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# A digital transformation strategy model for leadership in manufacturing: Considering the technological innovations to advance industry 5.0 in smart manufacturing

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**Purpose:** This study investigates how manufacturing leaders can effectively navigate the transition from Industry 4.0 (I4.0) to Industry 5.0 (I5.0) by leveraging technological and data management advancements. It aims to bridge the digital transformation (DTx) gap and proposes a robust strategy model focused on human–machine interaction and sustainability.

**Design/methodology/approach:** The study adopts a mixed-methods approach, combining a structured literature review with empirical insights from a quantitative survey of 2500 South African manufacturing leaders. The research applies statistical analysis and revises a seven-step DTx model to incorporate I5.0 technologies, including industrial artificial intelligence (IndAI) and human-centric smart manufacturing. Critical research factors are extracted from literature review and qualitative research. Most references are from 2020 onwards.

**Findings/results:** Findings reveal critical success factors for successful Industry 5.0 migration, highlighting the importance of resilience, human–machine collaboration, sensor technology, connectivity infrastructure and the four-layered IndAI integration. The article introduces a multi-layered DTx strategy model adaptable to future industrial paradigms, including a nascent Industry 6.0.

**Practical implications:** Manufacturing leaders can apply the refined DTx strategy model to enhance organisational readiness, technological agility and workforce alignment through 'worker back in the loop' considerations and ergonomics. The findings inform policies on upskilling, digital ethics and systems design for sustainable industrial growth.

**Originality/value:** This article extends prior DTx frameworks by integrating emerging Industry 5.0 concepts and proposing a future-oriented strategy model. It contributes novel insights into human-centric design, IndAI governance and leadership challenges in digitally evolving manufacturing contexts.

**Keywords:** digital transformation; Industry 5.0; smart manufacturing; human–machine interaction; leadership; sustainability; industrial AI.

## Introduction

The Fourth Industrial Revolution (4IR) has significantly reshaped global manufacturing by integrating disruptive technologies such as the Internet of Things (IoT), artificial intelligence (AI), virtual reality (VR), augmented reality (AR), big data analytics, cloud computing (CC), manufacturing execution systems (MES) and enterprise resource planning (ERP) (Clemons, 2022). In South Africa specifically, Gaffley and Pelser (2021) identified a digital transformation (DTx) gap of 47.7%, highlighting a critical need for improved digital capabilities among manufacturing leaders. Baslyman (2022) defines DTx as the strategic application of disruptive technologies facilitating smart manufacturing and operational efficiencies.

This article extends our previous research by exploring how technological advancements from Industry 4.0 (I4.0) transition towards Industry 5.0 (I5.0), emphasising human–machine interface (HMI) and human-centric smart manufacturing (HCSM). It proposes a comprehensive and more robust DTx strategy model for leadership in manufacturing as originally developed by Gaffley (2022). These findings indicate an emerging stage of DTx maturity within South Africa's industrial landscape.

## Literature review

This covers section 'Literature review' and section 'Industrial artificial intelligence opportunity in industry 5.0'. Clemons (2022) and Baslyman (2022) view DTx as the application of disruptive technologies to digitally transform the organisation. Jamwal et al. (2021) stated that the enablement of Industrial Internet of Things (IIoT) continuum of disruptive technologies initially proposed by Bordignon (2017) resulted in I4.0 or 4IR, introduced in 2011 by the German government aiming to improve efficiency in German manufacturing. Zheng et al. (2020) and Borregan-Alvarado et al. (2021) agree that a shortcoming of I4.0 is not much research being conducted in the sustainable supply chain, blockchain systems in logistics and sustainability conformance. Zheng et al. (2020) include large language models (LLMs), with Baslyman (2022) adding developments in the metaverse through extended reality (XR) enabling digital twin rollout through the replication of physical assets and machines with digital replicas forming key components of the IIoT continuum (Clemons, 2022).

### The paradigm shift of industry 4.0 and rise of industry 5.0 in smart manufacturing

Industry 4.0 introduced connectivity through IIoT-driven cyber-physical systems (CPS), enabling agile operations integrating physical assets with digital technologies, and 'synchroperation' is revolutionising the way in which manufacturing operations are managed. This shift synchronises human–machine–material interactions through agile and resilient operations driven by data analytics. It is supported by the Hyperconnected Physical Internet-enabled Smart Manufacturing System (HPISMS) and the Graduation Intelligent Manufacturing System (GiMS), which enhance visibility and traceability in manufacturing (Guo et al., 2021). There are two implementation progress measures for I4.0. One is INCIT's Smart Industry Readiness Index (SIRI) benchmarking tool from the Singapore Development Board where assessors evaluate and prioritise advancing I4.0 with actionable plans (Winter, 2023). The other Acatech's I4.0 Maturity Index evaluates six key trends: trustworthy data sources, industrial AI, operational migration to 5G connectivity, edge computing with cloud storage, team robotics and autonomous intralogistics systems (Kagermann & Wahlster, 2022).

The DTx gap is determined by recent global conflicts and disruptions such as coronavirus disease 2019 (COVID-19) highlighting limitations in resilience and sustainability within I4.0 frameworks and supply chain shortcomings (Borregan-Alvarado et al., 2021; Zheng et al., 2020). It encouraged the move to digitisation and automation with human intervention moved out of the loop. As a response, I5.0 emerged and addresses these shortcomings by integrating resilience frameworks with human-centricity and smart manufacturing principles, placing humans ('back in the loop') at the core of production processes. The focus is on worker welfare, sustainability and robust HMI central to the smart manufacturing process (Yang et al., 2024). Sarkar et al. (2024) highlight the International Standards Organization (ISO) White Paper (Johannsen, 2021) definition of smart manufacturing as improving operational performance through intelligent integration across cyber, physical and human spheres.

