HUMAN RESOURCE DEVELOPMENT COUNCIL

Beyond Automation: Digital Technology Adoption, GenAI Integration and Skills Readiness in the Manufacturing Sector

Survey conducted: April–June 2026 | N = 65 manufacturing enterprises

Key Statistics at a Glance

65
Enterprises Surveyed

61.5%
GenAI Technology Adoption

55.4%
Employee use

60.0%
Management encouragement

64.6%
Cloud Adoption

39.8%
Avg AI Integration

31.3% among enterprises with 10–49 employees
52.8% among those with over 250 employees

90.8%
Digital Tech: Important and Critical

only 13.8% have reached the Integrated/Mature or Advanced/Leading stages of digital transformation

Executive Summary

This report presents findings from a cross-sectional survey of 65 manufacturing enterprises in Mauritius conducted between April and June 2026. The study, undertaken by the Human Resource Development Council (HRDC), assesses the adoption of manufacturing-related digital technologies, skills gaps, Generative AI (GenAI) integration and workforce readiness among responding enterprises. Building on HRDC's 2022 study on automation, robotics and IIoT in the manufacturing sector (HRDC, 2022), it provides an indicative four-year perspective on the growing role of digital technology in manufacturing. The findings are based on a sample of enterprises in the Manufacturing sector.

The manufacturing sector remains one of Mauritius' key productive pillars, supporting employment, value creation and export capability across textiles and apparel, food and beverages, jewellery, chemicals, printing, precision engineering and related activities. However, the sector is now operating in a more demanding competitive environment, where productivity, quality assurance, cost control, sustainability compliance, speed-to-market and integration into global value chains are increasingly shaped by digital capability. The 2026 survey indicates that digitalisation is no longer peripheral to manufacturing operations: cloud computing, collaboration platforms, cybersecurity tools, IoT, AI and Generative AI are already entering enterprise workflows at varying levels of intensity. At the same time, the findings show that transformation remains uneven, with many enterprises constrained by budget limitations, internal expertise gaps, weak implementation capacity and insufficient access to targeted training. The strategic challenge for the sector is therefore not simply technology adoption, but the development of a digitally capable workforce and support ecosystem that can convert technology use into productivity gains, competitiveness and sustainable workforce transition.

Key Finding 1: Digital Technology is Now Mainstream

★ Basic ICT (92.3%), social networking and collaboration platforms (83.1%), digital platforms and apps (80.0%), and cloud computing (64.6%) are now widely adopted by responding manufacturing enterprises, suggesting progress relative to the 2022 baseline, subject to differences in sample, questionnaire design and measurement constructs.

Key Finding 2: Generative AI Has Reached the Sector

★ 61.5% of surveyed enterprises report current GenAI technology use; 55.4% report employee use of GenAI tools; and 60.0% actively encourage its adoption. Writing and editing is the leading reported GenAI work activity (47.7% of the full sample), while search and knowledge management is the leading reported GenAI tool/capability category (41.5%). These are distinct survey measures and together signal a shift in workforce practices requiring targeted skilling responses.

Key Finding 3: Moderate but Persistent Digital Skills Gaps

Across the five digital competency areas assessed, responding enterprises reported an average skills shortfall of approximately **29.3%**, placing the sector within the **moderate skills gap** range. This indicates that while the workforce is not starting from zero, existing digital capabilities remain insufficient to fully support technology adoption, AI/GenAI integration, data-driven operations and digital transformation. The finding points to the need for structured, role-based reskilling rather than ad hoc training.

Key Finding 4: Digital Transformation Remains Uneven

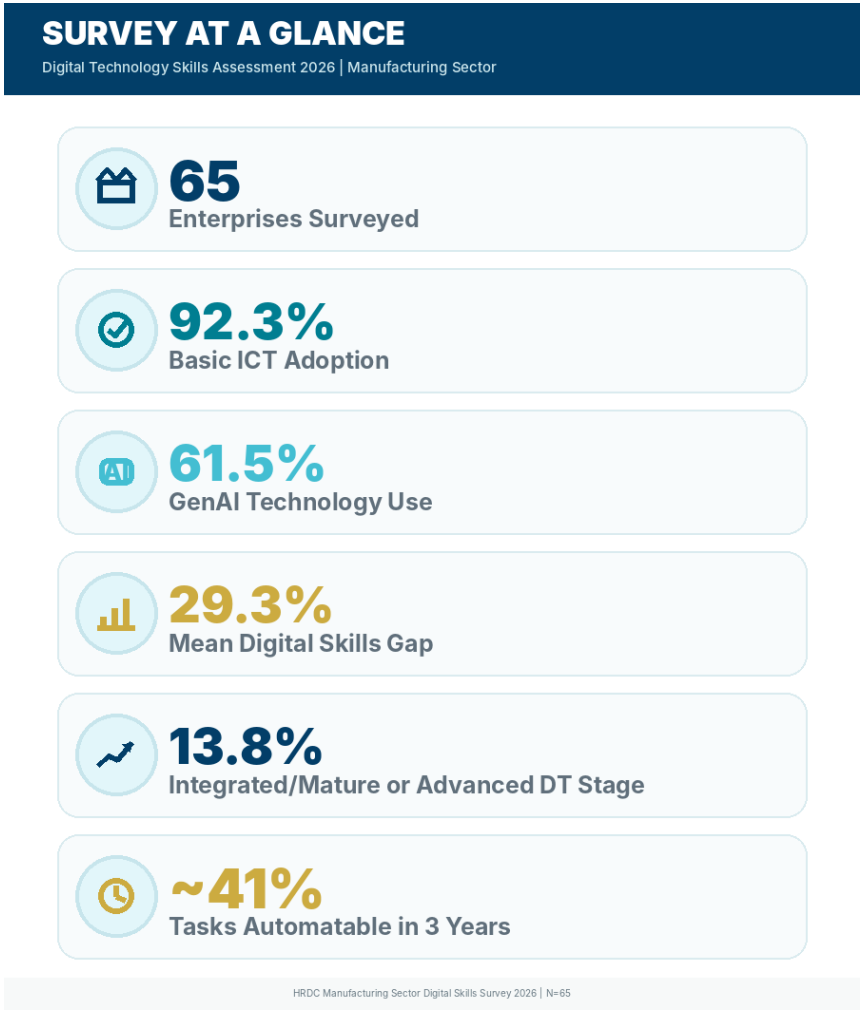
Only 13.8% of surveyed enterprises have reached the Integrated/Mature or Advanced/Leading stages of digital transformation. Budget constraints (53.8%) and internal skills gaps (40.0%) remain the foremost barriers to progress.

Key Finding 5: Task Automation Pressures Are Emerging

Across the survey's role-level automation estimates, approximately 41% of tasks are assessed as potentially automatable within the next three years. This overall role-level estimate is distinct from the unweighted mean of NASCO group averages shown in Figure 17 and underscores the need for proactive workforce transition planning and upskilling investment.

The report recommends targeted, occupation-based and practical digital-skills programmes; responsible AI and GenAI governance; stronger collaboration among HRDC, industry bodies and training providers; clustered support for SME digital readiness; and strategic use of existing Skills Development schemes and instruments. It also proposes a proportionate skills-intelligence cycle comprising a short annual pulse survey and a full manufacturing digital-skills assessment every three years.

Figure ES-1: Executive Summary — Survey at a Glance



Acknowledgement

The Human Resource Development Council (HRDC) extends its sincere appreciation to the manufacturing enterprises that participated in the survey conducted between April and June 2026, as well as to the industry associations and other stakeholders who supported the research process. Their contributions, insights and cooperation were instrumental in generating evidence on digital technology adoption, Generative Artificial Intelligence (GenAI) integration, workforce capabilities and emerging skills requirements within the manufacturing sector in Mauritius.

The HRDC also acknowledges the contribution of the representatives of manufacturing enterprises who participated in qualitative interviews conducted during 2025 and 2026, providing valuable operational perspectives that complemented the quantitative findings. The support of industry associations in facilitating engagement with enterprises further contributed to the development of this sectoral assessment.

This report draws on the findings of the 2026 enterprise survey, qualitative enterprise interviews, and desk-based analysis of relevant local and international literature and policy developments. Together, these sources provide an evidence base for assessing the sector's digital transformation readiness, identifying workforce skills gaps and formulating recommendations to strengthen skills development and support the adoption of emerging technologies.

The report was prepared by the Research and Projects Division of the HRDC.

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Table of Contents

Executive Summary 2
Acknowledgement 4
List of Figures 7
List of Tables 8
List of Abbreviations 9
1. Introduction 10
2. Local and International Literature Review 11
2.1 The Global Digital Transformation of Manufacturing 11
2.2 Skills Dynamics in the Digital Manufacturing Era 11
2.3 The Mauritian Manufacturing Sector: Local Context 12
2.4 Generative AI and the Future of Work in Small Island Contexts 14
3. Objectives and Methodology 15
3.1 Objectives 15
3.2 Research Design and Sampling 15
3.3 Data Analysis 16
3.4 Ethical Considerations and Limitations 16
3.5 Project Implementation and Quality Assurance 17
3.6 Interpretation Safeguards 17
4. Profile of Respondents 17
4.1 Enterprise Size 17
4.2 Sub-sector Classification 18
4.3 Years of Operation 18
4.4 Turnover Profile 18
4.5 Respondent Profile 19
5. Technology Adoption and Usage 19
5.1 Typology of Digital Technologies Used in the Study 19
5.2 Adoption Categories 20
5.3 Adoption Levels Across Technology Categories 20
5.4 Skills as a Barrier to Technology Adoption 22
6. Digital Transformation Maturity 23
6.1 Transformation Stage Distribution 23
6.2 Digital Transformation Stage by Enterprise Size 24
6.3 Stage by Turnover 24
6.4 Principal Barriers to Digital Transformation 25
7. Digital Skills Gaps and Competency Assessment 26
7.1 Skills Gap Measurement Framework 26
7.2 Top Job Roles and Current Technology Use, by NASCO Occupational Group 26
7.3 Overall Skills Gap by Competency Category 30
7.4 Skills Gap by NASCO Occupational Group 30
7.5 Task Automation Outlook by NASCO Occupational Group 31
7.6 Summary: Skills Gap and Automation by NASCO Occupational Group 32
7.7 Implications For Future Skill Development Programmes 33
8. Artificial Intelligence Integration 34
8.1 AI Maturity Categorisation Used for Interpretation 34
8.2 AI Integration Level 34
8.3 How Enterprises Determine AI-Related Training Needs 35
9. Generative AI Adoption and Governance 35
9.1 Employee Use and Enterprise Encouragement 35
9.2 GenAI Maturity Stage 36
9.3 Types of GenAI Tools Used 36
9.4 GenAI Work Activities 37
9.5 GenAI Expertise Level 38
10. Impact of Digital Technology on Jobs and Workforce 38
10.1 Overall Impact Assessment 38

10.2 Workforce-Related Effects of Digital Technology 39
10.3 Digital Technology Importance for Future Growth 39
11. Digital Technology Prospecting 40
12. Future Outlook: New Roles and Skills 40
12.1 Emerging Job Roles 40
12.2 Required Skills for Emerging Roles 40
12.3 Qualitative Insights: Sub-Sector Perspectives 41
13. Indicative Storyline: 2022 vs 2026 43
14. Recommendations and Way Forward 45
14.1 Implementation Roadmap for Action 50
14.2 Expected Role of HRDC 51
15. Conclusion 51
References 53

List of Figures

Figure ES-1: Executive Summary — Survey at a Glance
Figure 1: Project implementation and evidence flow
Figure 2: Enterprise Size Distribution (N=65)
Figure 3: Sub sectors (N=65)
Figure 4: Years in Operation (N=65)
Figure 5: Enterprise Turnover (N=65)
Figure 6: Respondent Role (N=65)
Figure 7: Manufacturing digital technology typology used in the study
Figure 8: Adoption categories used to interpret current-use rates
Figure 9: Adoption profile by original survey typology and adoption category (N=65)
Figure 10: The Digital Transformation Journey — Seven Maturity Stages
Figure 11: Digital Transformation Stage by Enterprise Size (N=65)
Figure 12: Challenges in Digital Transformation (Multiple Response, N=65)
Figure 13: Current Technology Tools in Use, by NASCO Major Group
Figure 14: Mean Skills Gap by Category Across All Roles
Figure 15: Skills Gap (%) by NASCO Major Group and Competency Category
Figure 16: Mean Overall Skills Gap by NASCO Major Group, Ranked (n=270 valid role entries)
Figure 17: Estimated Task Automation Potential by NASCO Major Group, Next 3 Years
Figure 18: AI Integration Maturity Scale Used for Interpretation
Figure 19: AI Systems Integration Level (N=65)
Figure 20: How Enterprises Determine AI-Related Training Needs (Multiple Response, N=65)
Figure 21: Generative AI Adoption in Manufacturing Enterprises (N=65)
Figure 22: GenAI Maturity Stage Among Eligible Valid Responses (n=38)
Figure 23: Types of GenAI Tools Used (Multiple Response; full sample N=65; eligible group n=39)
Figure 24: GenAI Work Activities (Multiple Response; full sample N=65; eligible group n=39)
Figure 25: Self-Rated GenAI Expertise Level Among Eligible Respondents (n=39)
Figure 26: Impact of Digital Technology on Jobs and Skills (Multiple Response, N=65)
Figure 27: Importance of Digital Technologies for Future Growth (N=65)
Figure 28: Digital Technology Prospecting Methods (Multiple Response, N=65)
Figure 29: Sub-Sectors Covered by HRDC Qualitative Interviews, 2025/2026
Figure 30: Indicative Comparison — Selected Digital Technology Metrics, 2022 and 2026
Figure 31: Five operational pillars for implementation
Figure 32: Progressive digital skills pathways for manufacturing
Figure 33: SME digital readiness support model
Figure 34: Recommended implementation roadmap for action

List of Tables

Table 1: Skills as a Barrier to Technology Adoption (Selected Technologies, N=65)

Table 2: Digital Transformation Stage by Enterprise Turnover (N=65)

Table 3: Top Five Most Frequently Cited Job Roles and Currently Used Technology Tools (n=270 valid role entries)

Table 3b: Technical/Production Job Roles Cited in the Survey, by Frequency (n=270 valid role entries)

Table 4: NASCO Major Occupational Groups — Illustrative Job Roles and Sample Sizes

Table 5: Mean Skills Gap (%) and Automation Potential (%) by NASCO Major Occupational Group

Table 6: Themes in Substantive Emerging-Role Mentions (Q22; 55 mentions from 27 enterprises)

Table 7: Qualitative Sub-Sector Themes from HRDC Manufacturing Enterprise Interviews (2025/2026)

List of Abbreviations

AI	Artificial Intelligence
AMM	Association of Mauritian Manufacturers
AR/VR	Augmented Reality / Virtual Reality
CAD	Computer-Aided Design
CEO	Chief Executive Officer
CRM	Customer Relationship Management
CT	Critical Thinking
DF	Digital Fluency
EDB	Economic Development Board
ERP	Enterprise Resource Planning
GDP	Gross Domestic Product
GenAI	Generative Artificial Intelligence
HR	Human Resources
HRDC	Human Resource Development Council
ICT	Information and Communication Technology
IFR	International Federation of Robotics
IIoT	Industrial Internet of Things
ILO	International Labour Organization
IoT	Internet of Things
IT	Information Technology
MES	Manufacturing Execution System
MEXA	Mauritius Exports Association
MITD	Mauritius Institute of Training and Development
ML/NN	Machine Learning / Neural Networks
MQA	Mauritius Qualifications Authority
NIST	National Institute of Standards and Technology
NPCC	National Productivity and Competitiveness Council
NSDS	National Skills Development Strategy
OEE	Overall Equipment Effectiveness
OECD	Organisation for Economic Co-operation and Development
PLC	Programmable Logic Controller
POS	Point of Sale
SCADA	Supervisory Control and Data Acquisition
SME	Small and Medium Enterprise
SPSS	Statistical Package for the Social Sciences
SUD	Software Use and Development
TOS	Technical Occupational Skills
TVET	Technical and Vocational Education and Training
UDS	Understanding Digital Systems
USD	United States Dollar
WEF	World Economic Forum

1. Introduction

The global manufacturing landscape is being fundamentally reshaped by the confluence of digital technologies, shifting labour markets, and evolving consumer demands. From the early adoption of computer-aided manufacturing and enterprise resource planning (ERP) systems to the present era of Generative Artificial Intelligence (GenAI), cloud-native operations, and industrial IoT, the sector has undergone successive waves of technological transformation. For small island developing states such as Mauritius, where the manufacturing sector remains a cornerstone of formal employment and export earnings, the challenge of keeping pace with this transformation while managing the workforce transition is both pressing and complex.

Mauritius's manufacturing sector is characterised by a diverse mix of sub-sectors, spanning textiles and apparel, food and beverage processing, jewellery, chemicals, printing, medical devices and precision engineering amongst others. In 2025, manufacturing generated Gross Value Added of approximately Rs 83.5 billion, accounting for 13.0% of national GVA, and registered real growth of 1.4%. For 2026, Statistics Mauritius forecasts manufacturing growth of 2.1%, with sectoral GVA reaching approximately Rs 89.1 billion and representing 12.9% of total GVA. Provisional figures for the first quarter of 2026 indicate that manufacturing accounted for 9.6% of Mauritian employment, equivalent to approximately 53,200 local workers and 16,000 foreign workers (Statistics Mauritius, 2026). The government's vision for a high-value, digitally-enabled manufacturing base is articulated through the National Skills Development Strategy (NSDS), the Digital Mauritius 2030 Strategic Plan, and successive National Budgets that have invested in Industry 4.0 readiness and automation support schemes.

The Human Resource Development Council (HRDC) plays a central role in matching skills development to the evolving needs of the labour market. Through its Levy-Grant Scheme, HRDC channels enterprise training investments and supports sectoral skills intelligence through research, industry engagement, and policy advisory functions. The present study is a continuation of HRDC's 2022 study on automation, robotics and IIoT in the manufacturing sector (HRDC, 2022), which established a baseline of manufacturing sector automation levels and identified critical skills gaps for Industry 4.0 readiness.

Since 2022, the digital landscape has shifted dramatically. The advent of large language models and GenAI tools such as ChatGPT, Claude, and Gemini has introduced new possibilities and new skills imperatives that were not part of the earlier research frame. Simultaneously, cloud adoption has accelerated, cybersecurity threats have intensified, and the pace of IoT integration across production, supply chain, and quality management has quickened. Against this backdrop, the HRDC undertook this 2026 study to assess the current state of digital technology adoption in the private manufacturing sector, map associated skills gaps, and generate evidence-based recommendations for skill development policy.

