprises in phase 1: Large (10), SMEs (21).

2. **Discover:**
   Proof-of-concept (PoC) intent and trials (unmeasured); per centage of enterprises in phase 2: Large (15), SMEs (29).

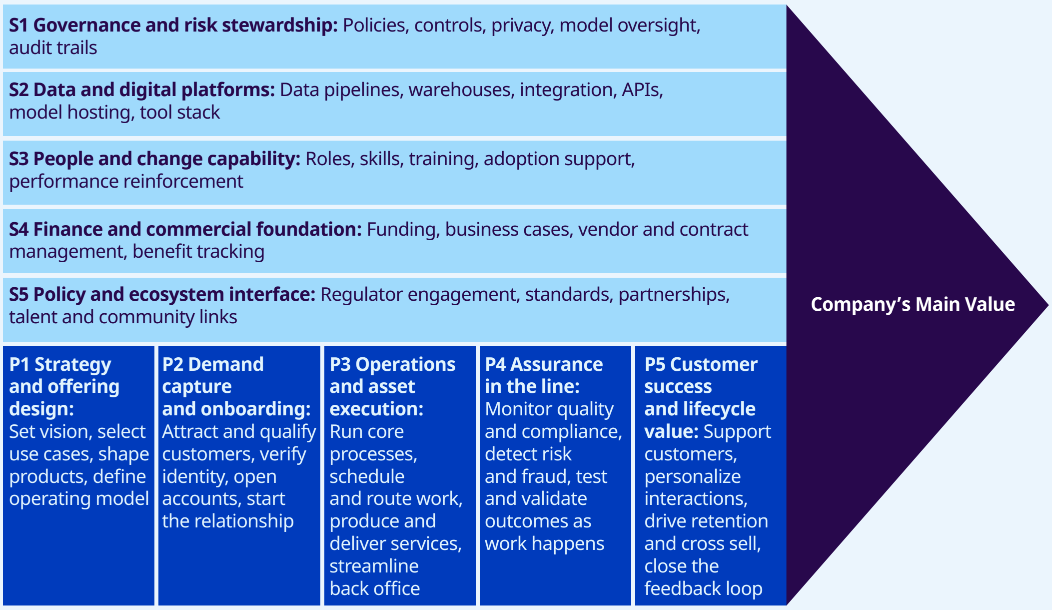
3. **Select:** Tools deployed for a limited group of employees (piloting, scoped, quantified); per centage of enterprises in phase 3: Large (35), SMEs (21).

4. **Prove:**
   Use cases deliver repeatable operational gains (validated, operational, repeatable); per centage of enterprises in phase 4: Large (25), SMEs (22)

5. **Embed:**
   AI initiatives integrated into core processes (integrated, governed, scaled); per centage of enterprises in phase 5: Large (15), SMEs (7).Data maturity emerged consistently as the boundary condition that determines how far adoption can progress. Firms with fragmented or non-digitized workflows struggle to deploy AI beyond isolated tasks, whereas those with integrated data platforms and established governance systems can support more complex use cases and move more confidently from initial trials toward embedded solutions. This progression shapes the observed distribution of adoption phases: large firms commonly reach mid- or late-stage implementation, while SMEs often remain at earlier developmental stages, irrespective of their strategic intent.

These patterns indicate that AI adoption is best understood as a set of localized deployments across business functions rather than a single "firm-level" state. Figure 4 therefore maps reported AI use cases onto the firm value chain (primary and support activities), providing a structured view of where AI is being applied—an essential step for interpreting which deployments are likely to translate into measurable productivity gains in Section 3.3.

▶ Figure 4: Mapping of reported AI use cases onto the firm value chain (P = primary activities; S = support activities).



Source: Authors' elaboration based on interview data.

Notes: The figure organizes interview-reported AI applications by value-chain function; examples shown are illustrative and do not imply prevalence unless explicitly indicated.

Two enabling factors for scaling AI adoption remain uneven across interviewed firms. Only around one-third report having an **AI usage policy**, and provision of **AI training** is also limited: about half of firms offer some form of AI training. Large firms are considerably more likely than SMEs to have an AI policy (45. vs 14. percent) and to train staff (65 vs. 29 percent)

Organizational constraints also evolve along this adoption path. Early-stage adopters predominantly cite internal capability gaps, such as insufficient data quality, legacy systems, or limited technical skills, as the main obstacles to further progress. More mature adopters increasingly face constraints external to the firm, including regulatory requirements, data residency rules, and vendor dependencies that limit system flexibility or reversibility. This shift underscores that adoption is not only a technological process but also an organizational and regulatory one, shaped by the broader ecosystem in which firms operate.