### Hybrid industry 4.0 to industry 5.0 coexistence or transition to an industry 6.0 foundation

Many organisations have a hybrid relationship between the two paradigms (Golovianko et al., 2023). The Duggal et al. (2022) hybrid model blends the smart processes of both paradigms and sets the foundation for Industry 6.0 (I6.0). Here AI and robotics are taken to a level where human or users' physical profiles are cloned as Pi-Mind clones or a digital twin of the user. These are designed to overcome the need to physically input product data to complete the manufacturing cycle; it is already integrated and cloned into the process. This becomes the differentiator for I6.0 where humans and machines learn collaboratively from each other (Duggal et al., 2022).

Resilience in Figure 1 is one of the most important enablers of I5.0 where Linnosmaa et al. (2021) suggest the introduction of a resilience framework comprising decision-making flowing from human operators assisted by decision support systems. In turn, this moves on to AI-driven autonomous control components with low level automation controls which can withstand internal or external negative disruptive influences and maintain its sustained operational performance which leadership must understand.

### Human–machine interaction

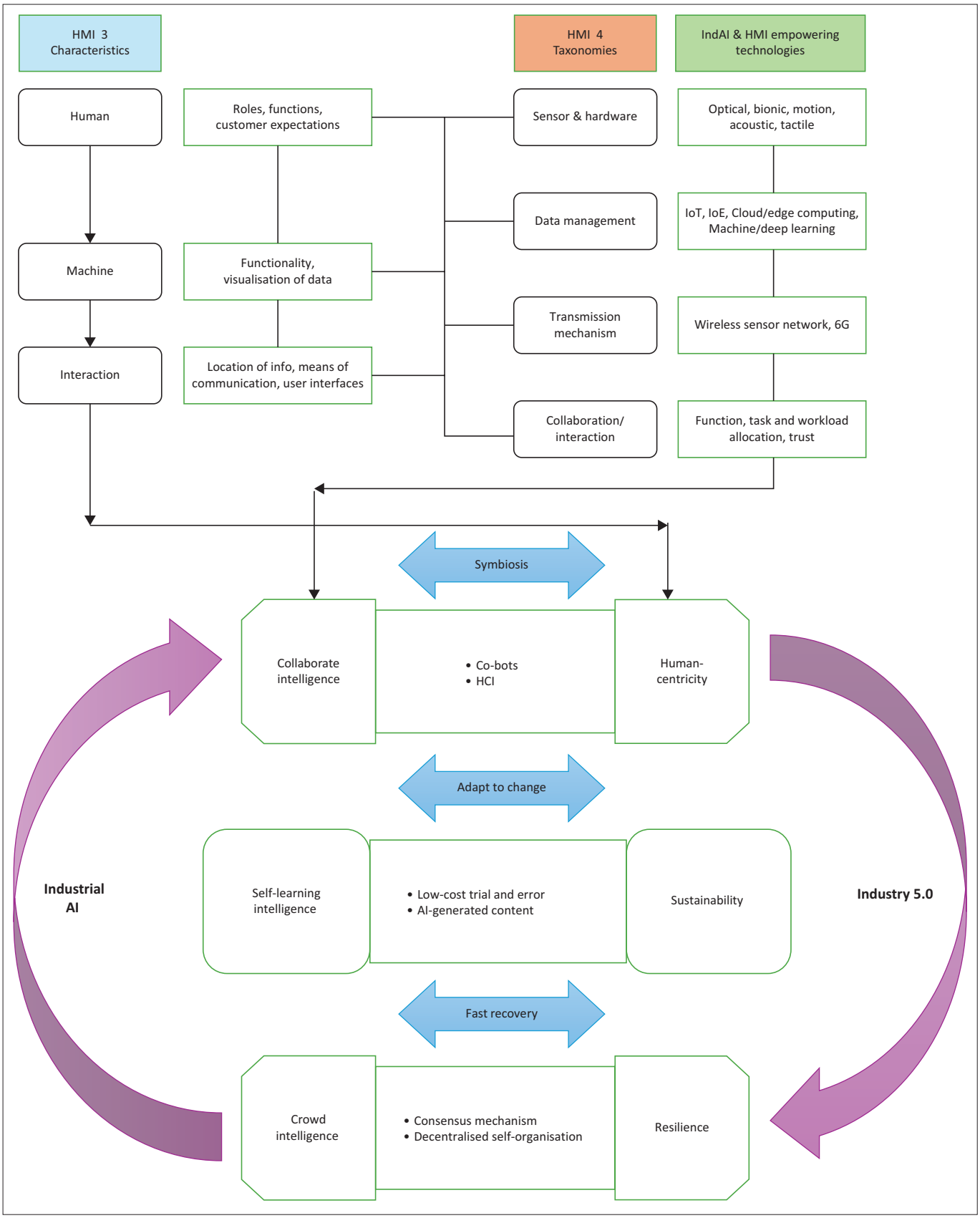
The future smart factory, according to Xu et al. (2021), incorporates cooperation between humans and machines where human-centricity, resilience and sustainability form core values. Yang et al. (2024) define HMI as integrating data processing transmission mechanisms with hardware and software collaboration. This enables optimising operator interaction efficiency, productivity and safety in HCSM. Combined with advanced technologies, this creates resilient and sustainable smart factories.

Figure 1 forms the basis of this study, integrating the three categories of HMI and four supporting category taxonomies which combine with IndAI, its empowering technologies and three cornerstones of I5.0 (Leng et al., 2024; Yang et al., 2024).

Figure 1 shows leadership how each category taxonomy and their empowering technologies are assessed against their contribution to the characteristics of HMI.