The report is structured as follows. After the literature review, the methodology and respondent profile are presented. Sections 5–12 examine technology adoption, digital maturity, skills gaps, AI and GenAI integration, workforce impacts, technology prospecting and emerging

roles. Section 13 provides an indicative 2022–2026 comparison, subject to the stated methodological differences. The report concludes with recommendations and areas for further study.

2. Local and International Literature Review

2.1 The Global Digital Transformation of Manufacturing

The Fourth Industrial Revolution (Industry 4.0), characterised by cyber-physical systems, the Internet of Things (IoT), artificial intelligence, and advanced analytics, is transforming manufacturing at unprecedented speed. Schwab (2016) argues that this revolution differs from previous industrial transitions not merely in scale but in the velocity of disruption and the breadth of its systemic impacts. The McKinsey Global Institute estimates that automation could displace up to 375 million workers globally by 2030 — approximately 14% of the global workforce — requiring substantial occupational transitions (Manyika et al., 2017).

At the enterprise level, digital transformation encompasses the integration of digital technologies into all areas of a business, fundamentally changing how enterprises operate and deliver value to customers (Vial, 2019). In manufacturing, this involves the adoption of cloud computing, big data analytics, AI-driven predictive maintenance, robotics, 3D/4D printing, augmented reality for quality inspection, and end-to-end supply chain digitalisation. The OECD (2023) identifies that enterprises which successfully undertake digital transformation report productivity gains of 15–40%, improved quality outcomes, and enhanced export competitiveness.

The emergence of Generative AI represents perhaps the most significant recent shift. Acemoglu and Restrepo (2022) note that unlike earlier automation waves that primarily displaced routine manual tasks, GenAI threatens to substitute for a wider range of cognitive, creative, and knowledge-intensive tasks. Goldman Sachs (2023) estimates that GenAI could automate up to 26% of work tasks in advanced economies, with white-collar knowledge workers facing greater exposure than previously assumed. For manufacturing, this encompasses design, quality documentation, supply chain management, HR functions, and customer-facing activities.

International benchmarks highlight the uneven adoption of digital technologies. The Republic of Korea, Singapore, and Germany lead in industrial robot density (IFR, 2023), while cloud computing and IoT adoption is highest in North American and Northern European manufacturers. A World Economic Forum (WEF, 2023) survey of manufacturing CEOs identified the lack of digitally-skilled workers as the single greatest barrier to digital transformation, ahead of financial constraints and technology availability.

2.2 Skills Dynamics in the Digital Manufacturing Era

The skills implications of digital transformation in manufacturing have been extensively studied. The WEF Future of Jobs Report (2023) identifies analytical thinking, creative thinking, resilience, flexibility, AI and big data literacy, cybersecurity skills, and design thinking as the fastest-growing skill areas for manufacturing workers. Conversely, manual dexterity, data entry, and routine administrative tasks are among the most rapidly declining skill areas.

Research by Brynjolfsson, Mitchell and Rock (2018) on the task composition of occupations suggests that the automation risk is not homogeneous across manufacturing sub-sectors. High-precision, bespoke production environments retain higher requirements for skilled human judgment, whereas high-volume, standardised production is more susceptible to automation substitution. This has direct implications for Mauritius, where the manufacturing sector encompasses both high-volume textile production and smaller-scale precision manufacturing for export.

Literature identifies several critical success factors for digital skills development in manufacturing. First, strong industry-education partnerships are essential for ensuring that training programmes remain current and aligned with workplace needs (ILO, 2022). Second, the role of management capability is central, without digital-literate leadership, enterprise-level digital transformation stalls (Fitzgerald et al., 2014). Third, the provision of learning pathways that accommodate employed workers through modular qualifications, micro-credentials, and workplace-based learning is critical to addressing skills gaps without disrupting production (OECD, 2021).

B

International Benchmark: Singapore's SkillsFuture Initiative

Singapore's SkillsFuture enterprise development scheme provides enterprises with funding for skills upgrading tied to digital transformation plans. Enterprises submit Industry Digital Plans (IDPs) aligned to sectoral roadmaps, and training grants are unlocked at each stage of the digital journey. This model of linking skills funding to digital maturity-stage assessment offers a useful comparator for Mauritius.

B

International Benchmark: Germany's Mittelstand Digital Centres

Germany's network of 26 Mittelstand Digital Centres provides SME manufacturers with practical support for digital transformation, including hands-on technology testing, pilot projects, and skills training subsidised by the Federal Ministry for Economic Affairs. The programme explicitly links technology adoption support with workforce qualification, addressing both sides of the skills-technology interface (BMWK, 2022).

2.3 The Mauritian Manufacturing Sector: Local Context

The manufacturing sector in Mauritius has undergone considerable structural change since the 1990s export-processing zone model built on preferential market access for textiles and sugar. The loss of Multi-Fibre Arrangement quotas and sugar protocol preferences necessitated a fundamental repositioning towards quality, design, and value-added production. Today, the sector is characterised by a dual structure: a group of large, internationalised enterprises with sophisticated production

systems, and a substantial SME component that faces greater constraints in accessing capital, technology, and skilled labour.

The HRDC's 2022 study surveyed 96 manufacturing enterprises and established that the sector was positioned at Automation Level 2 — with between 25–50% of processes automated on average. Industrial robots and advanced robotics remained largely absent from the local manufacturing landscape, with adoption concentrated in programmable logic controllers (38%), computer-supported design and manufacturing (36%), and material conveyor systems (31%). The study identified critical thinking (74%), people management (71%), and decision-making (69%) as the most sought-after skills by employers navigating automation transitions.

Crucially, the 2022 study found that 54% of enterprises relied on foreign training providers for technical skills development, reflecting a significant gap in local training supply for Industry 4.0-related competencies. Only 40% of enterprises had developed a formal strategy for automation, and 47% reported having no dedicated team responsible for driving automation implementation. These structural weaknesses in planning and capacity have informed the research design and agenda of the present 2026 study.

Independent evidence from outside the present survey lends further support to this picture of a sector still grappling with foundational digitalisation gaps. An industrial audit programme conducted by the Association des Manufacturiers Mauriciens (AMM) in partnership with EKIUM across a cross-section of Mauritian manufacturers, including several enterprises also represented in the present survey sample, found that the majority of audited sites still relied heavily on manual, paper-based systems for production data capture, quality control and maintenance records, lacked real-time production monitoring, and had no systematic mechanism for tracking core performance indicators such as Overall Equipment Effectiveness (OEE) (AMM/EKIUM AMIO, 2025). These findings, derived from site-level audits rather than self-reported survey data, corroborate the skills and infrastructure gaps identified in the present study and reinforce the case for a structured, sector-wide digital transformation support programme. More recent policy developments have sought to address these challenges. The National Skills Development Strategy 2020–2025 (HRDC, 2020) includes a dedicated stream for digital skills, and the Digital Mauritius 2030 Strategic Plan (Ministry of Technology, Communication and Innovation, 2018) outlines a vision for a digitally enabled economy by 2030. The policy environment has been further strengthened through the National Budget 2026–2027, which places AI, digitalisation, enterprise innovation and the modernisation of traditional sectors at the centre of the Government's Future-Ready Economy agenda. Government has committed, in collaboration with the private sector, to train 25,000 Mauritians in practical AI skills, including developers, entrepreneurs, SME owners, professionals and workers whose jobs are being transformed by AI. Together with initiatives targeting teachers, students and public officers, the Budget aims to enable or train 50,000 Mauritians in practical AI use over the coming year. A National AI Learning Platform, supported by an allocation of Rs 25 million, will provide structured training and certification, complemented by a Champion of AI Programme and national guidance on the responsible use of AI.

For manufacturing specifically, Government announced the formulation of an innovative industrial policy and the introduction of an Industry Bill

intended to modernise the legislative framework, rebuild the country's industrial and export base and reposition Mauritius as a globally competitive manufacturing hub. The planned high-technology Special Economic Zone at Côte d'Or is expected to attract investment in AI, digital industries and advanced manufacturing, alongside a national target to increase goods exports from USD 1.5 billion to USD 3 billion within five years. The Budget Annex also extends, until 30 June 2029, the investment tax credit available to manufacturing companies for expenditure on new plant and machinery, artificial intelligence solutions and patents. The credit amounts to 15% annually over three years, representing a total potential credit of 45% of qualifying investment. These enterprise incentives are accompanied by labour-market and training reforms. Micro-credentials will be integrated into the National Qualifications Framework to facilitate rapid and just-in-time upskilling and reskilling. The Budget also provides for a Skills-Interface Platform to strengthen coordination among employers, training providers and Government in priority sectors, alongside sectoral and national skills-intelligence activities. The Budget also provides for stronger competency and industry-experience requirements for TVET trainers. In parallel, the circular-economy programme and proposed Circular Economy Bill reinforce the growing importance of environmental management, resource efficiency and green manufacturing capabilities. Collectively, these measures create a more supportive policy environment for technology investment, but also increase the urgency of ensuring that manufacturing enterprises possess the workforce capabilities required to implement, govern and obtain productivity gains from these technologies.

Local-space synthesis: This study is grounded in the local manufacturing context: a sector that remains important for employment, GDP contribution and export capability, but where digital adoption is uneven across enterprise size, sub-sector, capital intensity and management capacity. The local evidence from the 2022 automation study and the AMM/EKIUM audit findings strengthens the rationale for a manufacturing-specific digital skills response rather than a generic ICT-sector response.

2.4 Generative AI and the Future of Work in Small Island Contexts

The rapid diffusion of GenAI tools into workplace settings represents a paradigm shift that has accelerated dramatically since 2022. Unlike earlier AI applications confined to specialist data science roles, GenAI is accessible to non-technical workers through conversational interfaces, fundamentally democratising AI use but simultaneously creating new risks around accuracy, intellectual property, and responsible use (European Commission, 2023). For small island developing states like Mauritius, the adoption of GenAI offers particular opportunities to overcome geographic and scale disadvantages by enabling SMEs to access world-class content generation, analysis, translation, and coding assistance at minimal cost.

However, recent evidence cautions against uncritical adoption. The Generative Artificial Intelligence Profile developed by the National Institute of Standards and Technology identifies several risks associated with GenAI, including the generation of confidently stated but inaccurate information, harmful bias, breaches of data privacy, exposure of confidential or proprietary information, intellectual property infringement and excessive human reliance on AI-generated outputs (Autio et al., 2024). For manufacturing enterprises in Mauritius, where technical documentation, product specifications, quality assurance, safety

procedures and export compliance require high levels of accuracy and traceability, GenAI outputs should not be treated as authoritative without appropriate human verification. Governance arrangements should therefore include clear acceptable-use policies, secure handling of enterprise data, verification of AI-generated content, protection of intellectual property and confidential information, and employee training in responsible use. The present study provides survey-based evidence on GenAI penetration and governance readiness among responding manufacturing enterprises.

3. Objectives and Methodology

3.1 Objectives

The report structure is designed to achieve the following specific objectives:

- To assess the current state of digital technology adoption and usage across private manufacturing enterprises in Mauritius;
- To evaluate enterprise digital transformation maturity and identify the principal barriers to progression;
- To map digital skills gaps across core competency categories for key occupational roles;
- To assess the penetration of Artificial Intelligence (AI) and Generative AI (GenAI) in manufacturing enterprises and identify associated skills needs;
- To determine the impact of digital technologies on job roles, tasks, and skills requirements;
- To provide an indicative comparison with the 2022 HRDC Automation and Skills Study; and
- To generate evidence-based recommendations for skills development policy and training programme provision.

3.2 Research Design and Sampling

A quantitative cross-sectional survey design was adopted, using a structured online questionnaire administered via the SurveyMonkey platform between April and June 2026. The target population comprised private manufacturing enterprises registered with the HRDC Levy Fund. A purposive sampling approach was employed, targeting 300 enterprises across different size categories and manufacturing sub-sectors to strengthen coverage of the sector's enterprise composition. The Association of Mauritian Manufacturers (AMM), the Mauritius Exports Association (MEXA), the Economic Development Board (EDB), the National Productivity and Competitiveness Council (NPCC) and other industry associations assisted in survey dissemination.

A total of 65 valid responses were received from manufacturing enterprises, providing coverage across the manufacturing sector while remaining survey-based rather than exhaustive. All 65 respondents were classified under the Manufacturing sector (including textile), confirming sectoral homogeneity of the sample. The questionnaire comprised 30 question blocks covering technology adoption (Q1), job roles and technology tools (Q2), digital skills gaps across five competency categories (Q3–Q7), task-automation estimates by role (Q8), digital transformation maturity and barriers (Q9–Q10), AI integration and training needs (Q11–Q12), GenAI adoption and governance (Q13–Q18), digital technology prospecting

(Q19), jobs impact and the strategic importance of digital technology (Q20–Q21), future roles and skills (Q22), and enterprise profile and follow-up information (Q23–Q30).

3.3 Data Analysis

Quantitative data were analysed using SPSS 18.0 and Microsoft Excel. Descriptive statistics, including frequencies, percentages, means and standard deviations, were computed as appropriate. Cross-tabulations examined relationships among enterprise size, turnover, digital-transformation stage, GenAI adoption and the strategic importance assigned to digital technologies. Skills-gap estimates from Q3–Q7 and task-automation estimates from Q8 were analysed at role level. Open-ended job titles reported under Q2 were cleaned, standardised and coded to the relevant NASCO major occupational group, using the National Standard Classification of Occupations applied by Statistics Mauritius and aligned with ISCO-08. The associated technology descriptions were separately standardised into broad tool categories to support analysis of current technology use by occupational group and to summarise the tools reported for the five most frequently cited job roles. Q22 responses were analysed thematically using substantive role mentions. Complementary qualitative interviews with 29 manufacturing enterprises conducted in 2025 and 2026 were used as contextual evidence, while the 2022 HRDC automation study was used only for indicative comparison where the measures were sufficiently comparable.

3.4 Ethical Considerations and Limitations

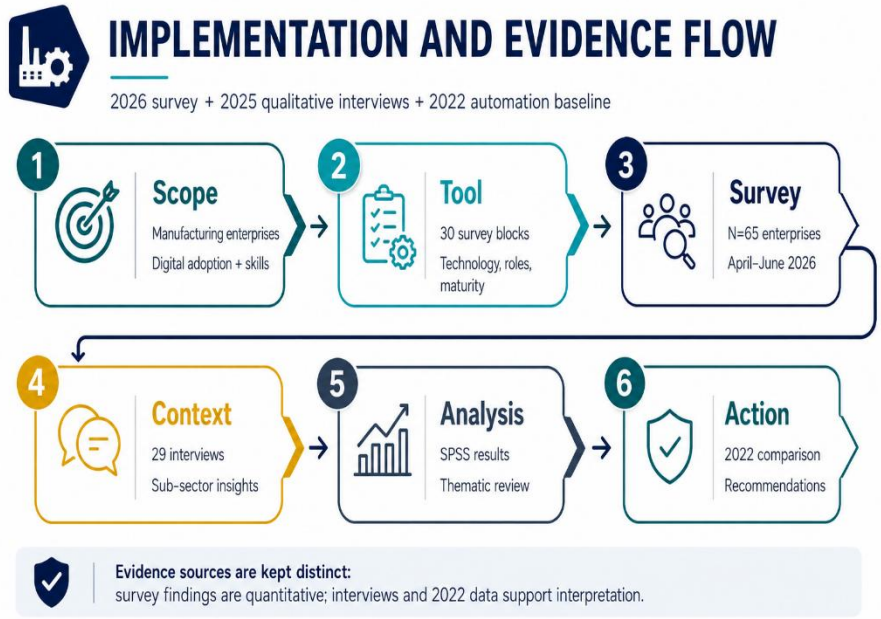
All respondents were assured of the strict confidentiality of their individual responses, with data reported exclusively in aggregate form. Enterprise names included in the dataset were provided voluntarily and are not linked to individual response profiles in this report. The primary limitations are the sample size of 65 enterprises and the purposive nature of the sample. The findings therefore provide a survey-based indication of digital technology adoption and skills readiness among responding manufacturers but should not be interpreted as a census of all manufacturing enterprises. Sub-sector analysis was not attempted because the sample may not capture the full diversity of experience across all manufacturing sub-sectors.

The self-reported nature of the skills-gap, AI-integration and task-automation estimates introduces potential response bias. Enterprise names (Q23), contact details (Q29) and follow-up consent (Q30) were used only for survey administration and were excluded from public reporting. Retrospective sub-sector classification and the complementary interview findings are clearly distinguished from direct questionnaire variables.

3.5 Project Implementation and Quality Assurance

The implementation process is presented as a structured manufacturing skills-intelligence exercise. As illustrated in Figure 1, it combines the 2026 enterprise survey, complementary qualitative interviews with 29 manufacturing enterprises, and an indicative comparison with the 2022 HRDC automation baseline, while keeping each evidence source methodologically distinct.

Figure 1: Project implementation and evidence flow



3.6 Interpretation Safeguards

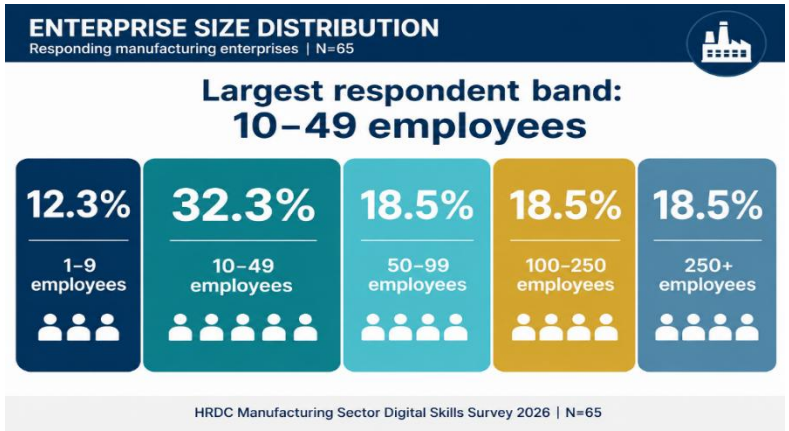
Four safeguards are important for interpretation. First, the findings are survey-based and should not be treated as a census of all manufacturing enterprises. Second, the results are self-reported and should therefore be read as enterprise perceptions of adoption, skills gaps and maturity rather than independently audited technical measurements. Third, sub-sector conclusions are avoided unless supported by complementary qualitative evidence, because the sample size does not support in-depth sub-sector generalisation. Fourth, the qualitative interviews and the 2022 comparison are used to strengthen interpretation and policy relevance; they are not merged statistically with the 2026 survey dataset.