Despite these differences in maturity and capability, optimism about the potential benefits of AI is widespread. Firms that have already implemented tools, particularly larger and more data-mature organizations, tend to express greater confidence in scaling further, whereas those still building foundational capabilities take a more cautious view. Across the sample, leaders generally conceive of AI as an assistant or work companion designed to enhance task performance, reduce workload pressure, and support higher-quality outputs. As the next section shows, whether these expectations translate into measurable productivity gains depends on governance and data readiness, and on firms' ability to measure outcomes consistently.

3.3 Measuring and gauging productivity

This subsection corresponds to the interview theme on how firms assess the effects of AI on performance. Key findings emerging from the interviews include:

- Most reported productivity gains are not empirically verified: only about one quarter of firms provided measurement evidence.
- Verification is concentrated in large and data-mature firms; SMEs report no verified cases.
- When measurement exists, the effects are substantial, including sharp reductions in task time, error rates and processing costs.
- Unverified claims tend to arise where workflows are not instrumented, i.e. not measured through system logs or KPIs, baselines are missing, or multiple changes occur simultaneously.
- Measurement capability strengthens as firms progress in data maturity and adoption stage.

Understanding whether AI adoption translates into productivity gains is central to this report yet the interviews reveal that systematic measurement remains limited across much of Kuwait's private sector. While a majority of firms describe perceived improvements, such as faster task execution, fewer errors, smoother workflows, only a minority have established baselines, tracked metrics or used controlled comparisons that allow these claims to be verified. This pattern reflects both the early stage of adoption in many organizations and the uneven development of data infrastructures necessary for rigorous measurement.

Across the sample, roughly three-quarters of reported productivity effects remain unverified. These cases typically arise where critical conditions for measurement are absent: work processes are not instrumented, no "before–after" baselines exist, several changes occur at once (making attribution difficult), or data remain scattered across unconnected systems. SMEs, in particular, reported no verified productivity gains, mirroring their broader challenges in data maturity and governance.

By contrast, verified cases — representing approximately one quarter of firms — demonstrate a more consistent and substantial pattern. These organizations, mostly large enterprises with integrated data platforms, were able to document effects with named workflows, baselines, method tags (e.g. A/B tests or controlled pilots) and at least one full reporting cycle. Where such evidence exists, the scale of the gains is notable: reductions of 60–98 per cent in task time for targeted workflows, substantial drops in document-processing costs, fewer customer service calls and reallocation of staff toward higher-value work. These examples point to the potential of AI to deliver meaningful performance improvements when embedded in well-defined processes and supported by robust measurement systems.

The link between data maturity and the ability to verify outcomes is strong. Firms with more advanced data infrastructures not only deploy AI more widely but are also better equipped to capture its effects in a measurable way. Conversely, organizations at early stages of digitalization tend to rely on qualitative impressions, which—while valuable—do not provide a basis for assessing impact or guiding investment decisions. As firms progress along the adoption path, improving data integration and establishing consistent measurement routines will be essential for translating perceived benefits into verifiable productivity gains.

Overall, the interviews indicate high expectations for AI, but they also underscore that demonstrated impact depends on two conditions: the existence of reliable data systems and the discipline to measure outcomes systematically. Both are necessary for firms to move from experimentation to evidence-based scaling, a pattern explored further in Section 3.4.

3.4 Challenges and governance

Interviews indicate that challenges to AI adoption in Kuwait's private sector are not static but evolve as firms move along the adoption path. Constraints differ markedly by firm size, data maturity and stage of implementation, underscoring that AI adoption is shaped as much by organizational and governance conditions as by technological capability.

For firms at early stages of adoption, internal capability constraints dominate. These include limited data quality, fragmented or non-digitized workflows, legacy IT systems and shortages of specialized technical skills. Such constraints are particularly pronounced among small and medium-sized enterprises, many of which lack formalized AI policies, dedicated governance structures or clear decision rights for AI initiatives. In these contexts, experimentation often stalls at the pilot stage, as firms struggle to move from initial trials to validated and scalable applications.