### Data management and connectivity

Cárdenas-Robledo et al. (2022) share that the IIoT connectivity enablement of technologies allows data exchange between people, systems and machines. The first taxonomy, data management, forms the basis for smart manufacturing

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AI, artificial intelligence; IoE, Internet of Everything; IoT, Internet of Things; HMI, human–machine interface; HCI, human-computer interaction.

**FIGURE 1:** Integration of human–machine interface's 3 iterations and 4 category classifications with three industry 5.0 cornerstones and industrial artificial intelligence empowerment technologies and intelligence learning.

enabling data integration, control and automation. Laroui et al. (2021) indicate that wireless transmissions are essential to the IIoT for reliability, security and timeless requirements, but cannot keep up with demand. Low latency (10 Gbps – 20 Gbps), high-band spectrum and fibre-enabled speed through 5G connectivity overcome this challenge.

Important aspects of data management and connectivity include data analytics with cloud and edge computing, together with machine and deep learning. Alouffi et al. (2021) advise that CC, a mature technology, employs flexible data management models with cybersecurity risks. Robust blockchain-based encryption mechanisms can effectively address intrusion and data leakage threats.

The Wang et al. (2022) opinion is that machine and deep learning algorithms are inseparable from the analysis of big data from manufacturing with correlation, prediction and regulation analysis characteristics. Edge computing, which possesses data closer to the source, mitigates latency concerns while supporting real-time industrial operations (Alouffi et al., 2021).

Machine learning algorithms have three learning categories according to Kotsiopoulos et al. (2021): supervised (given data with prediction labelling), unsupervised (discovering information from data), and reinforcement (given data and choosing actions for long-term reward). Unsupervised learning uses algorithms such as Bayesian networks and multiple linear regression. Supervised learning uses algorithms such as k-means and self-organising maps. Reinforcement learning uses algorithms such as PILCO and SMART.

Deep learning, although applied in manufacturing operations and processes, cannot guarantee industry safety and control requirements. Deep learning has applications in anomaly detection, image recognition, high dimensional data processing and natural language processing, relying on large data sets which become inaccurate when applied to smaller data sets. It is also associated with higher computational costs with higher hardware requirements (Kotsiopoulos et al., 2021).

Machine and deep learning have three key research development directions: task for quality and defects, technology algorithms for transforming industrial data to big data and industry-centred research on migration of new technologies from I4.0 to I5.0. The importance of deep and machine learning with industrial artificial intelligence (IndAI) as the brain of future smart factory scenarios will have key focus on human and environmental-related data areas of data analysis optimising the HMI experience (Kotsiopoulos et al., 2021).

Leadership must grasp how these support data management with the next taxonomy, a consideration of sensors in data detection.

## Sensor applications for data detection

Yang et al. (2024) agree with Kumar and Lee (2022) that I5.0 migration processes for smart manufacturing require five types of sensors:

- Acoustic is completed by voice recognition devices.
- Optical interacts via devices that detect eye movements.
- Haptic recognition focusses on nonaudio verbal communication such as vibration, touch, sound and temperature provided by wearable devices.
- Motion-based sensors, which collect data from the operating environment for efficiency improvement, are detected by camera or wearable devices.
- Tactile refers to operators recording process control on industrial devices and tablets.

## Data transmission mechanisms

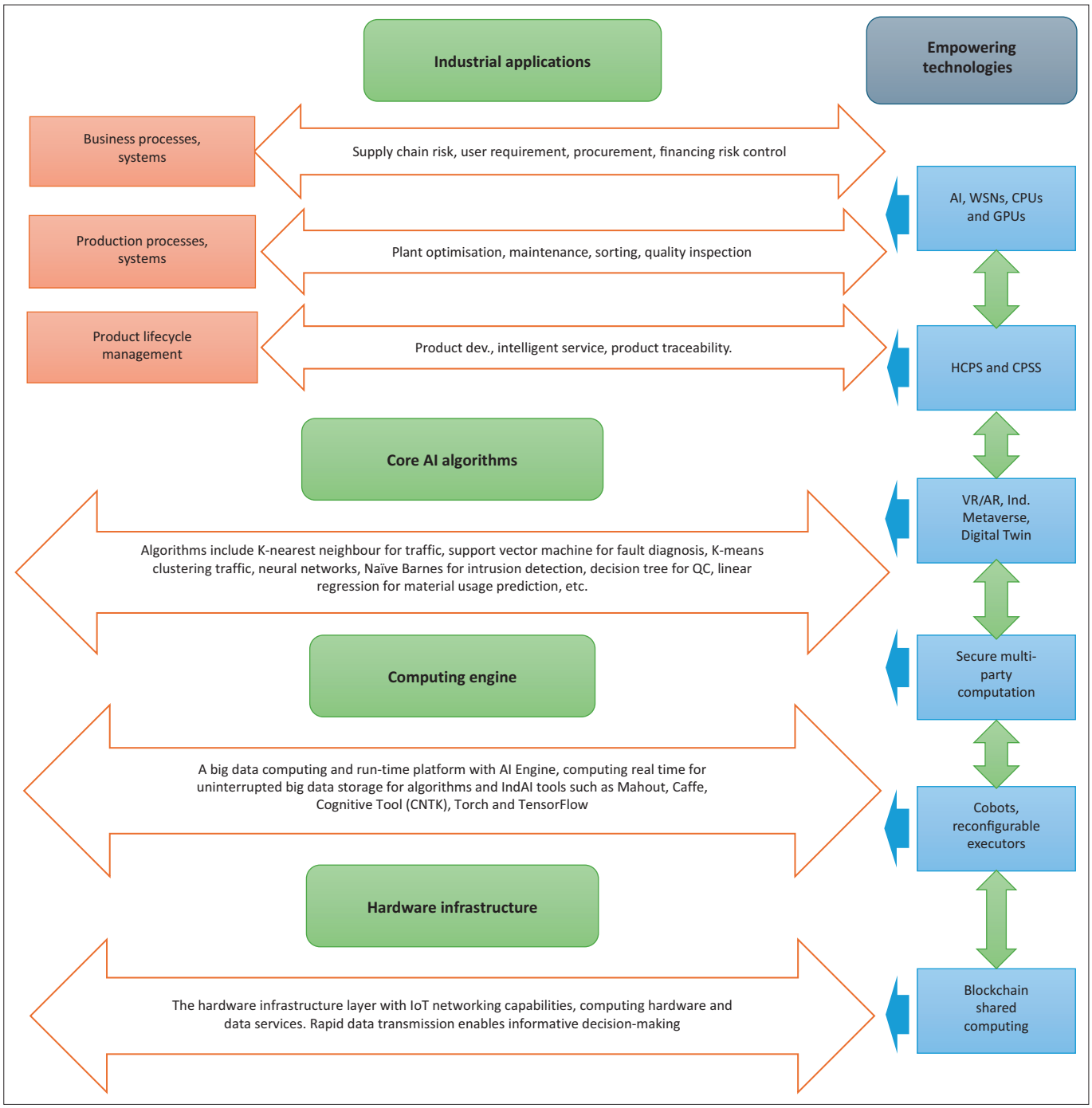
In the third taxonomy, according to Yang et al. (2022), manufacturing has two types of data transmission mechanisms: the wired Industrial Ethernet and wireless sensor network (WSN). Wireless spectrums are either 5G or 6G transmission mechanisms (Zong et al., 2019). Wireless sensor network is better suited as an enabling technology for I5.0. It meets human-centric and sustainability requirements through 6G connectivity with increased data speed and coverage (Yang et al., 2024).