4. Profile of Respondents

4.1 Enterprise Size

The 65 respondent enterprises span the full range of enterprise size categories, with a significant concentration in smaller enterprise bands broadly reflecting the structure of Mauritius's manufacturing sector. Enterprises employing 10–49 workers account for the largest share (32.3%), followed by those with 50–99 (18.5%), 100–250 (18.5%), and more than 250 employees (18.5%). Micro-enterprises with fewer than 10 employees represent 12.3% of respondents as shown in Figure 2.

Figure 2: Enterprise Size Distribution (N=65)

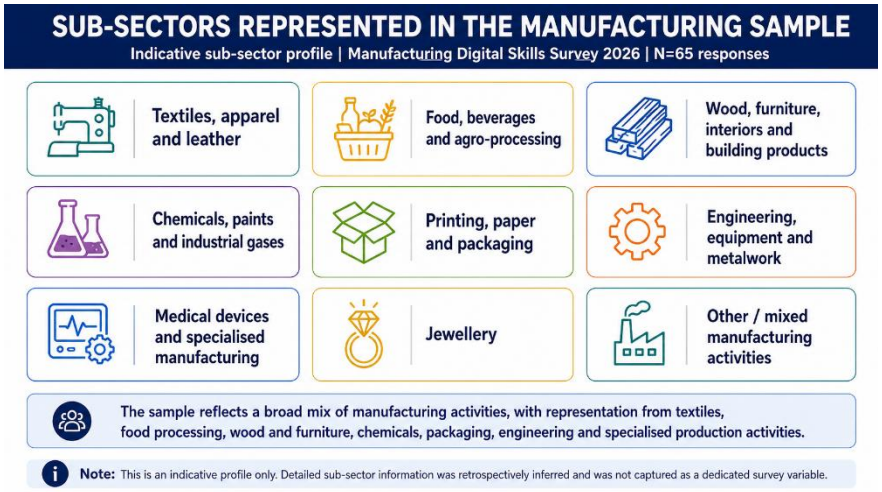


This size distribution is consistent with the dual structure of the Mauritian manufacturing sector, characterised by a large number of SMEs alongside a smaller cohort of larger enterprises that typically exhibit higher levels of automation and digital adoption. The inclusion of micro-enterprises (fewer than 10 employees) is particularly notable, as this segment has historically been under-represented in manufacturing skills research.

4.2 Sub-sector Classification

The sample shown in Figure 3 reflects a broad cross-section of manufacturing activities, including textiles and apparel, food and agro-processing, wood and furniture, chemicals, printing and packaging, engineering, medical devices, jewellery and other mixed manufacturing activities. As detailed sub-sector information was not collected directly through the questionnaire, the profile is indicative and based on a retrospective classification of respondents.

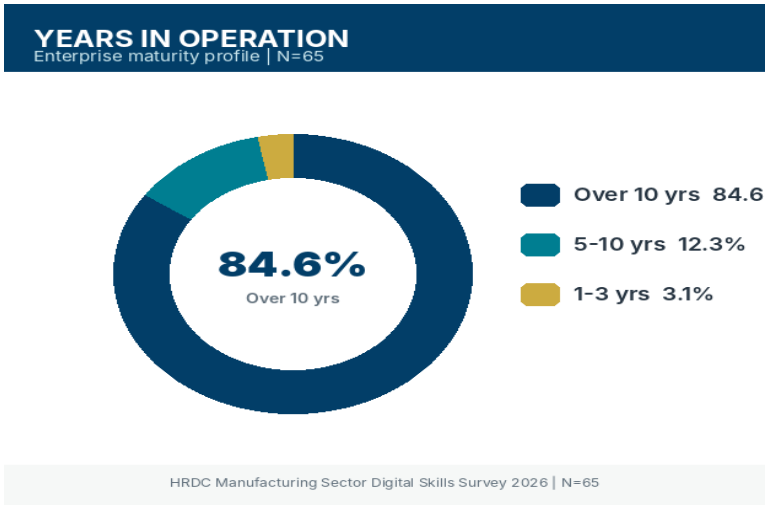
Figure 3: Sub sectors (N=65)



4.3 Years of Operation

Figure 4 shows that the survey sample is dominated by mature, well-established enterprises. Some 84.6% of respondents have been in operation for more than 10 years, and 12.3% for between 5 and 10 years. Only 3.1% of respondents are enterprises established within the past three years. This maturity profile is consistent with the 2022 study. It mirrors the respondent profile of the 2022 study, where the large majority of participating enterprises were also long-established firms. This suggests that digital adoption patterns reflect the experiences of established enterprises navigating technology transitions, rather than digitally-native start-ups.

Figure 4: Years in Operation (N=65)

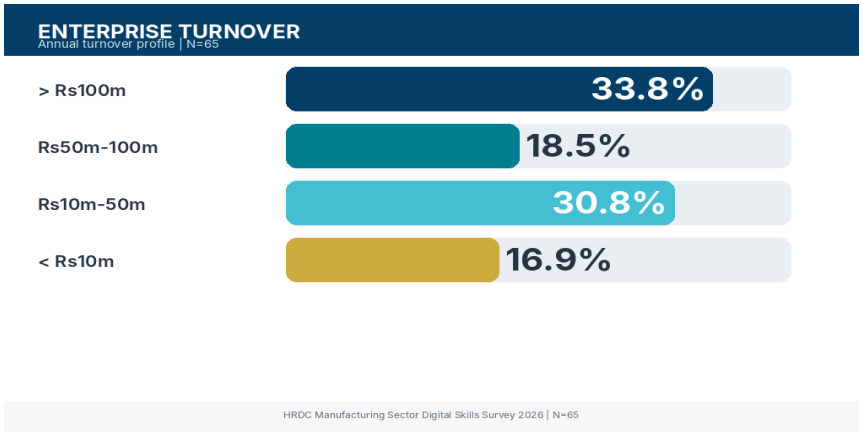


4.4 Turnover Profile

The turnover profile of respondents shows considerable variation, with 33.8% of enterprises reporting annual turnover exceeding Rs 100 million, 18.5% between Rs 50 million and Rs 100 million, 30.8% between Rs 10 million and Rs 50 million, and 16.9% below Rs 10 million. This spread

illustrated in Figure 5 indicates that the sample captured enterprises across the revenue spectrum, from micro and small enterprises to larger manufacturers, enabling analysis of how digital adoption and skills gaps vary by enterprise scale.

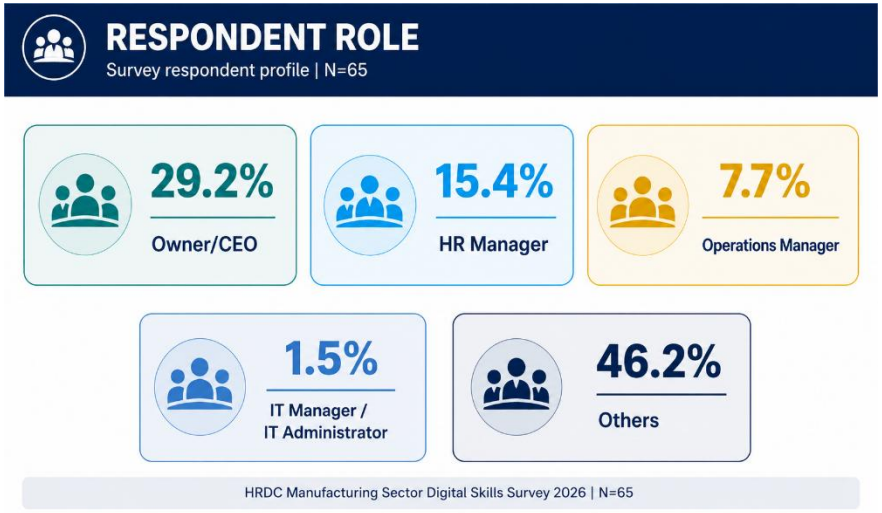
Figure 5: Enterprise Turnover (N=65)



4.5 Respondent Profile

The questionnaire was completed by a mix of senior leadership and functional managers as illustrated in Figure 6. Owners and CEOs account for the largest identified group (29.2%), followed by HR Managers (15.4%), Operations Managers (7.7%), and IT Managers (1.5%). A substantial proportion (46.2%) categorised themselves as 'Other', encompassing roles such as production managers, quality managers, and finance officers. The high proportion of owner-CEO respondents reflects the SME and ME-dominated nature of the sample and suggests that strategic digital decision-making in many enterprises is concentrated at the apex.

Figure 6: Respondent Role (N=65)



5. Technology Adoption and Usage

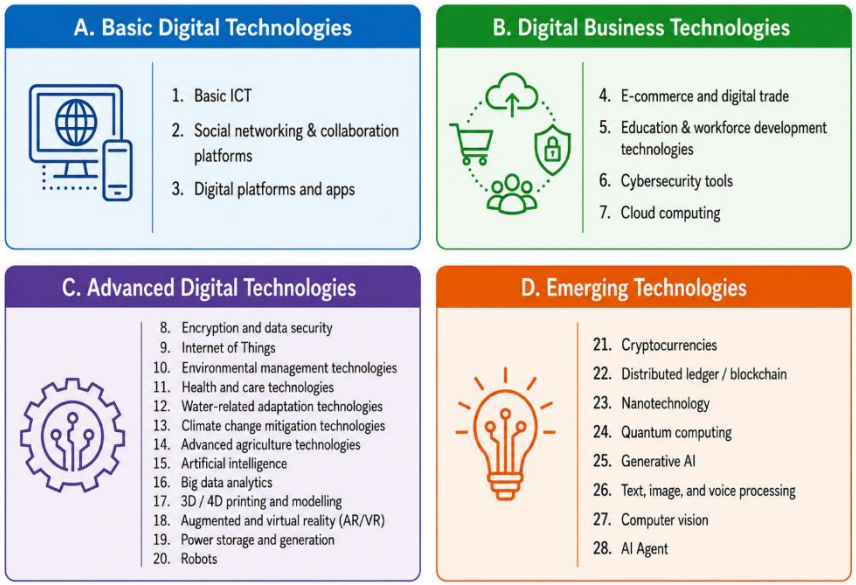
5.1 Typology of Digital Technologies Used in the Study

To support structured interpretation of the technology-adoption findings, the report retains the survey typology used in Question 1 and presented in Figure 7. The 28 technologies assessed were grouped into four categories: Basic Digital Technologies; Digital Business Technologies; Advanced Digital Technologies; and Emerging Technologies.

Using the typology keeps the analysis aligned with the survey instrument and avoids reclassifying technologies into analytical families that were not part of the questionnaire design. It also provides a clear basis for comparing adoption patterns across general-purpose, business-support, advanced and emerging technologies.

The typology is applied in Section 5.3 to show where adoption is concentrated across the original survey groupings, while retaining the exact technology-level percentages required to identify specific areas of strength, emerging uptake and limited adoption.

Figure 7: Manufacturing digital technology typology used in the study



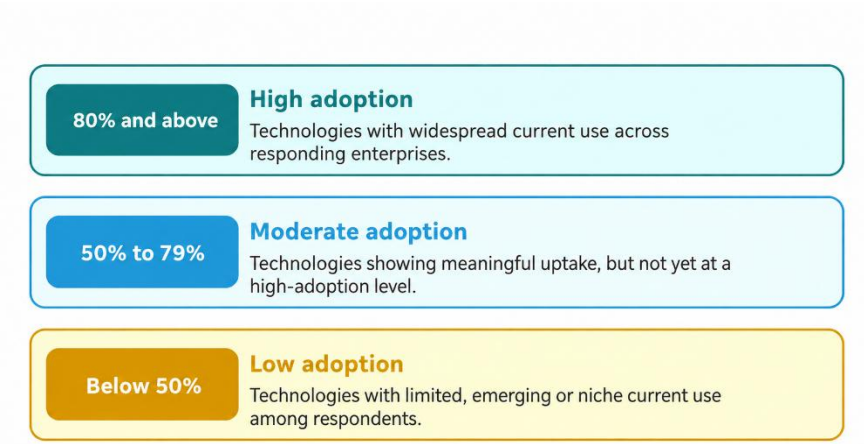
5.2 Adoption Categories

For analytical and dissemination purposes, the current-use rate of each technology was interpreted through the three indicative adoption categories and shown in Figure 8:

- **High adoption:** 80% and above;
- **Moderate adoption:** 50–79%; and
- **Low adoption:** below 50%.

These categories provide a consistent and transparent basis for comparing technologies with different levels of current use. They support interpretation but do not replace the exact technology-level percentages or imply that technologies within the same category have equal strategic relevance, cost or implementation requirements.

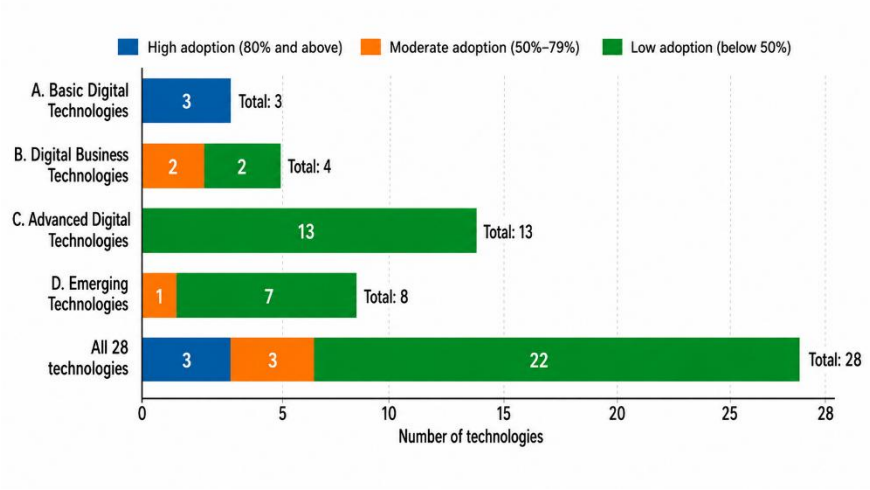
Figure 8: Adoption categories used to interpret current-use rates



5.3 Adoption Levels Across Technology Categories

Respondents were asked to classify each of 28 digital technologies as currently using, planning to adopt within two years, relevant but not yet using, or not relevant. To provide a clearer overview, Figure 9 maps the 28 technologies against the original four survey typology groups and the three adoption categories introduced in Figure 8. The figure reports the number of technologies within each typology group falling into each current-use band; the underlying analysis remains based on the exact technology-level percentages.

Figure 9: Adoption profile by original survey typology and adoption category (N=65)



Note: Counts show how many of the 28 technologies fall within each current-use band. High adoption = 80% and above; Moderate adoption = 50–79%; Low adoption = below 50%. The exact technology-level percentages remain the basis of interpretation.

The results show that adoption is strongly concentrated in the **Basic Digital Technologies** group. All three technologies in this category — Basic ICT (92.3%), social networking and collaboration platforms (83.1%), and digital platforms and apps (80.0%) — fall within the High Adoption band, confirming that foundational workplace digitalisation is now mainstream among responding manufacturers.

Within **Digital Business Technologies**, cloud computing (64.6%) and cybersecurity tools (61.5%) fall within Moderate Adoption, while e-commerce and digital trade and education and workforce development technologies remain below the 50% threshold. This suggests that selected enterprise-support technologies are gaining traction, although adoption remains uneven across business functions.

Advanced Digital Technologies remain predominantly within the Low Adoption category. IoT/IIoT (44.6%) and environmental-management technologies (41.5%) show the strongest uptake within this group but remain below the 50% threshold. Other advanced technologies — including encryption and data security, artificial intelligence, big data analytics, 3D/4D printing and modelling, AR/VR, power storage and generation, robots and other specialised technologies — are currently used by fewer than half of responding enterprises.

Within **Emerging Technologies**, Generative AI stands out as the only technology to reach the Moderate Adoption band, with 61.5% current use. The remaining technologies in this category — including cryptocurrencies, distributed ledger/blockchain, nanotechnology, quantum computing, text, image and voice processing, computer vision and AI Agent technologies — remain within the Low Adoption band.

High adoption. The High Adoption band is confined to three foundational technologies that are already embedded in everyday enterprise operations. This indicates that the manufacturing sector's basic digital infrastructure and workplace use of common digital tools are now well established among responding enterprises.

Moderate adoption. Only three technologies fall within the Moderate Adoption band: cloud computing, cybersecurity tools and Generative AI. This suggests that enterprises are beginning to move beyond basic digitalisation into selected higher-value capabilities, particularly in data handling, digital protection and AI-assisted work processes.

Low adoption. A total of 22 of the 28 technologies fall within the Low Adoption category, confirming that most advanced, production-facing and frontier technologies have not yet achieved broad diffusion across the sample. Low current use should not be interpreted as low future relevance; rather, it reflects the uneven depth of digital transformation across enterprises.

Within this Low Adoption category, IoT/IIoT and environmental-management technologies are among the most widely used, indicating meaningful but still sub-majority uptake. Their position relatively close to the 50% threshold suggests that these areas may be among the next technologies to move towards wider operational adoption if skills, budget and implementation constraints are addressed.

Generative AI is the clearest emerging-technology outlier. Although classified within Emerging Technologies, it records 61.5% current use and therefore sits within the Moderate Adoption band rather than alongside the lower-uptake frontier technologies. This illustrates the speed with which accessible GenAI tools have diffused into enterprise practice.

Overall, the profile indicates a sector that has widely adopted foundational digital tools and is increasingly using selected cloud, cybersecurity and GenAI capabilities, but has not yet achieved broad uptake of more advanced production-facing or frontier technologies. The manufacturing sector is therefore digitally active, but transformation remains uneven in depth.

Standout Finding

61.5% of responding enterprises report current Generative AI technology use, a technology category that barely existed in its present form at the time of the 2022 study. This represents one of the strongest recent adoption signals captured in the survey.

5.4 Skills as a Barrier to Technology Adoption

For technologies identified as either planned for adoption within the next two years or relevant but not currently in use, respondents were asked whether lack of internal skills was deterring adoption. The highest proportions of enterprises reporting skills as a deterrent were recorded for Artificial Intelligence, including machine learning and neural networks (16.9%), AI Agent technologies (16.9%), environmental-management technologies (16.9%), climate-change-mitigation technologies (15.4%), Generative AI (10.8%), computer vision (10.8%), IoT/IIoT (9.2%), big-data analytics (9.2%), AR/VR (9.2%), and encryption and data-security technologies (6.2%).

The concentration of skills barriers in AI, connected technologies and environmental applications indicates that enterprises face capability constraints in areas associated with the next phase of industrial transformation. These technologies typically require specialised technical knowledge, implementation capability and the ability to integrate new systems into existing operational processes.