Governance-related frictions appear across firms of all sizes and maturity levels. Interviewees frequently cited unclear ownership of AI initiatives, resistance to organizational change, uncertainty over accountability and difficulties in aligning AI projects with existing business processes. Even where technical pilots were perceived as successful, weak governance arrangements slowed progression from testing to operational deployment. These frictions suggest that governance capacity, rather than technical feasibility alone, plays a critical role in determining whether AI initiatives translate into sustained organizational change.

Among more mature adopters, particularly larger firms and those in regulated sectors such as financial services, the binding constraints increasingly shift beyond the firm. External and ecosystem-level barriers become more salient, including regulatory approval processes, data residency requirements and dependence on external vendors. Several firms reported concerns about limited access to system logs, model settings or export rights when relying on third-party AI solutions, which in turn restricts transparency, auditability and the ability to reverse or adapt systems over time. These issues were especially relevant for firms seeking to scale AI applications beyond isolated use cases and embed them into core operations.

Data governance sits at the intersection of internal and external constraints. Firms with more advanced data infrastructures and governance frameworks are better positioned to manage privacy, security and compliance requirements, but also encounter tighter regulatory scrutiny as AI use deepens. Conversely, firms with weak data foundations face internal bottlenecks that prevent them from reaching stages where external constraints would even become binding. This reinforces the finding that data maturity and governance capacity jointly condition the trajectory of AI adoption.

Overall, the evidence suggests a "constraint flip" as firms progress: internal capability and governance gaps dominate at early stages, while regulatory, policy and vendor-related constraints become more prominent at higher levels of maturity. This pattern highlights the importance of differentiated policy and organizational responses. While early-stage firms require support to build foundational data systems, skills and governance arrangements, more advanced adopters face challenges that depend on the broader regulatory and market environment. Addressing these challenges is therefore central to enabling firms to move from experimentation toward responsible and scalable AI deployment.

3.5 The future of AI

Interviews with enterprises reveal a broadly optimistic outlook regarding the future role of artificial intelligence in Kuwait's private sector, but also a cautious and conditional approach to further investment and scaling. Across the sample, firms widely perceive AI as a technology with significant potential to improve efficiency, quality and decision-making. At the same time, most organizations emphasize that future expansion depends on meeting a set of technical, organizational and regulatory conditions rather than on enthusiasm alone.

Optimism about AI is highest among firms with more advanced experience in implementation. Enterprises at later stages of adoption tend to report greater confidence in the technology's value, informed by hands-on experimentation and early results. By contrast, firms at earlier stages often express positive expectations while remaining hesitant to commit substantial resources until foundational capabilities, particularly related to data and governance, are strengthened. This pattern suggests that experience with AI both increases confidence and clarifies the constraints that must be addressed before scale is possible.

Investment decisions are therefore strongly gated. Firms indicate that scaling AI deployment requires, first, sufficiently mature data systems that allow integration across workflows; second, clear internal ownership and governance structures that define accountability and risk management; and third, an external environment that provides regulatory clarity, particularly with respect to data residency, compliance and vendor dependence. Where these conditions are not met, firms tend to remain in pilot mode or adopt a "wait and see" posture, even when expectations about AI's long-term potential are high.

Looking ahead, enterprises consistently describe a pathway in which AI creates greater value as data maturity improves. Firms with fragmented or partially digitized data infrastructures expect AI use to remain focused on isolated tasks. As data platforms become more integrated and governed, organizations anticipate expanding AI use toward core operational processes, customer-facing activities and, eventually, more strategic applications such as forecasting, planning and assurance functions. This progression underscores that future gains from AI are not primarily driven by the choice of tools, but by sustained investments in data foundations, skills and governance.

Across firms, AI is generally framed as a complementary technology rather than a substitute for human labour. Leaders frequently describe future deployments in terms of "assistant" or "work companion" models, with time savings expected to be redeployed toward higher-value activities. Whether these expectations translate into realized gains will depend on firms' ability to combine technological adoption with organizational change and workforce development.

Overall, the forward-looking evidence suggests that AI adoption in Kuwait's private sector is likely to deepen gradually rather than accelerate abruptly. Progress toward scale will be uneven, with larger and more data-mature firms advancing faster, while others remain constrained by foundational gaps. These dynamics point to the importance of targeted support mechanisms, shared infrastructure and clear rules to enable firms—particularly small and medium-sized enterprises—to move from experimentation toward sustained and productive use of AI.