### Wireless sensor network

Kandris et al. (2020) describe WSN as a series of nodes dispersed in space connected by wireless transmission measuring change fluctuations in the surrounding environment, processed by the node's processor which transmits the information to respective devices. Improvements such as miniaturisation, lower cost and higher sensitivity expand their application in multiple operational applications. Kahn et al. (2020), with Kumar and Lee (2022), advise that WSN has four infrastructure components, linked with IndAI industrial applications as shown in Figure 2:

- supply chain management
- manufacturing process control
- automation increasing with existing networks
- improved efficiencies in smart factories.

Wireless sensor network enables HMI with wearable sensors such as gloves or controlling robots. Mrugalska and Ahmed (2021) share that WSN's biggest challenges are data protection and system security. In smart manufacturing, management of increased demand for large data on time inevitably leads to cloud or external connection impacting security. Costs increase with upgrading and maintaining sensors continually to overcome variability across operations, with differing complex matrices of technology and data extraction being essential to avoid weak anti-attack across the operation. Leadership should understand that sensors detect the data and that networks connect and transmit data.

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VR, virtual reality; AR, augmented reality; AI, artificial intelligence; HCPS, human-cyber-physical systems CPSS, cyber-physical-social systems; CPU, central processing unit; GPU, general processing unit.

**FIGURE 2:** Reference framework of industrial artificial intelligence applications.

### Networks enabling low latency connectivity include 5G and 6G capability

Sadhu et al. (2022) explain that to withstand cyber-attacks, fast network authentication frameworks are used to defend data security and privacy issues. Multiple wireless devices used in a limited spectrum with channel congestion and resource allocation are significant challenges for the IIoT. The challenges of 5G connectivity have contributed to the paradigm shift development of 6G connectivity driven by continuous improvements in wireless connectivity (Zong et al., 2019).

Akyildiz et al. (2020) advise that 6G connectivity, although still in developmental stages, enables a fully connected world through a network operating in the terahertz band (THz) between microwaves and infrared bands. This offers wider resources, allowing pervasive AI and large-scale network automation. Further research in 6G connectivity is through the Internet of NanoThings and quantum communications with a major impact on wireless communications. Implementation challenges with sensors, WSN, 5G and 6G connectivity, data management in HMI and HCSM require attention.

## Human–machine interface implementation challenges, requirements and collaboration in human-centric smart manufacturing

Three main issues are associated with HMI implementation: the allocation of tasks, workload allocation and trust (Yang et al., 2024). Kumar and Lee (2022) point out that smart factories, having increased technological complexity, face two areas of challenge. Firstly, worker mental load requires increased skill for advanced operational equipment. Secondly, with physical workload decreasing, data management demand increases with provision and collection of data from human-centric smart manufacture (HCSM) processes.

Janssen et al. (2019) highlight that a lack of trust in a system by workers leads to differing device and equipment usage, reducing efficiency and safety as complex systems increase operator confusion. Sustained system use will encourage workers to adapt overcoming misuse and disuse.

Additional collaboration and implementation challenges include:

- High vendor costs associated with new HMI technologies such as brain computer interfacing (BCI) and 6G connectivity which includes hardware, training for worker trust in technology use with analytical output across multiple technologies (Janssen et al., 2019).
- Zhang et al. (2023) share that human-centric process planning, workshop scheduling, processing and assembly are cornerstones of HCSM factory design with the focus on human-centric needs as opposed to profit and efficiency, impacting lower margin manufacturers.
- More effort is required on human-related data central to HCSM, where the aim of such data is to provide humanised and personalised data to the worker or operator (Lu et al., 2022).
- Human–machine interface technology increases complexity across all levels of management, necessitating training for all in HMI technology, with personalised training best suited to develop optimum worker well-being with creativity and flexibility in their surrounding workspace (Grabowska, 2020).
- Human–machine interface security is divided into personal security and data protection. Blockchain encryption, although recommended, is challenged in three areas, namely IoT dependence, weakness in dealing with physical attacks and an immature technology requiring more work and research in dealing with network security and integration of people security (Zhang et al., 2023)
- Zhang et al. (2023) indicate that effective HMI implementation has the ability and adaptability to customer or user changes and needs in the external environment, usability of HMI is enhanced with effective personalised training for users with special needs, and flexibility with functional design.