The findings should nevertheless be interpreted alongside the wider digital transformation results in Section 6.4, where insufficient budget and resources constitute the most frequently reported barrier. Skills constraints therefore remain important but operate alongside financial, organisational and implementation-capacity limitations.

Table 1: Skills as a Barrier to Technology Adoption

Technology	Skills reported as a deterrent (%)
Artificial Intelligence (ML/NN)	16.9
AI Agent Technologies	16.9
Environmental-Management Technologies	16.9
Climate-Change-Mitigation Technologies	15.4
Generative AI	10.8
Computer Vision	10.8
IoT/IIoT	9.2
Big-Data Analytics	9.2
AR/VR	9.2
Encryption and Data-Security Technologies	6.2

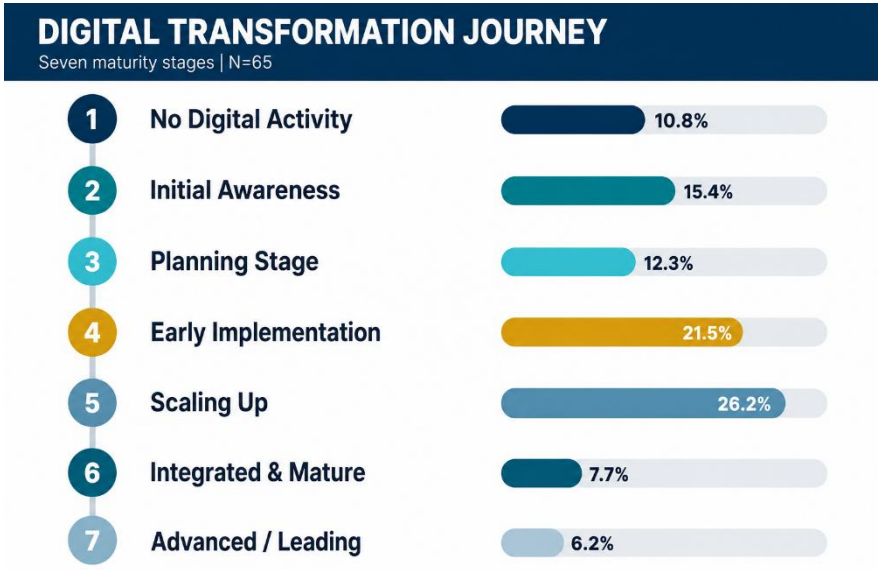
Note: Percentages are calculated against the full survey base of N=65. The skills-deterrent follow-up question was applicable only where a technology had been classified as either planned for adoption within the next two years or relevant but not currently in use. The percentages therefore represent the proportion of the full sample reporting skills as a deterrent and should not be interpreted as the percentage of only those enterprises eligible to answer the follow-up question.

6. Digital Transformation Maturity

6.1 Transformation Stage Distribution

Respondents were asked to self-assess their enterprise's current digital transformation stage using a seven-point maturity scale from 'No digital activity' to 'Advanced/Leading'. Figure 10 presents the distribution of enterprises across the maturity spectrum.

Figure 10: The Digital Transformation Journey — Seven Maturity Stages



The largest cluster of enterprises (26.2%) is at the 'Scaling Up' stage, indicating that digital solutions are being expanded across multiple departments. 'Early Implementation' accounts for 21.5% of enterprises, and 'Initial Awareness' for 15.4%. Encouragingly, 7.7% of enterprises have reached the 'Integrated and Mature' stage, and 6.2% classify themselves as 'Advanced/Leading', continuously innovating with AI, automation, and analytics. However, 10.8% remain at the 'No Digital Activity' stage, indicating that a non-trivial subset of enterprises has yet to initiate any form of digital transformation.

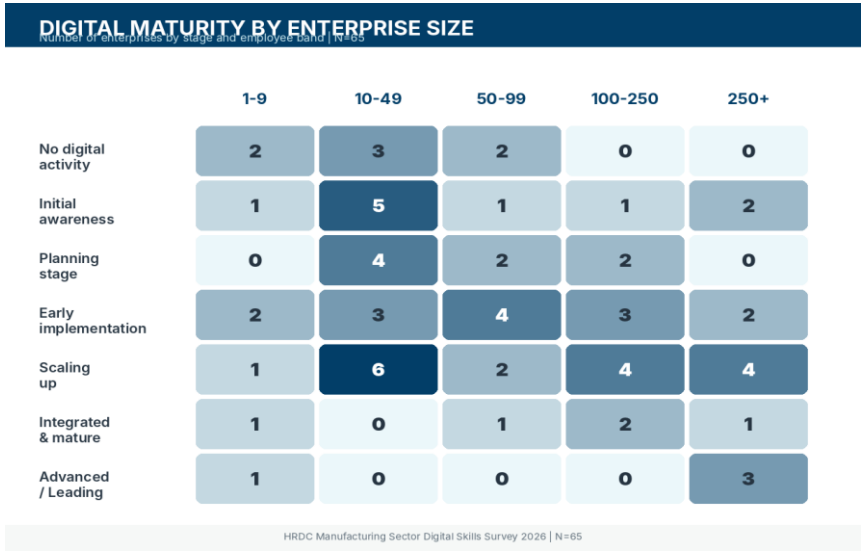
Areas of Concern

! Some 26.2% of responding enterprises are still at the earliest stages of digital transformation, either having no digital activity or only beginning to explore digital technologies. This shows that digital readiness varies considerably across the sector. The widening gap between digitally advanced enterprises and those that have yet to progress may hinder coordination across supply chains and limit overall sector competitiveness.

6.2 Digital Transformation Stage by Enterprise Size

Cross-tabulation of digital transformation stage with enterprise size reveals clear patterns of scale-linked digital maturity. The 'Advanced/Leading' category is dominated by enterprises with more than 250 employees (3 out of 4 enterprises), while the 'No Digital Activity' category is concentrated among micro and small enterprises (1–9 and 10–49 employee bands). The 'Scaling Up' stage shows the broadest distribution across size categories, suggesting that this represents the aspirational mid-point for enterprises of varying scale.

Figure 11: Digital Transformation Stage by Enterprise Size (N=65)



The findings in Figure 11 are consistent with international evidence that enterprise scale is a significant predictor of digital transformation progress, primarily because larger enterprises have greater capacity to invest in digital infrastructure, employ dedicated digital transformation staff, and absorb the transitional costs of upskilling (OECD, 2023). For Mauritius, where a large number of manufacturing enterprises are SMEs, this size-maturity correlation represents a structural challenge that policy must explicitly address.

6.3 Stage by Turnover

A similar pattern emerges from the cross-tabulation of digital transformation stage with enterprise turnover as seen in Table 2. Enterprises with turnover exceeding Rs 100 million are disproportionately represented in the 'Scaling Up' (8 enterprises), 'Integrated and Mature' (2),

and 'Advanced/Leading' (2) categories. Conversely, enterprises with turnover below Rs 10 million are concentrated in the 'No Digital Activity' and 'Initial Awareness' categories. The 'Planning Stage' shows notable representation from enterprises in the Rs 10–100 million turnover range, suggesting these mid-tier enterprises are actively developing digital roadmaps but have yet to move to implementation.

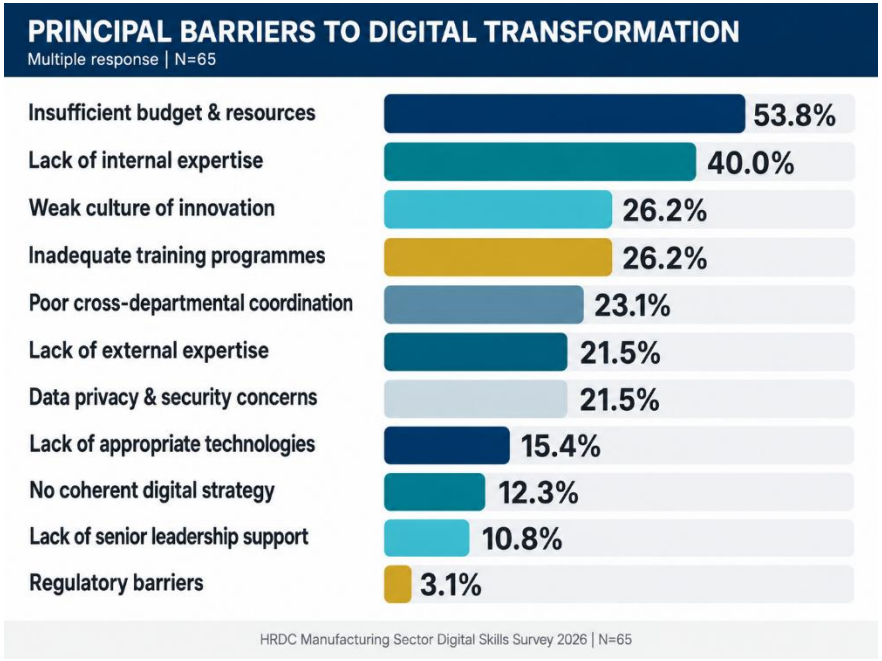
Table 2: Digital Transformation Stage by Enterprise Turnover (N=65)

Transformation Stage	< Rs10m	Rs10–50m	Rs50–100m	> Rs100m
No digital activity	2	4	0	1
Initial awareness	3	4	1	2
Planning stage	0	4	1	3
Early implementation	3	4	3	4
Scaling up	1	4	4	8
Integrated & mature	1	0	2	2
Advanced / Leading	1	0	1	2

6.4 Principal Barriers to Digital Transformation

Respondents were asked to identify the main challenges their enterprises face in implementing digital transformation from a predefined list of 11 options (multiple response). Figure 12 shows that insufficient budget and resources is the most commonly cited barrier (53.8%), followed by a lack of internal expertise (40.0%), weak culture of innovation and digital adoption (26.2%), and inadequate training programmes (26.2%). Poor cross-departmental coordination (23.1%), a lack of external expertise (21.5%), and data privacy and security concerns (21.5%) are also notable.

Figure 12: Challenges in Digital Transformation



(Multiple Response, N=65)

The primacy of budget constraints is consistent with the 2022 study's finding that financial constraints were a key inhibitor of technology adoption. However, skills-related barriers remain substantial: lack of internal expertise (40.0%) and inadequate training programmes (26.2%) together constitute a significant challenge cluster, reinforcing the central skills-development mandate of this study. Only 12.3% of enterprises cite a lack of coherent digital strategy as a barrier, suggesting that strategic awareness has improved since 2022, even if implementation capacity has not kept pace.

The survey findings are reinforced by separate on-site industrial audits conducted by AMM and EKIUM in 2025. While survey respondents identified limited budgets and a lack of internal expertise as the main barriers to digital transformation, the audits revealed additional operational constraints. These included continued reliance on manual and paper-based systems for recording production and maintenance information, limited capacity to monitor production performance in real time, and the absence of systematic tracking of key indicators such as equipment efficiency. As these findings were based on direct observation at manufacturing sites rather than enterprise self-reporting, they provide independent evidence of the sector's underlying digital-readiness gaps and strengthen the credibility of the survey results. The consistency between what enterprises reported and what auditors directly observed reduces reliance on self-reported perceptions alone and provides a more robust basis for concluding that manufacturing enterprises face significant digital-readiness constraints.

7. Digital Skills Gaps and Competency Assessment

7.1 Skills Gap Measurement Framework

For each of up to five job roles identified by the respondent, the survey collected a percentage estimate of the skills gap across five standardised digital competency categories: (1) Technical Occupational Skills — covering job-specific digital tasks; (2) Critical Thinking — encompassing structured problem solving, logical reasoning, and information literacy; (3) Digital Fluency and Digital Citizenship — covering digital literacy, collaboration, learning, and ethics; (4) Software Use and Development — including programming literacy, data analysis, and computational thinking; and (5) Understanding Digital Systems — encompassing data literacy, smart systems use, cybersecurity literacy, and tech enablement.

Respondents entered an indicative percentage gap for each role, using the following bands as an interpretation guide: No Gap (0%), Minor Gap (1–20%), Moderate Gap (21–40%), High Gap (41–70%), and Critical Gap (71–100%). The reported percentage estimates were analysed as entered; no midpoint conversion was applied. Data were available for Role 1 (n=65), Role 2 (n=65), Role 3 (n=54), Role 4 (n=51), and Role 5 (n=46), with lower response counts for Roles 3–5 because not all respondents identified five distinct roles. The role numbers reflect entry order only and do not represent seniority, occupational level or importance. Section 7.2 below classifies these same role entries — together with the technology tools respondents identified as currently in use for each role — by the National Standard Classification of Occupations (NASCO), and this NASCO classification is used consistently through the remainder of Section 7.

7.2 Top Job Roles and Current Technology Use, by NASCO Occupational Group

The survey asked each enterprise to list its top five job roles and, for each, the digital technology tools currently in use. This section analyses both parts of that question: which specific job roles are most frequently cited across the sector, what technology each commonly uses today, and how this pattern looks when the same 281 role entries are classified against the National Standard Classification of Occupations (NASCO), Statistics Mauritius's adaptation of the UN International Standard Classification of

Occupations (ISCO-08). NASCO is used consistently for the remainder of Section 7, replacing the entry-order Role 1–Role 5 labels with a standardised occupational classification comparable to official Mauritian labour force statistics.

Of the 281 role entries, 270 (96.1%) could be reliably coded to one of the nine NASCO major groups; the remaining 11 entries had no role information provided. No entries corresponded to NASCO Group 6 (Skilled Agricultural, Forestry and Fishery Workers), consistent with the manufacturing-sector scope of the survey.

Table 3 identifies the five specific job roles most frequently cited across the 65 responding enterprises together with the technology tools most commonly reported as currently in use for each.

Table 3: Top Five Most Frequently Cited Job Roles and Currently Used Technology Tools (n=270 valid role entries)

Job Role (merged spelling/plural variants)	Mentions	Share of Entries *	Most Commonly Cited Technology Tools Currently Used
Salesperson / Sales Representative	28	10.4%	CRM; Excel; Email; Word; POS
Director / CEO / Senior Management	15	5.6%	Email; Word; Excel; Power BI; Cloud
Administrative / Office Support	14	5.2%	Excel; Word; Email; Outlook
Accountant	11	4.1%	Excel; CRM; Email; Accounting software (Odoo)
HR Officer / Manager	10	3.7%	Excel; Word; Email; Payroll systems; Odoo/ERP

**share of all 270 valid entries*

Salesperson/Sales Representative is, by a wide margin, the single most frequently cited role in the sector, appearing in 10.4% of all valid role entries — more than the next two most-cited roles combined. Reported technology use for this role is dominated by CRM systems and basic office tools, indicating that sales functions across manufacturing enterprises are already digitally instrumented to a meaningful degree. Directors and other senior management roles rely predominantly on basic office productivity tools (email, Word, Excel) with only limited use of higher-order tools such as Power BI or cloud platforms — a pattern consistent with the elevated software and digital-systems gaps recorded for this group in Section 7.4. Administrative support and accounting roles show a similar basic-office-tool profile, while HR roles show emerging but still limited use of payroll and ERP systems. Table 4 maps the full set of role entries onto the nine NASCO major groups, with illustrative examples of the specific job titles coded to each, to make the classification transparent and auditable.

Table 3 above is dominated by administrative, sales and management roles, reflecting the fact that these functions are cited by name more often, and by a wider range of enterprises, than shop-floor and technical production roles. To ensure the sector's core technical occupations are not overlooked, Table 3b applies the same methodology to isolate the technical and production-related job roles cited in the survey. Because these roles are concentrated within a smaller number of enterprises and are each cited by only 1–9 of the 270 valid role entries, the counts are presented alongside, rather than merged into, Table 3, and should be read as illustrative of the range of technical occupations present in the sector rather than as precise prevalence estimates, several are included at very low counts specifically to give a sense of the sector's technical breadth.

Table 3b: Technical/Production Job Roles Cited in the Survey, by Frequency (n=270 valid role entries)

Job Role (merged)	Mentions	Share of Entries *	Most Commonly Cited Technology Tools Currently Used
Quality Controller / Quality Assessor	9	3.3%	Excel; Email; ERP; specialised QC software (LIMS, Minitab, inspection/audit systems)
Machine / Production Operator	7	2.6%	Largely None/Manual; where used: production-tracking tablets, automation/SOPO systems, ERP
Engineer / Maintenance Technician	7	2.6%	CAD/CAM software (AutoCAD, SolidWorks, Mastercam); maintenance software; Excel; emerging GenAI use
Production / Line Supervisor	6	2.2%	MES/SCADA/PLC systems; CMMS; Excel; Email
Machinist	2	0.7%	Word; specialised graphic/print software
Pattern Maker	2	0.7%	CAD pattern-making software (Gerber, Lectra); precision cutting/drafting
Sewing Machine Operator	1	0.4%	Industrial sewing equipment; no digital tool reported

**share of all 270 valid entries*

Quality Controller/QA is the most frequently cited technical role (3.3% of valid entries), followed by Machine/Production Operator and Engineer/Maintenance Technician (2.6% each), Production/Line Supervisor (2.2%), Machinist and Pattern Maker (0.7% each), and Sewing Machine Operator (0.4%). Reported technology use for these roles is markedly different from the administrative and sales roles in Table 3: Machine/Production Operator and Sewing Machine Operator entries are predominantly 'None/Manual' or equipment-specific with no digital tool reported, while Quality Controller/QA, Engineer/Maintenance Technician and Production/Line Supervisor entries show emerging but uneven use of specialised systems, ERP/CRM, CAD/CAM software, MES/SCADA/PLC interfaces and computerised maintenance management systems (CMMS), alongside the same basic Excel/email tools used sector-wide. The comparatively low mention counts in Table 3b, relative to Table 3, do not indicate that these occupations are rare in the sector. A role entry is not an employee headcount: one cited technical job title may represent multiple workers within an enterprise, while administrative and sales functions may be reported under several distinct titles. Role-mention counts should therefore not be interpreted as employment shares. Read alongside Table 4, where Craft and Related Trades Workers (n=16) and Plant and Machine Operators and Assemblers (n=15) are the two smallest NASCO groups by entry count yet record the highest skills gaps and automation exposure in Sections 7.4 and 7.5, Table 3b puts specific job titles to that same underlying concentration of technical risk.