▶ 4. Validation session and stakeholder feedback

4.1 Purpose and design of the validation session

A validation session was convened on 27 October 2025 at the Kuwait Chamber of Commerce and Industry (KCCI) to test the empirical findings derived from the enterprise interviews, assess their plausibility against operational realities, and identify any material gaps or misinterpretations. The session brought together senior executives and decision-makers from Kuwait's private sector, representing the six broad industry groupings covered in the study.

The objective was not to generate new quantitative evidence, but to stress-test the analytical interpretation, surface missing contextual factors, and explore implications for ecosystem-level action. The session combined a structured presentation of findings with moderated discussion, allowing participants to confirm, nuance, or challenge the results based on their experience.

The interviews were conducted during August and September 2025, the validation session was held in October 2025 and the report finalized January 2026.

Private sector validation session convened at the Kuwait Chamber of Commerce and Industry on 27 October 2025

4.2 Participation and sectoral coverage

Of 52 confirmed invitees, 40 participants attended, representing a broad cross section of Kuwait's private sector, including Financial Services; Energy, Materials and Industrial Mobility; Technology, Media and Telecommunications; Logistics, Transport and E-commerce Enablement; Lifestyle, Health and Environmental Markets; and Education and Training. Participants represented both large enterprises and smaller firms, with operational roles spanning strategy, operations, compliance, and digital transformation.

The attendance rate and diversity of participants indicate strong private-sector engagement and lend credibility to the validation exercise. While the session cannot be considered representative, it provided informed feedback from firms that play a significant role in Kuwait's non-oil economy and regional value chains.

4.3 Confirmation of core findings

Overall, participants confirmed that the main analytical patterns identified in the interviews accurately reflected their experience. In particular, there was broad agreement on three core findings:

i. AI adoption is strongly conditioned by firm size and data maturity, with larger, more digitally mature organizations able to move beyond pilots more consistently than SMEs.

ii. Most productivity claims remain unverified, reflecting gaps in data integration, baseline measurement, and attribution rather than a lack of perceived impact.

iii. Constraints evolve with maturity, shifting from internal capability gaps in early stages to regulatory, data residency, and vendor-dependence issues among more advanced adopters.

Participants recognized the internal coherence of the analytical framework linking motivation, data maturity, adoption phase, measurement practices, and constraints.

4.4 Points of discussion and nuance

While there was broad consensus, one recurring point of discussion concerned the assumption—common in public discourse—that AI adoption would inherently favour SMEs by lowering barriers to advanced technology. Several participants noted that the findings challenge this narrative. In practice, economies of scale, complementary capabilities (data governance, skills, change management), and financial resilience continue to advantage larger firms in moving from experimentation to scale.

Participants also highlighted contextual factors that shape adoption incentives in Kuwait, including relatively low labour costs in some functions, which can weaken the immediate business case for automation unless productivity gains are clearly measured and sustained.

These discussions did not contradict the study's findings but helped clarify why gaps between large firms and SMEs persist despite the availability of cloud-based AI tools.

4.5 Ecosystem-level constraints and coordination challenges

Beyond firm-level dynamics, the validation session placed strong emphasis on ecosystem constraints that individual organizations cannot resolve independently. Participants highlighted four interrelated issues:

i. Trust and supplier accountability: Firms expressed uncertainty about supplier practices, audit rights, liability, and exit options, particularly where AI systems rely on external vendors or cloud infrastructure.

ii. Regulatory asymmetries: Participants noted that regulatory obligations often fall on user organizations, while technology suppliers face fewer explicit duties, creating misaligned accountability.

iii. Data sovereignty and residency: Clarity over where data are stored, processed, and accessed was repeatedly identified as a precondition for scaling AI use, especially in regulated sectors.

iv. Coordination failures: Bilateral negotiations between firms and vendors create high transaction costs and inconsistent standards, particularly disadvantaging smaller organizations.

These issues reinforce the study's conclusion that adoption barriers increasingly lie outside individual firms once basic capabilities are in place.