For leadership, the goal of I5.0 is for humans and machines to work together without compromising workers' mental health when working with HCSM data and models. The four category taxonomies examine challenges associated with three characteristics of HMI for HCSM implementation which have associated benefits and opportunities emerging.

## Human–machine interface opportunities and benefits

New technologies driving the development of HMI include worker safety, health monitoring, and ergonomic workspace design. Aligned technologies include BCI, digital twins and the industrial metaverse (Yang et al., 2024).

### Ergonomic design, worker safety and health monitoring

Research has shown that workers in automated control environments are less sensitive to alarms. Early warning signalling devices are advised. Long-term vigilance and concentration over multiple controls lead to exhaustion and negligence. Comprehensive operator training can create trust in equipment and improve awareness. Human–machine interface design should consider worker mental orientation with regard to user-centred cognitive interfacing (Janssen et al., 2019).

Papetti et al. (2021) agree with the view of Janssen et al. (2019), adding that ergonomic design plays a big role in worker safety, reducing the cognitive workload and errors, thereby improving efficiency. Occupational diseases impacting worker health should be prevented using technology advancements such as BCI and digital twins.

### Brain–computer interface

Brain–computer interface technology, according to Saha et al. (2021), connects the human brain and external environment, which allows users to control devices through brain signals – either passively or actively. Passive BCI analyses the brain's unconscious signals and emotions which detect fatigue. Active BCI aligns with users' voluntary brain movements, allowing users to complete interactions with devices.

Brain–computer interface in industrial application promotes human–machine interaction and collaboration to better understand the intentions of each. As instructional signals increase, robots can be used more frequently to complete more complex tasks, reducing the psychological workload on workers, with BCI promoting the goals of I5.0 (Saha et al., 2021).

### The industrial metaverse

Collective reality (CR) encompasses all forms of computer-mediated realities (Anderson & Rainie, 2022). Virtual reality refers to a state in which an organism responds to artificial stimuli without recognising them as such, thus reducing cognitive load (LaValle, 2023). Augmented reality enhances real-world environments by overlaying digital content (McDonagh-Smith, 2022).

The *metaverse* represents the evolution of the internet from 2D to 3D within Web 3.0, offering persistent, multi-user,

immersive environments for real-time interaction via avatars. It supports social VR, gamified platforms and AR collaboration spaces developed from advances in XR (Mystakidis, 2022).

Yang et al. (2022) describe the *industrial metaverse* as a new industrial ecosystem where humans, machines and objects are seamlessly integrated into the physical industry through technologies such as blockchain, social computing, digital twins and decentralised autonomous systems. Similarly, Xie et al. (2024) highlight the industrial metaverse's potential to drive innovation in manufacturing. Guo et al. (2024) further conceptualise it as a five-layer system architecture comprising interaction, networking, configuration, fusion and interpretation layers operating across three types of spaces: cyber, social and physical.

Ren et al. (2024) highlight a practical application of the industrial metaverse at the BMW Debrecen factory, described as the world's first virtual factory, powered by Nvidia Omniverse capability, which enables file format compatibility and supports multi-user visualisation supporting industrial R&D. The industrial metaverse, integral to I5.0 with HMI, has numerous benefits and challenges that require understanding by leadership and more in-depth research.

### Cyber-physical systems and digital twins

A core component of the industrial metaverse is the CPS of which digital twins are the enabling technology. *Digital twins* utilise this capability to provide a virtual representation of a person, production system, product or service and can stand in for modelling and simulation (McDonagh-Smith, 2022). Lin and Han (2021), Fuller et al. (2020), Lu et al. (2020) share similar views that digital twins are and relate to an effortless integration of data between a physical machine and its digital replica. This is either in real time (online) or backed by historic data (offline) enabled through 3D computer modelling or multiphysics simulation. The goal is to gain a technological knowledge and foster a data-driven smart environment of a physical machine, physical process or a manufacturing process (Lu et al., 2020).

### Differences between the industrial metaverse and digital twins

The industrial metaverse has additional supporting technologies, but construction of the industrial metaverse cannot be done without the powerful components digital twins provide (Zheng et al., 2022). Two differentiating factors between the industrial metaverse and digital twins are that, firstly, the industrial metaverse can construct virtual spaces, independent of physical reality with greater creativity and human-centric goals as opposed to digital twins which, secondly, allows for the core of the industrial metaverse to be more value-oriented with the digital twins being more technology-driven. Both the industrial metaverse and digital twins and their use of AI require research in advancing capability within I5.0 goals and HCSM application, as shown in Figure 2, where implementation of IndAI employs these as empowering technologies in the core AI algorithm layer. With an understanding of the challenges, benefits and collaboration of HMI with its supporting technologies and taxonomies, the interaction with MES is required.

### Manufacturing execution systems and industry 5.0

Manufacturing execution system manages workshops across multiple functions, resource allocation and management, labour, process and quality management, document control, performance analysis, job scheduling, data collection and product unit scheduling (Yang et al., 2024). Shojaeinasab et al. (2022) indicate that the current MES systems available such as POMSNet Aquila, Siemens Opcenter, ABB MES, GE's Digital Proficy MES and DELMIAworks as commercial systems generally lack advanced intelligent levels.