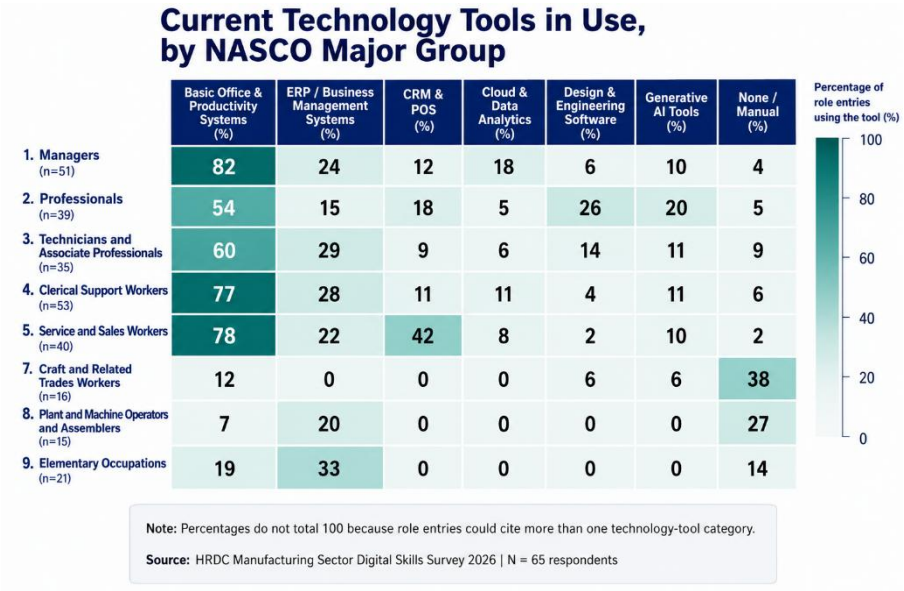
Table 4: NASCO Major Occupational Groups — Illustrative Job Roles and Sample Sizes

G	NASCO Major Group	n	Illustrative Job Roles Coded to this Group
1	Managers	51	Director; Production Manager; Operations Manager; HR Manager; Finance Manager
2	Professionals	39	Accountant; Engineer; Graphic Designer; Marketing Executive; Software Developer
3	Technicians and Associate Professionals	35	Production Supervisor; Quality Controller; Merchandiser; Procurement Officer; IT Officer
4	Clerical Support Workers	53	Admin/Administrative Officer; Storekeeper; Accounts Clerk; Cashier; HR Officer
5	Service and Sales Workers	40	Salesperson; Marketing Officer; Merchandiser (retail); Security; Customer Service Representative
6	Skilled Agricultural, Forestry & Fishery Workers	0	Not applicable — no entries in the sample

7	Craft and Related Trades Workers	16	Machinist; Pattern Maker; Cutter; Embroiderer; Printing Press Operator; Maintenance Technician
8	Plant and Machine Operators and Assemblers	15	Machine Operator; Sewing Machine Operator; Driver; Paper-Cutting Machine Operator
9	Elementary Occupations	21	General Worker; Packer; Warehouse Attendant; Apprentice

Clerical Support Workers (Group 4, n=53) and Managers (Group 1, n=51) are the two largest NASCO groups in the sample, followed by Service and Sales Workers (n=40) and Professionals (n=39). Craft and Related Trades Workers (n=16) and Plant and Machine Operators and Assemblers (n=15) are comparatively small in terms of role-entry representation within this survey, though, as Sections 7.4 and 7.5 show, they carry disproportionate weight in terms of skills gap and automation risk.

Figure 13: Current Technology Tools in Use, by NASCO Major Group



(share of role entries in each group citing each tool category; entries may cite more than one category)

Figure 13 shows that the use of digital tools varies considerably across NASCO occupational groups. Basic office and productivity systems are most widely reported among Managers (82%), Service and Sales Workers (78%) and Clerical Support Workers (77%), reflecting the greater use of general-purpose digital tools in administrative, managerial and customer-facing functions. Service and Sales Workers also record the highest use of CRM and point-of-sale systems (42%), consistent with the operational requirements of these roles.

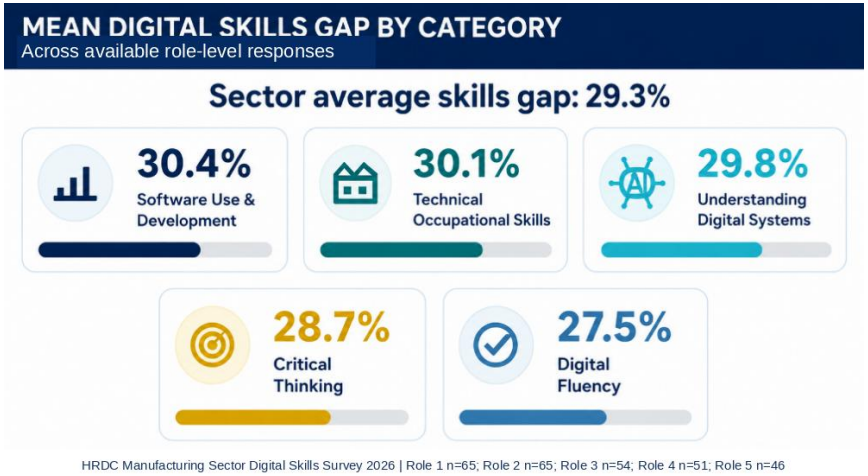
Technology use is more limited among production-oriented occupational groups. Craft and Related Trades Workers report relatively low use across most of the listed digital-tool categories, with 38% of role entries classified as 'None/Manual'. Plant and Machine Operators and Assemblers similarly show limited use of general-purpose digital tools, although 20% report use of ERP or other business-management systems and 27% are classified as 'None/Manual'. Elementary Occupations also show comparatively limited digital-tool exposure, although one-third of role entries (33%) report some use of ERP or business-management systems.

These differences should not in themselves be interpreted as evidence of a skills deficit, since the type and intensity of technology use are strongly influenced by the tasks associated with each occupation. Rather, Figure 13 provides a picture of current digital-tool exposure across occupational groups. When considered alongside the skills-gap and task-automation findings in Sections 7.4 and 7.5, it helps identify occupational groups for which future digitalisation may require more targeted and role-specific skills development.

7.3 Overall Skills Gap by Competency Category

Figure 14 presents the mean skills gap percentage across all roles for each of the five competency categories. The data reveal a broadly consistent gap profile, with all five categories falling within a narrow 27.5–30.4% range. Software Use and Development exhibits the highest mean gap (30.4%), followed by Technical Occupational Skills (30.1%), Understanding Digital Systems (29.8%), Critical Thinking (28.7%), and Digital Fluency (27.5%). The survey average gap across all categories stands at 29.3%, placing it within the 'Moderate Gap' band.

Figure 14: Mean Skills Gap by Category Across All Roles based on available role-level valid responses

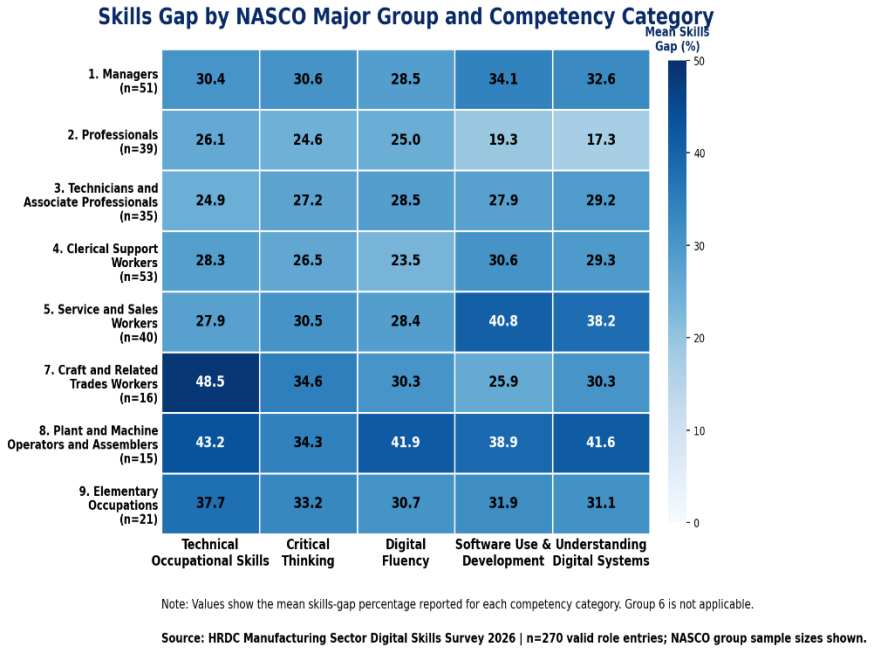


Role 1 n=65; Role 2 n=65; Role 3 n=54; Role 4 n=51; Role 5 n=46

7.4 Skills Gap by NASCO Occupational Group

Section 7.3 reported the overall sector-wide skills gap across all roles combined at 29.3%. This section disaggregates that figure by NASCO major occupational group, using the classification introduced in Section 7.2, to identify the occupational groups in which skills gaps are concentrated and the specific competency dimensions affected.

Figure 15: Skills Gap (%) by NASCO Major Group and Competency Category



(n=270 valid role entries; Group 6 not applicable)

A clear skills-gap gradient emerges across occupational groups. Plant and Machine Operators and Assemblers (Group 8) record the highest overall gap, at 40.0%, with elevated gaps across every competency dimension, including Digital Fluency (41.9%) and Understanding Digital Systems (41.6%). These findings are consistent with the group's limited current exposure to digital technologies and indicate a need for foundational digital upskilling alongside occupation-specific technical training.

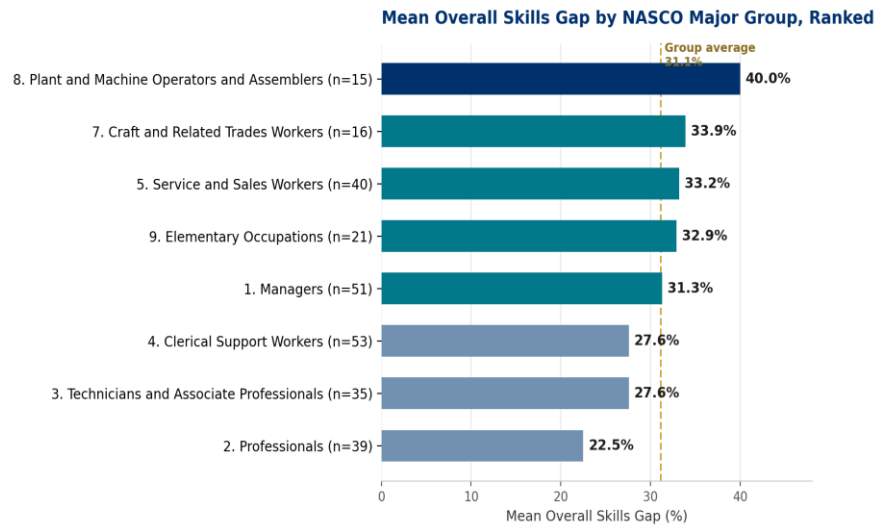
Craft and Related Trades Workers (Group 7) record the highest gap observed for any individual competency dimension in the survey: 48.5% in

Technical Occupational Skills. This is accompanied by comparatively limited use of current technology tools. Elementary Occupations (Group 9) also record a relatively high overall gap of 32.9%, consistent with their limited exposure to digital tools and systems.

At the other end of the spectrum, Professionals (Group 2) report the lowest overall gap, at 22.5%, particularly in Software Use and Development (19.3%) and Understanding Digital Systems (17.3%). This is consistent with the group's comparatively higher use of design and engineering software and generative-AI tools, as shown in Figure 13.

Managers (Group 1) report a moderate-to-high overall gap of 31.3%, exceeding the gaps recorded among Professionals and Technicians and Associate Professionals. The gaps are concentrated in Software Use and Development (34.1%) and Understanding Digital Systems (32.6%). This indicates that digital skills gaps are present not only among operational and shop-floor workers, but also within the leadership layer responsible for overseeing digital transformation and AI-adoption decisions.

Figure 16: Mean Overall Skills Gap by NASCO Major Group, Ranked (n=270 valid role entries)



* *Unweighted mean of NASCO group averages: 31.1%*

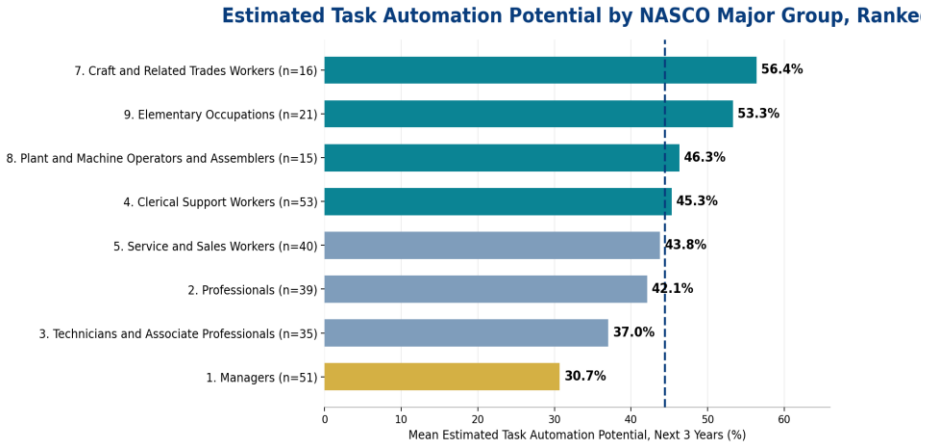
Read together, Figures 15 and 16 confirm that the manufacturing sector's digital skills gaps are not evenly distributed. They are particularly concentrated among Plant and Machine Operators and Assemblers, Craft and Related Trades Workers, and Elementary Occupations—occupational groups closely associated with production, operational and shop-floor functions. A separate and notable gap is also evident among Managers, highlighting the need for differentiated interventions addressing both operational workforce capabilities and digital leadership competencies.

7.5 Task Automation Outlook by NASCO Occupational Group

Respondents also provided assessments of the likely extent of task automation within each role over the next three years. Across the survey's valid role-level estimates, the overall mean automation exposure is

approximately 41%. Figure 17 presents the mean estimates by NASCO occupational group; its dashed reference line shows the unweighted mean of the eight NASCO group averages (44.4%), which is a different summary statistic from the overall role-level mean.

Figure 17: Estimated Task Automation Potential by NASCO Occupational Group, Next 3 Years



(NASCO group means; n=270 valid role entries; dashed line = unweighted mean of group averages)

Automation exposure is uneven across occupational groups. Craft and Related Trades Workers (Group 7) record the highest estimated automation potential (56.4%), 12.0 percentage points above the unweighted mean of the NASCO group averages shown in Figure 17. Elementary Occupations (53.3%) and Plant and Machine Operators and Assemblers (46.3%) also record comparatively high estimates. Managers record the lowest group mean (30.7%), while Professionals stand at 42.1%. These figures represent respondents' estimates of task automation potential within roles and should not be interpreted as forecasts of job losses.

Automation exposure also varies by enterprise size. Mean estimates range from 32.2% among enterprises with 10–49 employees to 52.6% among those with more than 250 employees, with the 1–9, 50–99 and 100–250 employee bands clustering close to the overall mean (approximately 41%). This pattern mirrors the size-linked digital maturity differences identified in Section 6.2, suggesting that larger enterprises are both further along in digital transformation and more exposed to near-term automation of existing tasks.

The combination of results for Craft and Related Trades Workers is particularly significant for workforce planning: this group's overall skills gap (33.9%) is not the highest in the survey, yet its estimated automation exposure is the highest. This supports a pre-emptive review of task content, digital-adjacent competencies and reskilling options. Because the automation measure is self-reported and task mixes vary across enterprises, it should not be interpreted as a forecast that these occupations will be displaced.

7.6 Summary: Skills Gap and Automation by NASCO Occupational Group

Table 5 consolidates the complete set of mean skills gap and automation estimates by NASCO occupational group, bringing together the results presented separately in Sections 7.4 and 7.5.

Table 5: Mean Skills Gap (%) and Automation Potential (%) by NASCO Occupational Group

Mean Skills Gap (%) and Automation Potential (%) by NASCO Major Occupational Group

NASCO Major Group	n	Tech. Occ. Skills (%)	Critical Thinking (%)	Digital Fluency (%)	Software Use & Dev (%)	Understanding Digital Systems (%)	Overall Gap (%)	Automation Potential (%)
1. Managers	51	30.4	30.6	28.5	34.1	32.6	**31.3**	**30.7**
2. Professionals	39	26.1	24.6	25.0	19.3	17.3	**22.5**	**42.1**
3. Technicians and Associate Professionals	35	24.9	27.2	28.5	27.9	29.2	**27.6**	**37.0**
4. Clerical Support Workers	53	28.3	26.5	23.5	30.6	29.3	**27.6**	**45.3**
5. Service and Sales Workers	40	27.9	30.5	28.4	40.8	38.2	**33.2**	**43.8**
7. Craft and Related Trades Workers	16	48.5	34.6	30.3	25.9	30.3	**33.9**	**56.4**
8. Plant and Machine Operators and Assemblers	15	43.2	34.3	41.9	38.9	41.6	**40.0**	**46.3**
9. Elementary Occupations	21	37.7	33.2	30.7	31.9	31.1	**32.9**	**53.3**

7.7 Implications For Future Skill Development Programmes

Implications for future skill development programmes are as follows:

(i) because NASCO is the classification used in Statistics Mauritius labour force statistics, the results in Table 5 can be read alongside national occupational employment data to help inform prioritisation, indicative cohort sizing and the rationale for resource allocation;

(ii) Plant and Machine Operators and Elementary Occupations (Groups 8–9) warrant priority validation because they combine among the highest measured skills gaps with high automation exposure in this survey; national occupational employment data should be considered separately when estimating sector-wide reach, cohort size and resource requirements;

(iii) Craft and Related Trades Workers (Group 7) merit a distinct, pre-emptive reskilling track focused on redeployment and digital-adjacent competencies, since this group's estimated automation exposure is the highest in the survey while its measured skills gap, though still elevated, is comparatively less extreme, meaning it could otherwise be under-prioritised on a gap-only view; and

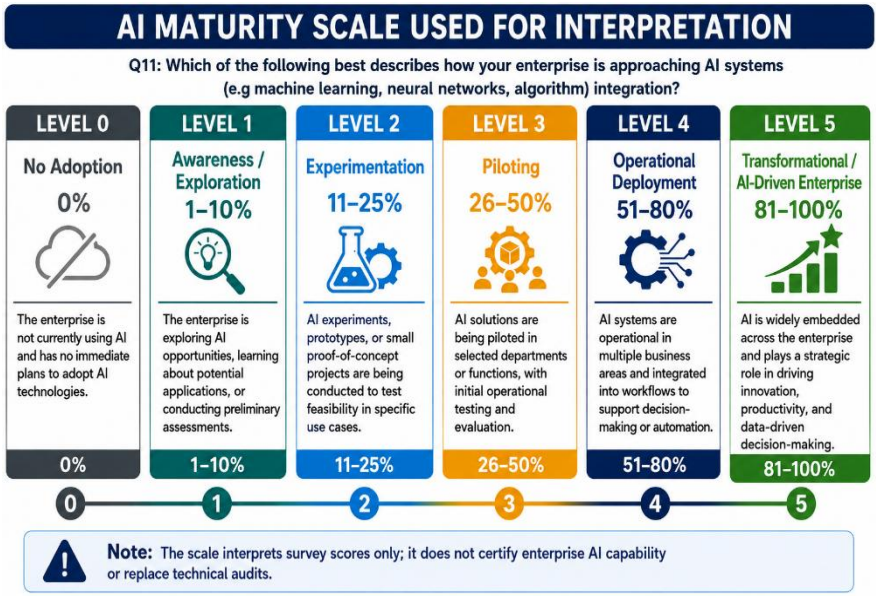
(iv) Managers (Group 1) require a leadership-specific digital upskilling track, since their gap in Software Use and Development and Understanding Digital Systems is not one that automation will resolve and instead constrains enterprise-wide digital transformation from the top down.