4.6 Role of the Kuwait Chamber of Commerce and Industry

Participants consistently pointed to the KCCI as a potential neutral convening platform capable of reducing coordination costs across the ecosystem. Suggested roles included facilitating dialogue between firms, regulators, and technology providers; supporting shared learning; and helping translate operational experience into practical guidance or voluntary standards. This role is envisioned to support trust-building, information exchange, and alignment among stakeholders.

4.7 Implications for interpretation of findings

The validation session strengthens confidence that the study's findings should be read as credible, practice-based patterns, while also underscoring their limits. The discussions reaffirm that productivity gains from AI are conditional on data maturity, governance, and measurement capacity, and that policy-relevant bottlenecks increasingly concern ecosystem coordination rather than technology availability alone.

These insights inform the policy considerations outlined in the next section.

5. Policy considerations and conclusions

5.1 Key messages from the evidence

This study provides enterprise-level evidence on how artificial intelligence is currently being adopted in Kuwait's private sector and where constraints to productivity-enhancing deployment arise. Five core messages emerge clearly from the interviews and the validation session.

- First, AI adoption is real but uneven. Most participating enterprises express strong interest in AI and are actively experimenting with tools, yet adoption depth varies substantially by firm size, sector, and data maturity. Large and digitally mature firms are more likely to move beyond pilots, while many SMEs remain at early or exploratory stages.
- Second, productivity gains are widely claimed but rarely verified. While enterprises frequently report efficiency improvements, only a minority are able to substantiate these claims through systematic measurement using baselines, comparable metrics, and persistence over time. Verified productivity effects are concentrated in large firms and in operationally stable environments.
- Third, data maturity and governance are the binding constraints. The ability to adopt and scale AI is closely linked to the quality, integration, and governance of enterprise data. Firms deploy AI only as far as their data foundations allow, and gaps in data infrastructure limit both adoption and credible measurement of impact.
- Fourth, SMEs face structural disadvantages. Although AI tools are increasingly accessible, smaller firms lack the complementary capabilities—data systems, internal expertise, governance capacity, and financial resilience, which would be required to move from experimentation to sustained deployment. Without targeted support, adoption risks reinforcing existing productivity gaps.
- Finally, policy and ecosystem conditions matter most at transition points, particularly when firms seek to move from pilots to scale. At higher levels of maturity, internal capability constraints give way to external barriers, including regulatory uncertainty, data residency requirements, and vendor dependence.

These messages frame the policy considerations outlined below.

5.2 Policy priorities to support Effective AI adoption

The evidence suggests that policy interventions are most effective when they address enabling conditions rather than promoting specific technologies. Four priority areas emerge from the enterprise perspective.

i. Strengthening data foundations

Enterprises consistently identified data quality, integration, and governance as prerequisites for AI adoption and productivity measurement. Policy efforts could therefore focus on:

- Supporting shared or sector-level data infrastructures where appropriate, particularly for SMEs.
- Promoting interoperable data standards and practical guidance on data governance.
- Encouraging approaches that reduce the cost and complexity of building foundational data capabilities.

Improved data foundations not only enable AI deployment but also make productivity effects observable and verifiable.

ii. Building skills and organizational capability

Skills constraints were repeatedly cited as a barrier, not only in technical roles but also in management and governance functions. Enterprises emphasized the need for:

- Practical, use-case-oriented AI skills rather than abstract certifications.
- Capacity to evaluate vendors, design pilots, and assess business cases.
- Targeted support for SMEs, where limited internal expertise amplifies adoption risks.

Policies that link skills development directly to live enterprise use cases appear more likely to translate into adoption and impact.

iii. Improving measurement and accountability

A central gap identified in the study is the absence of systematic productivity measurement. Enterprises expressed demand for:

- Simple, standardized measurement templates tied to named workflows.
- Guidance on establishing baselines and tracking outcomes over time.
- Approaches that distinguish verified results from perceived benefits.

Improving measurement capacity helps firms make informed investment decisions and reduces the risk of overestimating AI’s impact.

iv. Reducing regulatory and ecosystem frictions

As firms mature in their use of AI, external constraints increasingly shape adoption decisions. Key issues raised include:

- Uncertainty around data residency, cloud use, and compliance responsibilities.
- Vendor dependence and limited exit or audit rights.
- The absence of trusted mechanisms to assess supplier practices.

Enterprises highlighted the value of regulatory clarity, time-bound testing environments, and mechanisms that lower transaction costs—particularly for smaller firms—without weakening safeguards.