To enhance MES capabilities, recent research explores the integration of AI to improve efficiency, safety, quality and productivity. Additionally, digital twins are being developed to bridge MES with the physical environment, enabling real-time monitoring, review and data capture. Augmented reality is also proposed as a means of facilitating greater human–system interaction and collaboration within MES environments. These technological advancements for leadership are critical to realising the vision of I5.0 in HCSM and warrant further investigation, particularly regarding their alignment with sustainability goals and IndAI (Tao et al., 2024).

## Industrial artificial intelligence opportunity in industry 5.0

Figure 1 depicts the Leng et al. (2024) description of I5.0 evolution as a shift towards human-centric manufacturing, prioritising workers' needs as central to the manufacturing process over purely technological advancement. This transition fosters a symbiotic relationship between humans and machines within an industrial community grounded in shared values. Realised through sustainable, circular manufacturing practices such as recyclability and waste reduction, this approach supports the vision of a super-smart, low-impact society (Morris et al., 2023).

A key differentiator of I5.0 is its enhanced compatible human–robot interface, enabling more intelligent cobots tasks that require higher levels of human critical thinking and instruction (Maddikunta et al., 2022). By integrating IndAI systems into supply chains and production floors, I5.0 supports more cost-effective, human-centric manufacturing (Leng et al., 2024). However, leadership faces challenges in DTx because of limited awareness of AI regulations and insufficient understanding of IndAI technologies. Leng et al. (2024) agree with Morris et al. (2023), emphasising the need for caution in applying IndAI models and algorithms, noting risks such as overuse of advanced code, misuse of low-end AI in complex scenarios and prioritising physical output over thoughtful software development (Table 4).

## Levels and grades of industrial artificial intelligence

Morris et al. (2023), specify three grades of AI, artificial narrow intelligence (ANI), artificial super intelligence (ASI) and levels of artificial general intelligence (AGI). Industrial artificial intelligence can be broken into five levels (lower to higher): reactive, knowledgeable, learnable, autonomous and shareable. To determine which grade of AI a model belongs to simplifies the designing of appropriate models and algorithms with manufacturing digital upgrading is difficult. Cost-effective application and system reliability are critical to unlock the power of IndAI. Leadership must be aware of these IndAI levels and grades to ensure the optimum configuration is selected (Morris et al., 2023).

## Linkage of industrial artificial intelligence opportunities and industry 5.0 fundamentals

Figure 1 shows I5.0 has three considerations (Ghobakhloo et al., 2022): firstly, human-centricity where workers return to the centre of manufacturing acting as the main process decision-makers. Secondly, sustainable development through recycling, reusing, reducing waste and environmental impact with the industrial ecology forming good symbiotic development patterns. Thirdly, resilience, where brittleness is a system problem and not easy to correct as evidenced by the COVID-19 pandemic in global supply and value chains. Key resilience issues (Leng et al., 2024) in I5.0 include modularised manufacturing, flexible business processes, predictive controls, adaptable production capacity and a flexible strategic value chain. Such robust industrial systems essential to I5.0 require further investigation. Industry 5.0 fundamentals (sustainability, resilience and human-centricity) are symbiotically linked with the three IndAI opportunities (collaborative, self-learning and crowd intelligence) as shown in Figure 1 (Leng et al., 2024):

- Collaborative intelligence is the integration of humans and AI through smart devices like cobots, which enhances human tasks by combining empathetic design with AI's ability to learn and adapt to human behaviour. In I5.0, this synergy aims to merge human intuition, leadership and social skills with the precision and efficiency of machines, maximising the potential of both (Leng et al., 2022b).
- Self-learning intelligence enables machines to continuously acquire knowledge and autonomously develop decision-making capabilities by identifying patterns within data. Advanced self-learning AI refines its intelligence through trial and error, offering cost-effective problem-solving and generating optimal solutions in novel environments, thus driving its own evolution (Leng et al., 2024).
- Crowd intelligence enhances resilience to disruptions through collective intelligence in human–machine hybrids and swarm intelligence in bio-machine systems. These systems gather information through interaction, cooperation and competition, enabling rapid reorganisation and balanced manufacturing responses. Individual decisions contribute to a shared pool of solutions, strengthening overall problem-solving capacity (Leng et al., 2023).

Kim et al. (2020) share that modelling agents can empower both humans and machines resulting in four significant areas of benefit: (1) collaborative decision-making through democratised access to AI models; (2) a new form of self-organising intelligence aligned with interoperability, data sovereignty, privacy, modularity and scalability; (3) increased governance supporting beneficial network behaviour and (4) IndAI in a more favourable decentralised position can attract users. Leadership must understand that designing appropriate models and algorithms that upgrade the manufacturing industry is of greater importance to unlocking the power of IndAI (Leng et al., 2024).

## Unlocking the power of industrial artificial intelligence for industry 5.0

In Figure 2, Leng et al. (2024) show in detail components of a four-layer reference framework for IndAI applications consisting of the hardware infrastructure, core algorithm, computing engine and industrial application layers with their supporting and empowering technologies.

Industrial artificial intelligence implementors are advised to follow these four key principles. It is crucial for leadership to understand these, which leads to consideration of the contribution of empowering technologies for implementing IndAI.

## The empowering technologies for implementing industrial artificial intelligence

The empowering and aligned technologies for implementing IndAI impact the four-layered architecture as shown on the right of Figure 2. These include cobots, secure-multiparty computation (SMPC), human-cyber-physical systems (HCPS), cyber-physical-social systems (CPSS), central processing units (CPUs), general processing units (GPUs) and AI with digital twins, and blockchain shared computing:

- **Layer 1 – industrial applications:** Central processing units and GPUs are essential to AI and deep learning applications. Central processing units manage inputs and outputs for the entire system, execute software programmes and control task scheduling. Heat generation by CPU processing requires attention. General processing units manage large data computing processing tasks aligned to matrix operations and deep neural networks, identifying defects upfront. General processing units are good at large data computing and processing tasks aligned with matrix operations and deep neural networks, particularly capable of identifying defects in advance (Mittal et al., 2022).