8. Artificial Intelligence Integration

8.1 AI Maturity Categorisation Used for Interpretation

The AI integration score was collected on a 0–100 scale and interpreted through six non-overlapping maturity bands: Level 0 – No Adoption (0%); Level 1 – Awareness or Exploration (1–10%); Level 2 – Experimentation (11–25%); Level 3 – Piloting (26–50%); Level 4 – Operational Deployment (51–80%); and Level 5 – Transformational or AI-Driven Enterprise (81–100%). The maturity scale provides a consistent framework for interpreting the survey scores and distinguishing between enterprises that are exploring AI, testing specific applications, piloting solutions, deploying AI operationally or embedding it strategically across the organisation. It is intended solely as an interpretive tool and does not certify enterprise AI capability or replace a technical assessment.

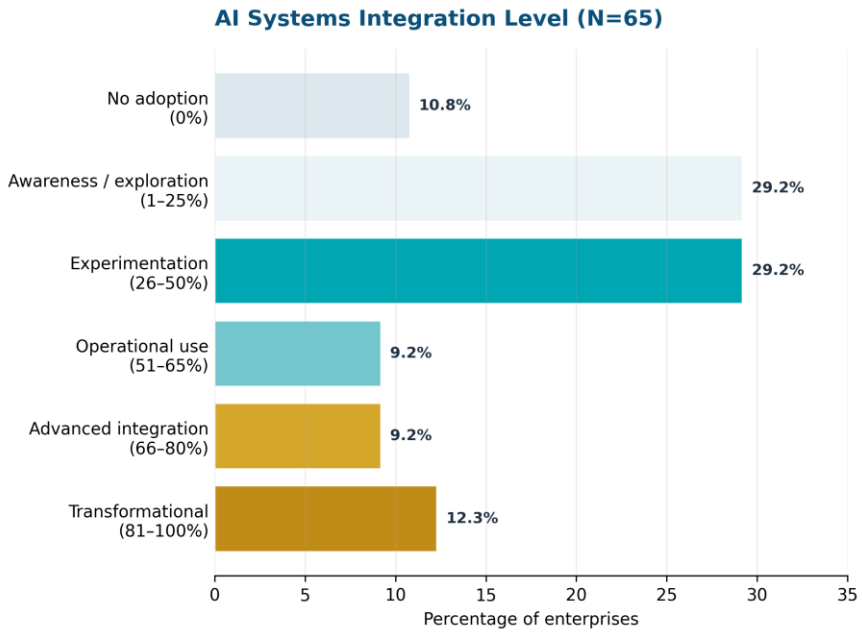
Figure 18: AI Integration Maturity Scale Used for Interpretation



8.2 AI Integration Level

Respondents provided an overall percentage score reflecting the extent to which AI systems, including machine learning, neural networks and algorithmic decision-support tools, are integrated into enterprise operations. Scores ranged from 0%, indicating no current integration, to 100%, indicating wide strategic embedding. Figure 19 presents the distribution across the six interpretive maturity levels.

Figure 19: AI Systems Integration Level (N=65)



The mean AI integration score is 39.8%, with a standard deviation of 31.0%, indicating substantial variation across respondents. The mean falls within Level 3 – Piloting (26–50%), meaning that the average enterprise is moving beyond awareness but has not yet reached consistent operational use across the organisation.

The distribution comprises 10.8% at No Adoption, 29.2% at Awareness or Exploration, 29.2% at Experimentation, 9.2% at Piloting, 9.2% at Operational Deployment and 12.3% at the Transformational level.

Taken together, 69.2% of respondents score at or below 50%, while 30.8% score above 50%. The pattern is therefore concentrated in the lower-to-intermediate maturity levels, although a smaller group reports advanced or transformational integration.

The score is self-reported and should be interpreted as an enterprise perception of integration rather than as a technical certification of AI capability.

AI

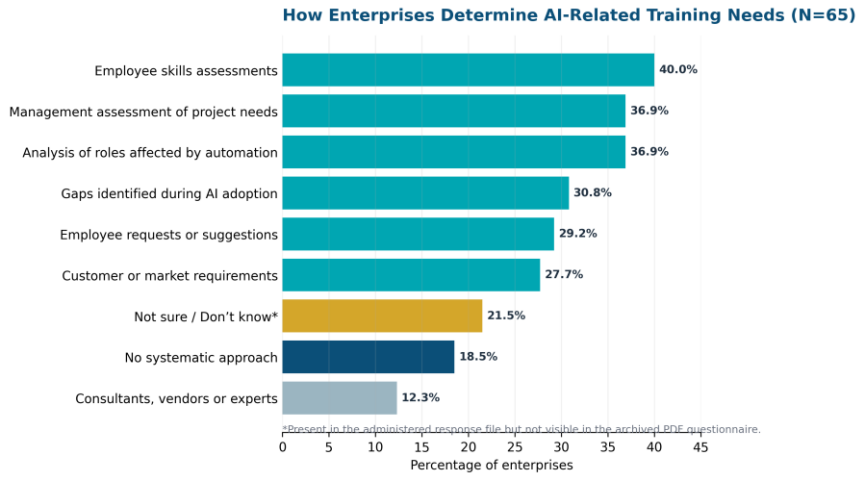
Average AI Integration Score Places the Sample at the Piloting Stage

The mean score of 39.8% falls within Level 3 – Piloting. This indicates meaningful activity beyond initial awareness, but AI remains concentrated in selected applications and functions rather than being consistently embedded across most enterprises.

8.3 How Enterprises Determine AI-Related Training Needs

Enterprises were asked how they determine AI-related training needs, with multiple responses permitted. Employee skills assessments are the most common approach (40.0%), followed by management assessment of project-specific requirements (36.9%) and analysis of roles affected by automation or AI (36.9%). Gaps identified during digital or AI adoption are cited by 30.8%, employee requests by 29.2%, and customer or market requirements by 27.7%. A further 21.5% selected “Not sure / Don’t know” in the administered response file; this response option is not visible in the archived PDF questionnaire. Some 18.5% reported no systematic approach and 12.3% relied on consultants, vendors or industry experts.

Figure 20: How Enterprises Determine AI-Related Training Needs (Multiple Response, N=65)

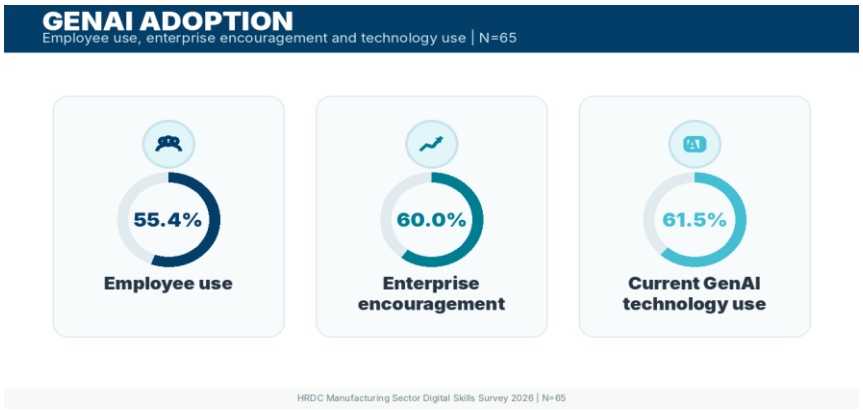


9. Generative AI Adoption and Governance

9.1 Employee Use and Enterprise Encouragement

The survey findings show that GenAI tools are already present among a majority of responding manufacturing enterprises. Some 55.4% report employee use and 60.0% state that GenAI use is encouraged at enterprise level, as shown in Figure 21. The broader technology-adoption question records 61.5% current GenAI technology use. The difference among these measures is expected: technology presence, employee use and formal enterprise encouragement capture related but distinct aspects of adoption.

Figure 21: Generative AI Adoption in Manufacturing Enterprises (N=65)



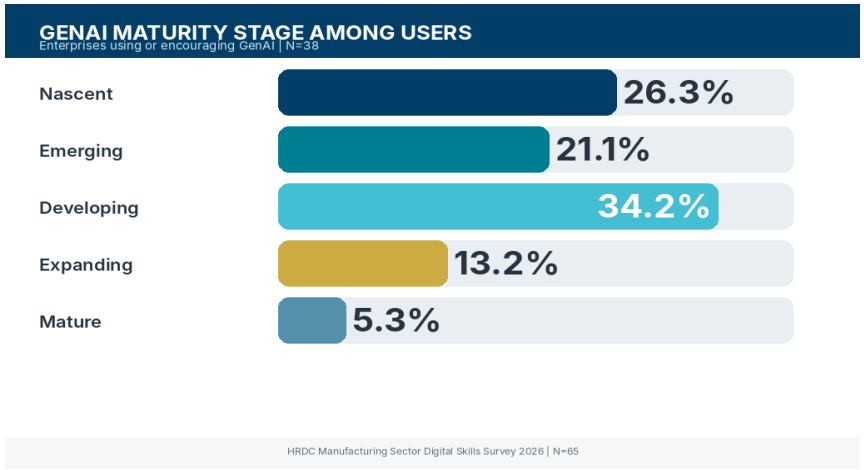
GenAI Adoption by Enterprise Size

Cross-tabulation of GenAI employee use with enterprise size reveals that mid-sized enterprises (100–250 employees: 75%; 50–99 employees: 67%) show higher GenAI adoption rates than micro-enterprises (1–9: 37.5%) or the largest enterprises (250+: 50%). This 'mid-market' adoption bulge may reflect the combination of sufficient scale to invest in productivity tools and the agility to adopt them without the governance friction of larger organisations.

9.2 GenAI Maturity Stage

Among the 38 enterprises that encouraged GenAI use and provided a valid response, the majority are at the 'Developing' stage (34.2%), where GenAI implementation is changing certain workflows and increasing efficiency. 'Nascent' (26.3%) and 'Emerging' (21.1%) together account for nearly half of valid responses, indicating that most responding adopters are still in the early phases of integration. Only 13.2% are at the 'Expanding' stage and 5.3% at 'Mature', where GenAI is fundamentally changing how work is done as illustrated in figure 22.

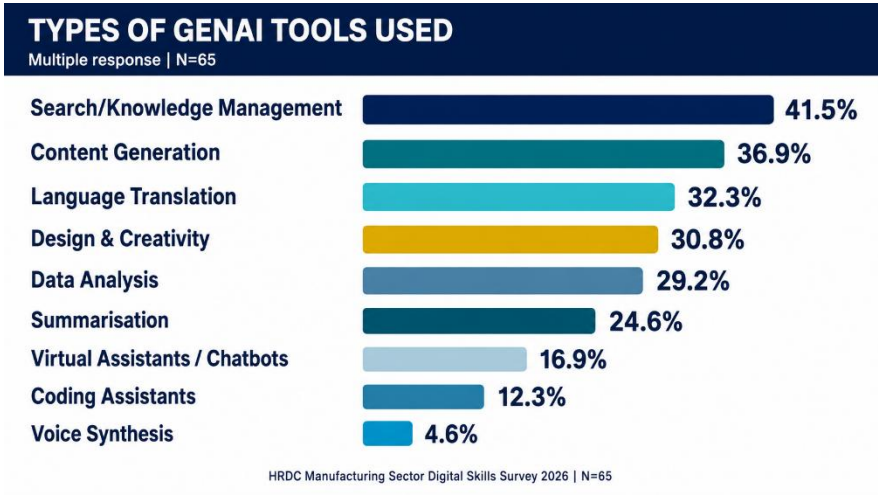
Figure 22: GenAI Maturity Stage Among Eligible Valid Responses (n=38)



9.3 Types of GenAI Tools Used

Enterprises that encouraged GenAI use were asked about the tools or capabilities used. Search and Knowledge Management was reported by 27 enterprises, equal to 41.5% of the full sample and 69.2% of the 39 eligible enterprises. Content Generation was reported by 36.9% of the full sample (61.5% of eligible enterprises), Language Translation by 32.3% (53.8% of eligible), Design and Creativity by 30.8% (51.3% of eligible), and Data Analysis by 29.2% (48.7% of eligible). Coding Assistants represented 12.3% of the full sample, while Voice Synthesis represented 4.6%.

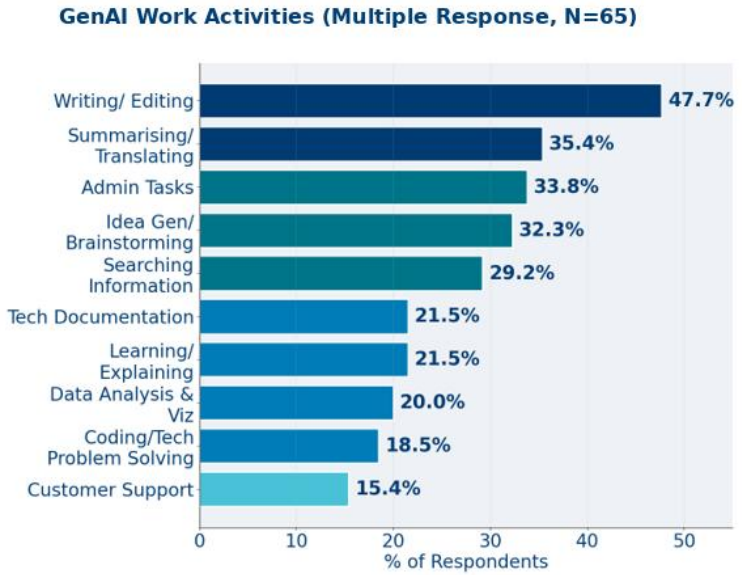
Figure 23: Types of GenAI Tools Used (Multiple Response; percentage of full sample, N=65; eligible group n=39)



9.4 GenAI Work Activities

Writing and Editing is the leading work activity, reported by 31 enterprises: 47.7% of the full sample and 79.5% of the 39 eligible enterprises. It is followed by Summarising and Translating (35.4% of the full sample; 59.0% of eligible), Administrative Tasks (33.8%; 56.4%), Idea Generation and Brainstorming (32.3%; 53.8%), and Searching for Information (29.2%; 48.7%). Technical Documentation Support and Learning or Explaining Complex Topics each account for 21.5% of the full sample, while Data Analysis and Visualisation accounts for 20.0%.

Figure 24: GenAI Work Activities (Multiple Response; percentage of full sample, N=65; eligible group n=39)

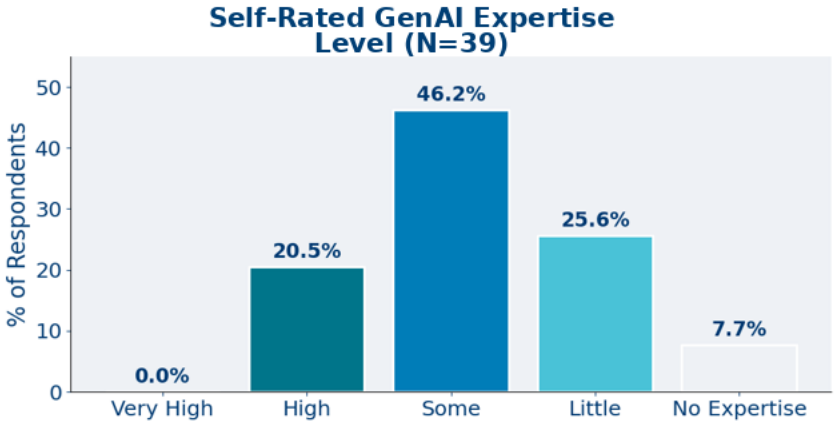


The dominance of language-centric use cases, writing, summarising, translating, reflects the accessibility of large language model interfaces for non-technical users and the multilingual context of Mauritius (where French, English, and Creole coexist in workplace communications). The relatively high use for translation (32.3%) is particularly notable, as it may reflect the multilingual documentation requirements of export-oriented manufacturing enterprises. Coding and Technical Problem Solving (18.5%) is the most technically-advanced GenAI use case currently in evidence, with implications for the future integration of GenAI into production systems management and automation programming.

9.5 GenAI Expertise Level

Among the 39 enterprises that encouraged GenAI use, self-rated expertise is predominantly at the 'Some Expertise' level (46.2%), followed by 'Little Expertise' (25.6%), 'High Expertise' (20.5%) and 'No Expertise' (7.7%). No enterprise rated itself as having 'Very High Expertise'. This profile suggests that GenAI use is spreading faster than formal competency development: enterprises are using GenAI tools while systematic approaches to training, governance and quality assurance for AI-generated content are still developing. This creates risks related to accuracy, intellectual property, and data privacy that enterprises and policymakers will be required to proactively address.