5.3 Concluding remarks and next steps

This report provides an exploratory but policy-relevant snapshot of AI adoption in Kuwait's private sector, grounded in enterprise interviews and validated through structured dialogue with business leaders. The findings underline that AI can contribute to productivity gains, but only when embedded in broader organizational, data, and governance capabilities.

The study also demonstrates the value of collaboration between the ILO and the Kuwait Chamber of Commerce and Industry in generating evidence that reflects operational realities. Repeating similar exercises over time, potentially combining qualitative interviews with targeted survey, would help track progress, refine policy responses, and monitor whether productivity effects become more widespread and measurable.

Ultimately, AI adoption in enterprises is not constrained by technology alone. It depends on data foundations, skills, governance, and ecosystem conditions that shape firms' ability to move from experimentation to scale. Addressing these factors will be central to ensuring that AI contributes meaningfully to productivity growth in Kuwait's private sector.

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Appendix

AI & Productivity interview questionnaire

Name of interviewee	
Role title	
Institutional affiliation	
Industry	
Relevant experience (AI, robotics, data science, other)	Based on the respondent's self-evaluation before/at the beginning of the interview
Date of interview	
Name of interviewer	

Company	*Insert official company name*
No of employees	*Insert no of employees*
Turnover	Insert revenue
Products / services	Insert types of products produced / services provided

Introduction: Why are we consulting you?

The International Labour Organization (ILO) - in collaboration with the Kuwait Chamber of Commerce and Industry (KCCI) - is conducting a study to understand the impact that artificial intelligence (AI) might have on productivity. Our study aims to understand the adoption of current AI tools, their contribution to company performance, and the challenges that companies face in adopting them.

We aim to better understand a) the decision processes that lead to firms to adopting AI-systems, and b) to assess the return on AI-investment.

Our study focuses on the use of AI, i.e. in the possible adoption of AI technology in an enterprise's operations and workforce. Where necessary and appropriate we will also seek understanding of the development of AI, i.e. whether a company is creating/adapting AI as a product or service for its customers.

We take a broad view on AI tools, including wearables, agent-based AI such as the allocation of work shifts or performance management, generative AI, and robotic process automation.

We have prepared 5 questions for you that you can answer openly. For some of the questions, we will provide some illustrations or follow-up questions that you may use as guidance to your answer. We estimate that the whole interview takes about 25 minutes, i.e. approximately 5 minutes per question.

Interview questionnaire: company leads

AI and productivity questionnaire (semi-structured guideline)

Block 1: Motivation for using AI tools:

1. Are you using AI Tools?

   a. If no, then: What is your motivation for not using AI tools?

   b. After asking 1A, skip to Block 4 then Block 5a.

2. What is the key factor driving AI adoption in your company?

For illustration some possible aspects are (not exhaustive): Productivity or efficiency gains? (Which ones?) Competitive pressure? Quality improvements? Cost reductions? (Which costs?) Economic Uncertainty or strategic resilience?

Block 2: Use and adoption of AI tools:

3. How is your company currently using AI?

a. Are there specific units or workflows that you are targeting for AI use?

b. Into which functions in the workflow are these AI applications integrated?

c. Did you need to make changes to internal operations or your business model?

Block 3: Measuring and gauging productivity:

4. How do you measure or plan to measure how AI affects the company's productivity and where do you see its effects?

What key performance indicators (KPIs) are you tracking to assess the impact of your AI investment on your company's performance?

How have these KPIs evolved since you started using AI tools?

Have you seen an improvement in the quality of the work as employees use AI?

Where in your company do you see AI improving business operations and outcomes?

Is AI improving identification of risks and disruptions to the company?

Block 4: Challenges and governance

5. I am going to ask you about a list of challenges regarding AI adoption. If it is a challenge, please tell us why.
    a. Costs
    b. Quality of output
    c. Governance
    d. Regulation
    e. Integration with existing systems
    f. Privacy and security concerns
    g. Employee expertise
    h. Employee resistance
6. Have you discontinued any AI tools?

Block 5: The future of AI

7. If 1b, then what would it take for you to adopt AI?
8. How do you see AI increasing your company's performance in the future?
9. Which KPIs do you expect to perform particularly well, which other KPIs do you believe will be less affected?
10. What additional investments do you think your company needs to make to fully benefit from AI adoption?

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