Human-cyber-physical systems control lifecycle processes, and CPSS bring personalised services for humans placing workers at the centre of the manufacturing system to interact with machines via intelligent HMIs (Leng et al., 2023). Digital

twins are an enabler of HCPS through intelligent decision-making systems. Human-cyber-physical systems and CPSS have challenges with security and privacy using IndAI (Yilma et al., 2022):

- **Layer 2 – core AI algorithm:** The industrial metaverse and digital twins, with SMPC and cobots, empower IndAI and could be established to enhance all aspects of the operation, safety, flexibility and reliability (Leng et al., 2024).
- **Layer 3 – computing engine:** Cloud-enabled SMCP allows large-scale development of costly IndAI training models with edge computing for operational efficiency. Cobots aligned with the computing engine and big data platform and AI engine are enabled by deep learning frameworks. They interact with people and can be rapidly redeployed and reprogrammed and relaunch into the synchroperation area (Leng et al., 2022b).
- **Layer 4 – hardware infrastructure:** Blockchain, a decentralised secure technology, relies on SMPC and cloud to provide secure product lifecycle production through its tamper-proofing authenticity verification (Leng et al., 2022a).

Leadership must grasp the challenges associated with the contribution of the aligned empowering technologies in implementing IndAI. Future research requirements are covered in section 'Limitations and future research directions'.

### Manufacturing and sustainability for industry 5.0

Van Erp et al. (2024) describe I5.0 as the integration of sustainability, resilience and human-centricity into industrial value creation. They propose a two-dimensional model incorporating design and operations referred to as the DesOps model for the DTx of I4.0 to I5.0 and HCSM having two criteria. Ecosystem and culture creation, which embodies four structural components of foresight, maturity assessment, objectives with key results and training. In turn, the first two components, foresight and maturity assessment, house system design, domain-specific design and continuous feedback, making up the design component of the model or Des. The last two components, objectives with key results and training, house continuous system integration, implementation and monitoring, making up the operations component of the model or Ops. The resultant DesOps model is fully integrated across all components and impacting all parameters of I5.0 sustainability, resilience and human-centricity (Van Erp et al., 2024).

In summary, leadership in manufacturing is advised to embrace and enhance all aspects of HMI, HCSM, HCI, I4.0 to I5.0 migration, worker back in the loop with worker safety, privacy and personal data protection, sensors, connectivity, data management and analytics, networks 5G or 6G and challenges associated with HMI implementation, future direction and trends. In addition, the impact of IndAI on I5.0 and HCSM, its architecture layers, grades and levels, characteristics and unlocking the power of IndAI with empowering technologies requires a thorough understanding with aspects of future IndAI research directions.

## Research methods and design

### Research methodology

The original quantitative study targeted CEOs from a stratified sample of 2500 South African manufacturing businesses capable of DTx (Gaffley & Pelser, 2021). A structured questionnaire evaluated via SPSS software measured variables including demographics, data handling practices, leadership digital capability, strategy development frequency, and human capital skills development. Statistical methods included descriptive statistics, one-sample t-tests, chi-square tests, Pearson's correlation, Spearman's correlation, ANOVA, factor analysis and binomial tests (Gravetter et al., 2020). Gaffley and Pelser (2021) in the original quantitative research established that leadership in manufacturing had to understand the technological advances in the digital era and how these shape the digital future of their organisations. The research showed leadership had experience but lacked technical dexterity, with the younger generations technically adept but lacking experience. The cost of DTx projects requires C-suite agreement for budget compilation, spending and monitoring (Gaffley & Pelser, 2021).

Sarkar et al. (2024) conducted qualitative research into the critical success factors (CSFs) for smart manufacturing transition to I5.0, developing an interrelated CSF model from their findings. Their research was conducted across a sample of seventeen experienced senior manufacturing executives (Table 1) ranging from 7 to 22 years drawn from heavy manufacturing, technological transformation specialists, quality control, machinery parts and components and supply chain. Their research findings, through application of the Bayesian best-worst method (B-BWM), crystallised fourteen CSFs pertinent to I5.0 for a sustainable future (Table 3).

### Research objectives

The study's research objectives are directed at leadership to enhance their understanding of the technological advances in DTx gap analysis with migration of I4.0 to I5.0:

- To identify technological advancements facilitating migration from I4.0 to I5.0 in smart manufacturing.
- To determine the DTx gap with regard to data management, technology advances, skills and culture adaptation for I5.0 in smart manufacturing.
- To determine the CSFs that would support a revised DTx strategy model for leadership in manufacturing.

## Results

Modification of the initial DTx model Gaffley (2022) is enabled from research findings in this article encompassing I5.0 advances in technology upgrades, data management, retrieval and storage, HMI, HCSM and IndAI applications. The qualitative research from Sarkar et al. (2024) in Table 1,

pertinent to sustainability, skills, culture and smart manufacture for migration to I5.0, provides 14 CSFs central to the study in Table 3. With these CSFs forming the base of a systematic literature review, section 'Literature review' provides an additional 14 CSFs on migration to I5.0 focusing on technology improvements around HMI taxonomies and characteristics, implementation benefits and connectivity in Table 2 (Leng et al., 2024; Yang et al., 2024). The literature review in section 'Industrial artificial intelligence opportunity in industry 5.0' focuses on the linkage of IndAI implementation with I5.0, Figure 2, identifying a further 9 CSFs in Table 4 (Leng et al., 2024). The resultant 37 CSFs are coded for inclusion in steps 1 to 6 of the revised DTx leadership model in section 'A digital transformation strategy model for leadership adaptation to industry 5.0 smart manufacturing implementation'.