Figure 25: Self-Rated GenAI Expertise Level Among Eligible Respondents (n=39)

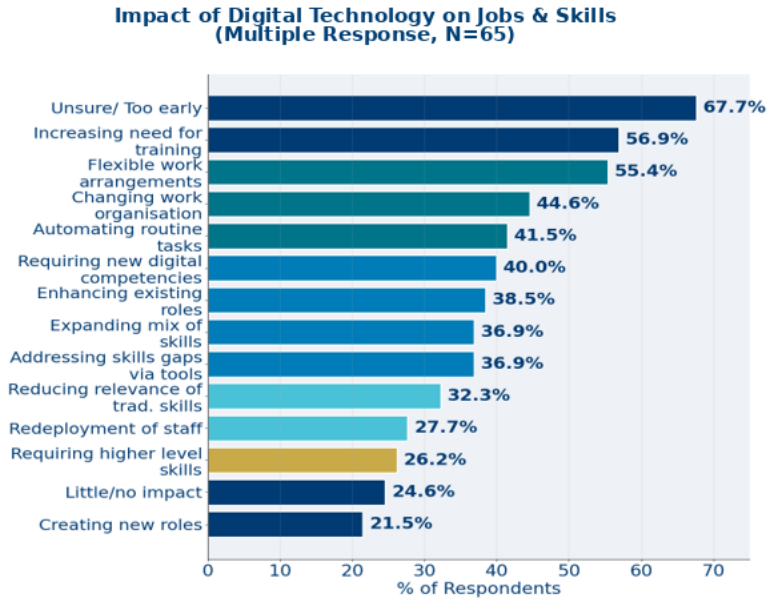


10. Impact of Digital Technology on Jobs and Workforce

10.1 Overall Impact Assessment

Respondents were presented with 14 impact statements across five dimensions and could select multiple responses. Figure 26 presents the distribution. 'Unsure/Too early to say' was selected by 67.7%; however, 31 of the 44 enterprises selecting it also identified at least one substantive impact. Only 13 enterprises, representing 20% of the full sample, selected uncertainty without another impact. The result therefore indicates uncertainty about the full extent or direction of change rather than an absence of observable effects.

Figure 26: Impact of Digital Technology on Jobs and Skills (Multiple Response, N=65)



Among substantive impact responses, the increased need for employee training and development is the most widely acknowledged (56.9%), followed by the enablement of more flexible work arrangements (55.4%). Changing how work is organised through digital workflows and technology-enabled collaboration is noted by 44.6% of enterprises. Automating simple or routine tasks is acknowledged by 41.5%, and the requirement for employees to develop new digital competencies by 40.0%. These findings collectively affirm that digital technology is actively reshaping work organisation and skill requirements, even if precise impact mechanisms remain uncertain for many enterprises.

Interpretation Note on Uncertainty

Because multiple responses were allowed, the 67.7% selecting "Unsure/Too early" cannot be treated as a mutually exclusive group. Most of these respondents also selected specific impacts. Only 13 enterprises (20.0% of the sample) selected uncertainty alone.

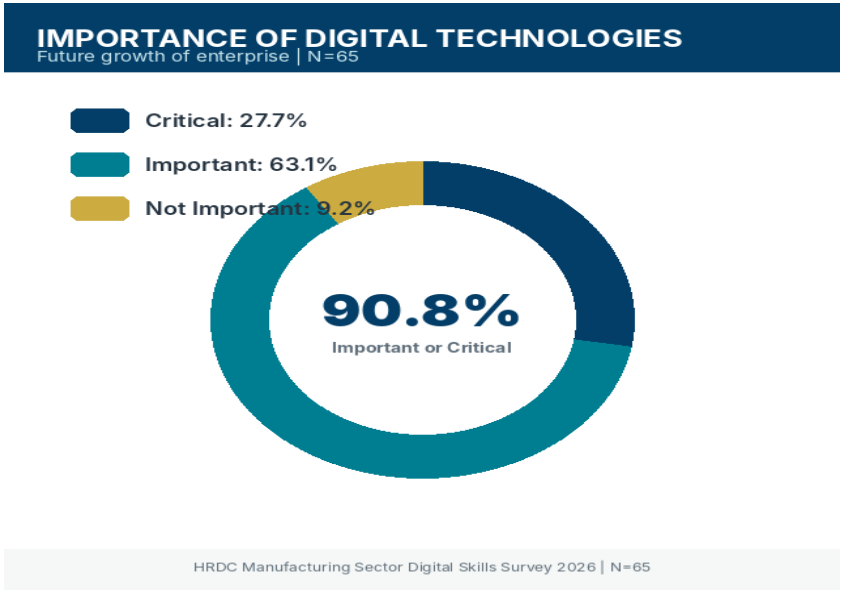
10.2 Workforce-Related Effects of Digital Technology

The data show multiple workforce-related effects associated with digital technology adoption. The increased need for employee training and development is the most commonly reported effect (56.9%), aligned with HRDC's skills-development mandate. More flexible work arrangements are reported by 55.4% of enterprises, reflecting broader changes in work organisation enabled by digital tools. Redeployment of employees within the enterprise is reported by 27.7%, while 21.5% report the creation of new roles requiring digital skills. Some 32.3% report that certain traditional skills are becoming less relevant, while 24.6% indicate that digital technology has so far had little or no observable impact on jobs and skills, as shown in Figure 26.

10.3 Digital Technology Importance for Future Growth

A clear consensus emerges on the strategic importance of digital technologies for enterprise growth. A combined 90.8% of respondents rate digital technologies as either 'Important' (63.1%) or 'Critical' (27.7%) for the future growth of their enterprise, with only 9.2% rating them as 'Not Important'. This represents a substantial shift in strategic orientation compared to the 2022 study and aligns with the broader evidence that enterprise leadership's perception of digital technology's strategic value is a key enabling condition for digital transformation investment.

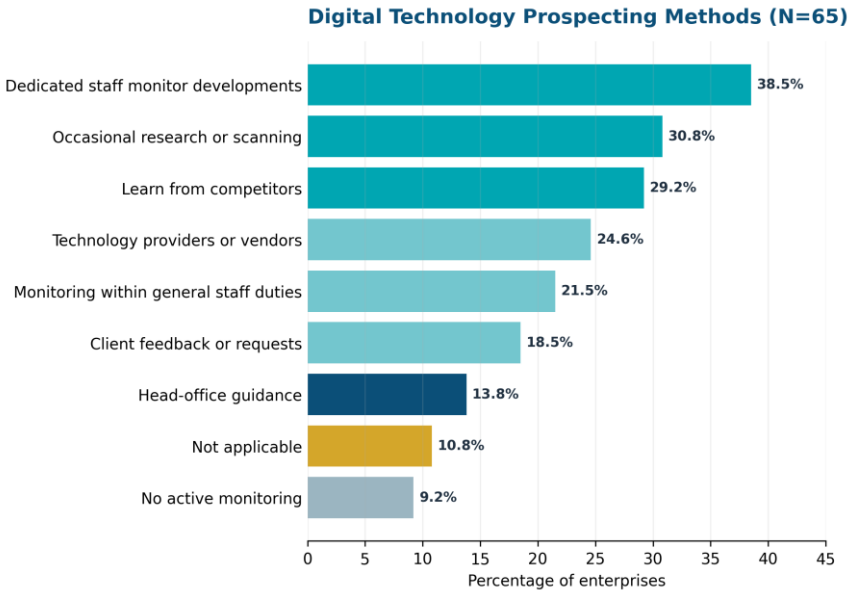
Figure 27: Importance of Digital Technologies for Future Growth (N=65)



11. Digital Technology Prospecting

Digital technology prospecting, the systematic monitoring of emerging technologies, market trends, and sector developments to inform enterprise investment decisions, is a critical upstream capability for successful digital transformation. Enterprises were asked to describe their approaches to identifying relevant digital technologies.

Figure 28: Digital Technology Prospecting Methods (Multiple Response, N=65)



The most common prospecting approach is the use of dedicated staff to monitor digital developments (38.5%), followed by occasional research or scanning (30.8%) and learning from competitors (29.2%). Technology providers or vendors are used by 24.6%, monitoring forms part of general staff responsibilities in 21.5%, and client feedback identifies opportunities for 18.5%. Head-office guidance accounts for 13.8%, while 10.8% selected 'Not applicable' and 9.2% reported no active monitoring.

Although more than one-third have dedicated monitoring capacity, prospecting remains uneven and is often dependent on periodic scanning, competitors or external signals. This capability could be supported through proportionate, curated technology intelligence linked to validated manufacturing needs, without the need to create a resource-intensive real-time structure.

12. Future Outlook: New Roles and Skills

12.1 Emerging Job Roles

Respondents were invited to identify up to three new roles expected over the next two years and the associated skills. After excluding 'None', 'N/A' and 'Unknown', 55 substantive role mentions were coded into six themes. The counts below in Table 6 refer to role mentions and should not be interpreted as the proportion of all 65 enterprises.

12.2 Required Skills for Emerging Roles

The required skills associated with these role mentions include data analysis and visualisation, AI and automation literacy, process control, MES/ERP operation, digital marketing and content creation, e-commerce, CAD/3D design, cybersecurity, systems coordination and digitally enabled project management. The recurring requirement is 'digital-plus-domain' capability: enterprises generally seek workers who combine manufacturing or business knowledge with digital skills rather than purely technical specialists. Table 6 summarises the six themes and their mention counts.

Table 6: Themes in Substantive Emerging-Role Mentions

Theme	Roles	Skills
AI, data & digital analysis (13 mentions)	Data Analyst / Digital Process Analyst AI Coordinator AI Engineer Data Expert AI System Administrator; Agentic Workflow Supervisor	Data analysis and visualisation; scripting; MES/ERP understanding; AI/ML implementation; workflow automation; AI governance; critical thinking
Other operational & business roles (13 mentions)	Production Supervisor; Supply Chain Officer; Storekeeper; Operations/Business Analyst; Quality Controller; Financial Officer; Merchandiser	Domain/operations expertise; computer literacy; business analysis and monitoring; process/quality oversight; financial forecasting; client liaison; digital workflow use
Automation & digital production (11 mentions)	Automation/Process Control Specialist; Robotics and Automation Engineer; MES Supervisor; Factory Process Automation Coordinator; Production Systems Coordinator; Machine Specialist	PLC/SCADA/MES operation; industrial automation and IIoT; predictive maintenance; troubleshooting; production scheduling and KPI reporting; CNC systems
Digital marketing, e-commerce & customer channels (9 mentions)	Digital Marketing Specialist; E-commerce/Online Showroom Manager; Website Manager; Remote Advertising Officer; Showroom Assistant	Social media management and content creation; SEO and analytics (e.g. Google Analytics); online platform and catalogue management; customer support/live chat; networking
Digital design, product development & R&D (6 mentions)	Digital Sampling/3D Specialist; Graphic Designer; Product Developer; R&D Officer; AI-assisted Designer	CAD/3D design and digital prototyping; artwork/creative design; client-facing presentation; automated product development; innovation and trend research
IT & systems coordination (3 mentions)	IT Specialist/Coordinator; Computer Systems Analyst; IT Project Manager	Cloud and infrastructure management; cybersecurity; AI systems integration; IT project delivery

Mention counts shown against each theme refer to the 55 substantive role mentions coded from 27 enterprises; roles and skills listed are illustrative examples drawn from respondents' own wording, not an exhaustive list.

12.3 Qualitative Insights: Sub-Sector Perspectives

Complementary qualitative interviews conducted by HRDC's Research and Projects Division with 29 manufacturing enterprises during 2025/2026—spanning textiles, food and beverage processing, Light engineering, medical devices, precision manufacturing, metal and plastics, paper and paper products, printing and packaging, leather, jewellery, furniture and wood and chemicals — provide sub-sector depth that the present survey's

sample size did not permit (see section 3.4). While methodologically distinct from the 65-enterprise digital technology survey, these interviews offer a valuable complementary lens on the workforce dynamics underlying the quantitative findings.

Figure 29: Sub-Sectors Covered by HRDC Qualitative Interviews, 2025/2026

Digitalisation levels vary markedly by sub-sector: precision manufacturing, medical devices, and parts of food processing show the deepest digital penetration, while oil processing, metal and aluminium, and several textile sub-segments remain predominantly manual. Automation intensity shows similar heterogeneity — several textile and beverage producers report automation levels of 60–75% on specific production lines, while leather goods and jewellery production remain almost entirely manual by the nature of the craft. Hard-to-fill positions cluster around industrial and mechanical engineers, process and machine operators, maintenance technicians, food technologists, laboratory analysts, and skilled machinists and jewellers, with several enterprises reporting persistent reliance on expatriate labour to fill these roles.

Training culture across the interviewed enterprises is described as predominantly in-house and ad hoc, with structured programmes concentrated among larger, group-affiliated enterprises. An ageing workforce and low interest among young Mauritians in production-floor roles were raised as structural concerns across almost all sub-sectors, compounding the skills availability constraints identified in the main survey. Sustainability practices are emerging in food, textile, and oil processing (recycling, biogas, eco-materials) but remain limited in metal and plastics processing.

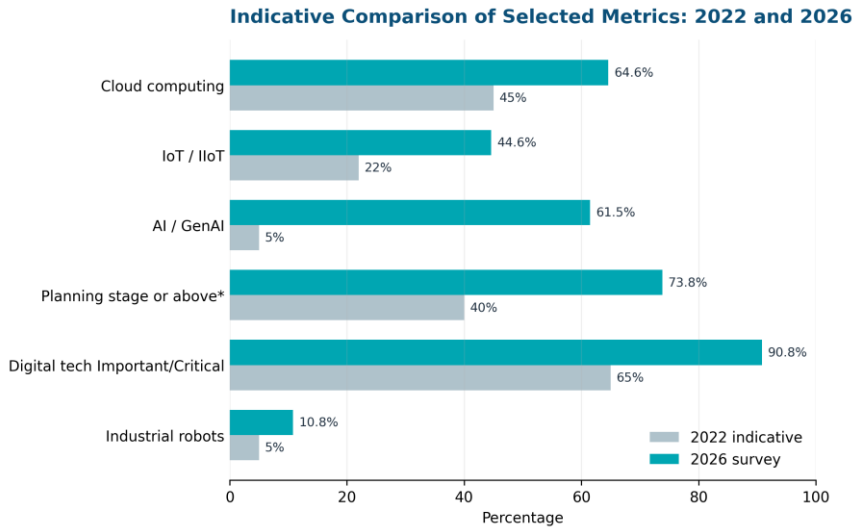
Table 7: Qualitative Sub-Sector Themes from HRDC Manufacturing Enterprise Interviews (2025/2026)

Theme	Key Findings (29 Manufacturing Enterprises, 2025/2026)
Workforce Composition	30–3,000 employees per enterprise; 40–70% expatriate share in operator/technician roles at several large enterprises; locals concentrated in admin and management
Hard-to-Fill Jobs	Industrial and mechanical engineers, process/machine operators, maintenance technicians, food technologists, lab analysts, machinists, jewellers
Training Culture	Mostly in-house and ad hoc; limited use of external training institutions; structured programmes needed in automation, maintenance and soft skills
Digitalisation	Stronger in precision manufacturing, medical devices and food; weak in oil, metal and textile sub-segments
Sustainability	Emerging in food, textile and oil (biogas, recycling, eco-materials); limited in metal and plastics
Ageing / Migration	Ageing workforce and high expatriate dependence, notably in textile and metal; low local youth interest
Obsolete Roles	Manual packers, pattern-makers, repetitive assembly workers
Emerging Roles	Automation/robotics engineers, mechatronics technicians, industrial data analysts, predictive maintenance specialists, CAD/CAM designers, sustainability coordinators, e-commerce managers
Growth Outlook	Moderate growth (5–10% over five years); strongest in food, precision manufacturing and medical devices

13. Indicative Storyline: 2022 vs 2026

Another aim of the study was to assess the evolution of digital technology adoption and skills readiness since the 2022 Automation Study. Differences in sample size, questionnaire design and measurement constructs require caution. Figure 30 therefore presents an indicative comparison only; proxy measures are explicitly identified and should not be treated as direct like-for-like trends.

Figure 30: Indicative Comparison — Selected Digital Technology Metrics, 2022 and 2026



Cloud computing current use stands at 64.6% in 2026, compared with an estimated 45% moderate-use indicator in 2022. IoT/IIoT current use is 44.6%, compared with approximately 22% moderate use in 2022. GenAI technology use is now reported by 61.5%, whereas AI adoption was nascent

in the earlier study. Digital technologies are rated Important or Critical by 90.8% in 2026. Separately, 48 of 65 enterprises (73.8%) place themselves at the Planning stage or above under Q9; this is a digital-maturity proxy and does not show that every enterprise has a formal documented digital strategy.

Despite these advances, several structural challenges from 2022 persist. Industrial robots and advanced robotics remain minimally adopted (10.8% in 2026 vs approximately 5% in 2022), suggesting that capital-intensive automation has not accelerated despite policy incentives. This aggregate figure masks considerable sub-sector heterogeneity. Complementary interview evidence collected across 29 manufacturing enterprises in 2025 indicates that a subset of textile and beverage producers already operate at 60–75% automation on specific production lines, while leather goods, jewellery, and parts of food processing remain almost entirely manual by the nature of their production processes. The 10.8% robotics-adoption figure should therefore be read as an average across a highly bifurcated sector rather than a uniform sectoral position.

Dependence on foreign training providers was not directly measured in the 2026 questionnaire and should not be presented as a like-for-like survey comparison. However, the 2022 finding, complementary interviews conducted in 2025 and continuing gaps in the local supply of advanced digital and AI training indicate that access to specialised provision remains a structural concern. This is contextual evidence rather than a direct 2026 survey metric. The skills barrier to technology adoption, while no longer the single top barrier—having been displaced by budget constraints—nevertheless remains a major constraint, reaffirming the centrality of HRDC's skills development mandate.

Progress Assessment 2022–2026

The indicative 2022–2026 comparison suggests progress in mainstream digital technology adoption among surveyed enterprises — particularly in cloud, IoT and GenAI — while recognising the differences in sample, questionnaire design and measurement constructs. However, the transformation trajectory is best described as broad but shallow: many enterprises have adopted accessible digital tools without deepening their transformation to integrate AI, analytics, and automation at a systemic level. Closing this depth gap requires a second wave of investment in advanced skills, digital leadership capability, and enterprise-level transformation support.

14. Recommendations and Way Forward

The findings call for a practical response focused on validated skills needs, occupation-based programme design, responsible AI use, SME participation and continuous follow-up. Employers already have access to substantial refunds for eligible training (90%), including AI-focused programmes. The immediate priority is therefore to use HRDC's existing sectoral and national skills development instruments more strategically for needs that individual enterprise applications do not adequately address.

These needs include common occupational gaps, specialised technical areas requiring shared facilities or imported expertise, short modular pathways for employed workers, constraints affecting SME participation and emerging AI and GenAI governance risks. The proposed response is aligned with the Skills-Interface Platform, sectoral and national skills intelligence, micro-credentials and practical AI capability envisaged in the 2026–2027 Budget.

Figure 31: Five operational pillars for implementation

Pillar 1: Validate Priorities and Maintain Proportionate Skills Intelligence

The survey provides a sector-level baseline, but it should not automatically be converted into training projects without further validation. HRDC could use the Skills-Interface Platform to bring together employers, industry associations, training providers, MITD, universities, MQA, NPCC, EDB and relevant public institutions through small occupation- or technology-specific discussions.

Priority validation areas should include:

- production operations, supervision and automation;
- engineering, maintenance and industrial digital technologies;
- supply chain, procurement, warehousing and logistics;
- quality assurance, laboratory systems, traceability and digital compliance;
- management, finance, HR and administrative functions;
- responsible AI and GenAI use; and
- SME digital readiness and participation constraints.

The discussions would confirm the occupations concerned, workplace technologies, expected competency level, programme duration, preferred delivery arrangements, available training supply and the ability of enterprises to release employees. The immediate output should be a concise Manufacturing Digital Skills Priority Plan separating programmes that can proceed quickly, programmes requiring curriculum development and areas requiring further technical assessment.

A short annual pulse survey could focus only on fast-changing areas such as AI, GenAI, automation, difficult-to-fill roles, immediate training needs and evidence of workplace application. The full assessment should be repeated every three years rather than creating a resource-intensive real-time platform at this stage.

In practice, this validation step is what keeps the survey findings from being converted directly into training programmes. A statistical gap identified in the survey (for example, a low score on a particular technology) only becomes a priority once employers confirm, through the Skills-Interface discussions, that the occupation is real, that enterprises are able to release staff for training, and that a workable delivery format exists. This ensures training investment follows demand that is both evidenced by the survey and deliverable on the ground, rather than risking programmes that enterprises cannot practically take up.

Pillar 2: Mount Targeted, Occupation-Based and Practical Training

Training should be designed around actual job functions and workplace applications rather than generic digital literacy. The occupation-based findings show that production, engineering, supply-chain, quality, management and business-support roles require different combinations of technical, digital and analytical capability.

Priority programme areas for validation and development are set out below:

1) **Production operators and supervisors**
   - digital production monitoring and electronic data capture;
   - human–machine interfaces and basic machine-control skills;
   - sensors, IoT and connected production equipment;
   - digital quality checks, traceability and production documentation;
   - data interpretation for production decisions; and

• safe work and workforce adaptation in increasingly automated environments.

2) **Engineering, maintenance and technical personnel**

• PLC and industrial automation fundamentals;
• industrial IoT installation, operation and basic troubleshooting;
• computerised maintenance-management systems;
• predictive and preventive maintenance using production data;
• sensors, condition monitoring and equipment diagnostics;
• CAD, digital modelling and technical documentation;
• industrial cybersecurity; and
• energy and resource-efficiency technologies.

Supply chain, procurement, stores and logistics personnel

• ERP-based inventory and procurement management;
• warehouse and stock-management systems;
• digital traceability and supply-chain documentation;
• data analytics for demand, inventory and supplier performance;
• e-procurement and supplier-management platforms; and
• AI-supported forecasting and planning.

Quality, laboratory, safety and compliance personnel

• digital quality-management systems and electronic records;
• data integrity, traceability and document control;
• statistical process control and quality-data analysis;
• digital compliance and audit preparation;
• environmental monitoring and sustainability data; and
• responsible use of AI for technical documentation and reporting.

3) **Managers and business-support personnel**

• digital transformation planning and change leadership;
• data-based decision-making and dashboard interpretation;
• ERP and integrated business systems;
• AI-assisted administration, finance and HR processes;
• cybersecurity, confidentiality and data governance; and
• management of workforce transition arising from automation.

Delivery should be practical, workplace-compatible and linked to the processes and equipment used by participating enterprises. Specialised programmes may require technical facilities, demonstrations, technology providers or external expertise.

Pillar 3: Establish Responsible AI and GenAI Use in Manufacturing

The rapid diffusion of GenAI into enterprise workflows requires an immediate governance response. Training should cover not only tool use, but also verification of outputs, confidentiality, data protection, intellectual property, human oversight and the appropriate handling of technical, quality, safety and export-compliance information.

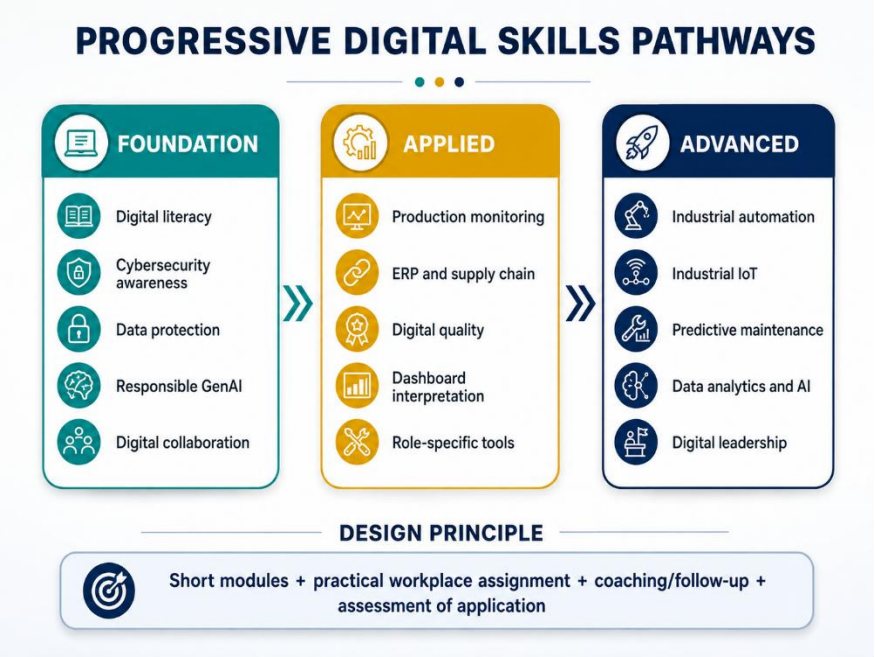
• prepare a concise Responsible GenAI Guide for manufacturing workplaces;
• develop a standard enterprise acceptable-use template covering approved uses, prohibited data, verification and accountability;
• mount role-specific AI and GenAI literacy programmes for managers, supervisors, quality staff, supply-chain personnel, HR, finance and technical staff;
• include practical exercises based on manufacturing documentation, analysis, planning and decision-support tasks; and

• encourage participating enterprises to adapt the template to their own risk profile and internal controls.

The objective is not to certify that an enterprise is AI-ready. It is to equip managers and employees to use AI tools productively and safely while retaining human responsibility for decisions and technical outputs.

Pillar 4: Develop Modular Digital Skills Pathways and Use Existing Schemes Strategically

The mean digital skills gap of 29.3% across the competency categories, together with the overall role-level automation estimate of approximately 41%, points to a substantial reskilling requirement. Manufacturing enterprises cannot always release employees for long programmes; provision should therefore be short, stackable and progressively linked to recognised micro-credentials or qualifications where appropriate.



Each pathway should combine:

• a foundation module;

• an occupation-specific application module;

• practical workplace assignments or improvement projects;

• coaching, demonstrations or technical follow-up; and

• assessment of workplace application.

Potential pathways include Digital Foundations, Production and Operations, Engineering and Maintenance, Supply Chain and Logistics, Quality and Compliance, and Digital Leadership. Internationally recognised learning content may be used selectively, but it should be contextualised to Mauritian manufacturing operations and complemented by practical application.

Figure 32: Progressive digital skills pathways for manufacturing

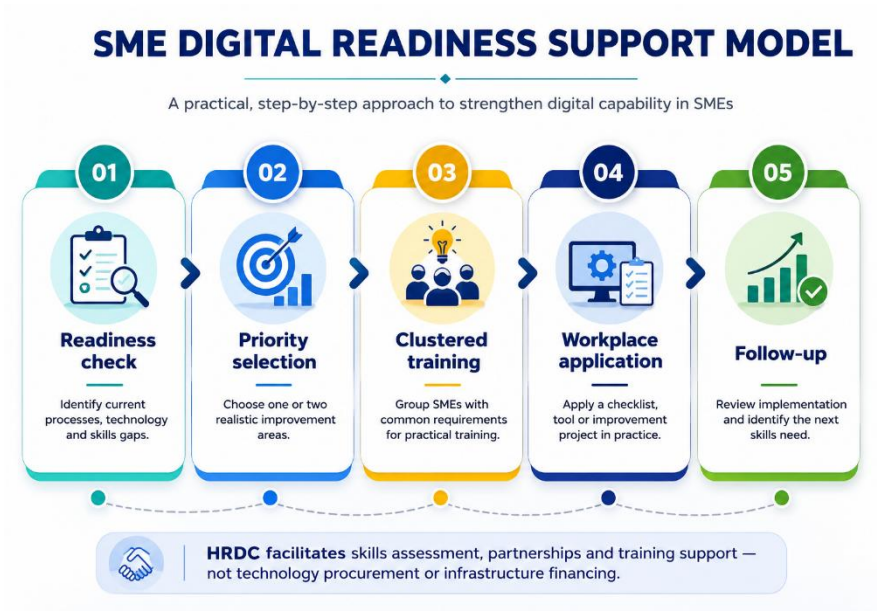
The Sectoral Skills Development Scheme should be used for common industry needs requiring customised programmes, shared specialist expertise, demonstrations, pilot delivery or collaboration among enterprises. Cluster-based applications are appropriate where specialised demand is too small or costly for one SME to address alone. Public training institution-led or industry association-led interventions may be used where demand has been validated and no suitable programme currently exists. Employment-oriented schemes may separately support entry-level pipelines for verified vacancies in production, maintenance, logistics, quality and digital production-support roles.

Support should not duplicate standard courses already available to enterprises. It should concentrate on validated gaps requiring customised, shared, specialised or occupation-specific intervention.

Pillar 5: Strengthen SME Digital Readiness through Clustered Support

Micro and small enterprises employing fewer than 50 workers represent 44.6% of the responding sample, and the earliest digital-transformation stages are concentrated mainly among smaller enterprises. Their constraints extend beyond training fees and include limited internal expertise, small cohort sizes, difficulty releasing employees and uncertainty about which technology and skills investments are most relevant.

Figure 33: SME digital readiness support model



Priority actions could include:

- develop a concise Manufacturing SME Digital Readiness Checklist focused on processes, technologies and skills;
- conduct targeted SME discussions through the Skills-Interface Platform to validate needs and delivery constraints;
- work with AMM, MEXA, EDB, NPCC and relevant associations to prepare practical digital-skills guides;
- facilitate cluster-based training where enterprises share common needs but cannot individually form viable cohorts;
- link training to practical tools such as production logs, maintenance schedules, quality checklists, inventory dashboards, traceability templates and GenAI acceptable-use guides;

• include demonstrations, coaching or workplace follow-up where required; and

• use short modules, blended delivery and repeated cohorts to minimise disruption to operations.

HRDC should remain within its skills-development mandate. It should facilitate needs validation, collaborations, draft programme development and training support; it should not operate as a technology-procurement consultant or finance enterprise digital infrastructure.

The Business Case for Digital Skills and Transformation

Independent evidence from the AMM/EKIUM AMIO industrial audit and transformation exercise provides a useful business case for structured digital transformation. Participating manufacturers reported indicative improvements of 15–20% in Overall Equipment Effectiveness, reductions of 10–15% in operational costs, reductions of 30–40% in quality defects and non-conformities, extensions of 20–25% in equipment asset life, and reductions of 30–40% in stock and work-in-progress levels.

These figures are not findings of the present survey and should remain clearly attributed to the independent industry exercise. They may nevertheless be used in dissemination and enterprise-engagement materials to demonstrate that digital skills development is valuable when it contributes to measurable improvements in productivity, reliability, quality, resource use and decision-making.

14.1 Implementation Roadmap for Action

The recommendations should be implemented in stages. The roadmap below moves from evidence validation to programme design, pilot delivery, workplace application, evaluation and scale-up, while remaining within HRDC's existing mandate and skills development instruments.

Figure 34: Recommended implementation roadmap for action

Immediate priority actions

- disseminate the findings;
- produce a Manufacturing Digital Skills Priority Plan;
- map existing local training supply against validated needs;
- develop three initial pilot proposals: Digital Production Monitoring for Operators and Supervisors; Industrial IoT and Predictive Maintenance for Technical Personnel; and Responsible GenAI and Data Governance for Managers and Business-Support Functions;
- develop at least one SME cluster pilot, such as digital inventory, production monitoring, maintenance readiness or digital quality and traceability; and
- conduct a short annual pulse survey and repeat the full assessment after three years.

14.2 Expected Role of HRDC

HRDC's role should remain focused on generating skills intelligence, facilitating structured dialogue, strengthening linkages between enterprises and the training system, supporting responsive programme design and evaluating whether supported interventions address validated labour-market needs as follows:

- identify and validate priority skills needs;
- convene enterprises, providers, industry associations and relevant public institutions;
- facilitate the mounting of customised and modular programmes;
- support eligible interventions through appropriate existing schemes;
- encourage practical, workplace-based delivery and follow-up;
- monitor participation, outputs and evidence of workplace application; and
- periodically update the evidence base and programme priorities.

This approach is more feasible as it converts the study findings into a manageable programme of action while aligning with HRDC's mandate, the Skills-Interface Platform, sectoral skills intelligence, micro-credentials and practical AI capability.

15. Conclusion

This study provides a detailed enterprise-level assessment of the adoption of manufacturing-related digital technologies, skills gaps and workforce readiness in the Mauritian private manufacturing sector. Conducted four years after HRDC's 2022 study on automation, robotics and IIoT in the manufacturing sector (HRDC, 2022), the findings reveal a sector in active but uneven digital transition: foundational and intermediate technologies have achieved broad adoption among respondents; cloud computing and IoT are becoming important operational infrastructure; and GenAI has arrived rapidly, with 61.5% reporting current technology use, 55.4% reporting employee use and 60.0% actively encouraging its use.

Yet the persistence of structural challenges—a 29.3% mean digital skills gap, budget and expertise constraints limiting transformation depth, minimal adoption of advanced robotics and frontier technologies, and contextual evidence of continuing constraints in local provision of high-level technical training—underscores that the sector's digital transformation remains a work in progress. The pace of technological

change, particularly in GenAI and AI integration, is accelerating faster than enterprise governance and workforce readiness frameworks can absorb, creating new risks alongside the productivity opportunities that digital adoption promises.

HRDC is positioned at the nexus of these challenges and opportunities. Through the Levy-Grant Scheme, existing sectoral and national skills-development instruments, research and intelligence functions, sectoral committee engagement and its convening role across government, industry and training providers, HRDC has the mandate and tools to coordinate an evidence-based response. The proposed agenda is to validate priorities, mount occupation-based practical programmes, establish responsible sectoral AI and GenAI use, develop modular pathways, support Manufacturing SME participation through clustered delivery, and maintain proportionate sectoral skills intelligence through an annual pulse survey and a full assessment every three years.

Mauritius's ambition to position its manufacturing sector as a high-value, digitally-enabled contributor to the national economy will ultimately be determined not by the availability of technology, which is increasingly accessible and affordable, but by the depth, quality, and adaptability of the human capital that deploys, operates, governs, and continuously improves it. The findings of this study reaffirm that investing in the digital capabilities of the manufacturing workforce is not a cost to be managed, but a strategic imperative to be seized.

> **Looking Ahead**
>
> A short annual pulse survey should monitor fast-changing areas such as AI, GenAI, automation, difficult-to-fill roles and immediate training needs. A fuller manufacturing digital-skills assessment should be repeated every three years, allowing sufficient time for programme implementation and workplace outcomes to emerge.

References

Acemoglu, D. and Restrepo, P. (2022) 'Tasks, automation and the rise in US wage inequality.' Econometrica, 90(5), pp.1973–2016.

AMM/EKIUM AMIO (2025) L'Indistri Dime – Livre Blanc Industrie 4.0. Mauritius: Association des Manufacturiers Mauriciens.

Autio, C., Dunietz, J., Hall, P., Jain, S., Roberts, K., Schwartz, R., Stanley, M. and Tabassi, E. (2024) Artificial Intelligence Risk Management Framework: Generative Artificial Intelligence Profile. NIST AI 600-1. National Institute of Standards and Technology.

BMWK (2022) Mittelstand-Digital: Netzwerk der Mittelstand-Digital Zentren. Berlin: Federal Ministry for Economic Affairs and Climate Action. Available at: www.mittelstand-digital.de

Brynjolfsson, E., Mitchell, T. and Rock, D. (2018) 'What can machines learn, and what does it mean for occupations and the economy?' AEA Papers and Proceedings, 108, pp.43–47.

European Commission (2023) AI Act: Regulation of the European Parliament and of the Council Laying Down Harmonised Rules on Artificial Intelligence. Brussels: European Commission.

Fitzgerald, M., Kruschwitz, N., Bonnet, D. and Welch, M. (2014) 'Embracing digital technology: A new strategic imperative.' MIT Sloan Management Review, 55(2), pp.1–12.

Goldman Sachs (2023) Generative AI Could Raise Global GDP by 7%. New York: Goldman Sachs Economic Research.

Government of Mauritius (2026) Budget Speech 2026–2027. Ministry of Finance, Mauritius.

Government of Mauritius (2026) Annex to the Budget Speech 2026–2027. Ministry of Finance, Mauritius.

HRDC (2020) National Skills Development Strategy 2020–2025. Mauritius: Human Resource Development Council.

HRDC (2022) Fostering Automation, Robotics and IIOT in the Manufacturing Sector: A Skills Perspective (RP 05/22). Mauritius: Human Resource Development Council.

IFR (2023) World Robotics Report 2023. Frankfurt: International Federation of Robotics.

ILO (2022) World Employment and Social Outlook 2022: Trends in the Demand for Skills. Geneva: International Labour Organisation.

Manyika, J. et al. (2017) Jobs Lost, Jobs Gained: Workforce Transitions in a Time of Automation. McKinsey Global Institute.

Ministry of Technology, Communication and Innovation (2018) Digital Mauritius 2030 Strategic Plan. Port Louis: Government of Mauritius.

OECD (2021) OECD Skills Outlook 2021: Learning for Life. Paris: OECD Publishing.

OECD (2023) OECD Digital Economy Outlook 2023: Shaping an Enabling Environment for the Digital Transformation. Paris: OECD Publishing.

Schwab, K. (2016) The Fourth Industrial Revolution. Geneva: World Economic Forum.

SMEDA (2023) SME Development in Mauritius: Annual Report 2022/2023. Mauritius: Small and Medium Enterprises Development Authority.

Statistics Mauritius (2024) National Accounts of Mauritius 2024. Port Louis: Statistics Mauritius.

Statistics Mauritius (2025) National Accounts of Mauritius 2025. Port Louis: Statistics Mauritius.

Statistics Mauritius (2026) National Accounts of Mauritius 2026, first quarter. Port Louis: Statistics Mauritius.

Vial, G. (2019) 'Understanding digital transformation: A review and a research agenda.' Journal of Strategic Information Systems, 28(2), pp.118–144.

WEF (2023) The Future of Jobs Report 2023. Geneva: World Economic Forum.