**TABLE 1:** Overview of experts (critical success factor for industry 5.0 migration).

| Expert ID | Area of expertise | Designation | Experience in years |
|---|---|---|---|
| E1 | Supply chain and inventory | Associate professor | 14 |
| E2 | Steel manufacturing | Head (operations) | 22 |
| E3 | Steel manufacturing | Senior manager | 18 |
| E4 | Steel manufacturing | Business consultant | 19 |
| E5 | Technological transformation | Business consultant | 9 |
| E6 | Technological transformation | Business consultant | 7 |
| E7 | Smart manufacturing | Senior consultant | 11 |
| E8 | Supply chain and Industry 4.0 | Lead, planning and management | 14 |
| E9 | Supply chain and Industry 4.0 | Assistant manager support | 7 |
| E10 | Digital technology management | Manager (support) | 18 |
| E11 | Machine parts manufacturing | General manager | 16 |
| E12 | Machine parts manufacturing | Senior manager | 13 |
| E13 | Senior business analyst (manufacturing) | Senior business analyst | 9 |
| E14 | Technology management | Senior executive | 12 |
| E15 | Quality control | Senior officer | 11 |
| E16 | Quality control | Deputy manager (quality) | 13 |
| E17 | Technology innovation management | Senior executive | 19 |

*Source*: Sarkar, B.D., Shardeo, V., Dwivedi, A., & Pamucar, D. (2024). Digital transition from industry 4.0 to industry 5.0 in smart manufacturing: A framework for sustainable future. *Technology in Society, 78*, 102649. https://doi.org/10.1016/j.techsoc.2024.102649

## Connectivity and data transmission, human–machine interface implementation challenges and opportunities

Author contributions in section 'Human–machine interaction' to 'section Manufacturing execution systems and industry 5.0', Table 2, provide 14 CSFs supporting future developments in data management, sensors, hardware, WSN networks with 5G and 6G network connectivity for data, HMI and HCSM.

## Critical success factors for sustainability in industry 5.0 smart manufacturing

The qualitative research in section 'Research methods and design', Sarkar et al. (2024) identifies 14 CSFs encompassing economic, social and environmental

**TABLE 2:** Connectivity, human-machine interface implementation challenges, benefits and opportunities critical success factor identification.

| Critical success factors extraction | Expansion of critical success factors | I(1–15) | U(1–15) | I × U Rank |
|---|---|---|---|---|
| **Connectivity CSFs** | **Managing data transmission mechanisms** | | | |
| 1. Sensors and hardware selection (T) | Select from five types by application: acoustic, sound, haptic, motion, tactile sensors | - | - | - |
| 2. WSN or Industrial Ethernet connectivity (T), (D) | Decide and select whether Ethernet or WSN is more suited to I5.0 with four components considered: power supply, communication stack, middleware and data aggregation | - | - | - |
| 3. Data management and analytics (T), (D) | Edge computing, deep learning, machine learning with data analysis | - | - | - |
| 4. 5G or 6G low latency networks (L), (B), (T) | Consider intermittent IoT disturbances that limit 5G, evaluate 6G (more research required) | - | - | - |
| **HMI implementation CSFs** | **Challenges associated with implementation** | | | |
| 5. Technology development costs (B) | BCI and 6G technologies are costly, manage vendors carefully | - | - | - |
| 6. Human-centric concept (H) | HCI in HCSM environment focus on human needs as opposed to profit and efficiency | - | - | - |
| 7. Centralised employee training (H), (L) | HMI complexity requires personalised training | - | - | - |
| 8. Personal security, data protection (D), (H), (B) | Blockchain introduction to protect both personal data and network security | - | - | - |
| 9. Consider four broad HMI implementation guidelines (T), (H), (B) | (a) Adaptability to external customer changes, (b) centralised training for HMI usability, (c) accessibility for special need users, (d) flexibility with functional design | - | - | - |
| **HMI in HCSM benefit CSFs** | **Opportunities associated with benefits** | | | |
| 10. HMI comprises ergonomic design, worker safety and health monitoring (L), (H), (B) | Implement sensors detecting early warning worker fatigue and stress<br>Consider ergonomic design to increase efficiency and prevention of occupational diseases | - | - | - |
| 11. BCI (T), (H), (L) | Technology required to connect the human brain with the external environment either active or passive | - | - | - |
| 12. The industrial metaverse (T) | Decide on application where physical parameters are replicated in digital context in manufacturing | - | - | - |
| 13. Consider digital twins with CPS application (T) | Providing digital replication of human or production system for simulation and predictive modelling | - | - | - |
| 14. I5.0 and MES systems (T), (L) | Review application of 11 multi-functional MES applications (first paragraph section 'Manufacturing execution systems and industry 5.0')<br>Review ongoing research with AI and MES, digital twins in the intelligent layer of MES | - | - | - |

*Source*: Author interpretation from Leng, J., Zhu, X., Huang, Z., Li, X., Zheng, P., Zhou, X., Mourtzis, D., Wang, B., Qi, Q., Shao, H., Wan, J., Chen, X., Wangm, L., & Liu, Q. (2024). Unlocking the power of industrial artificial intelligence towards industry 5.0: Insights, pathways, and challenges. *Journal of Manufacturing Systems, 73*, 349–363. https://doi.org/10.1016/j.jmsy.2024.02.010; Yang, J., Liu, T., Liu, Y., & Morgan, P.L. (2024). Human-machine interaction towards industry 5.0: Human-centric smart manufacturing. *Digital Engineering, 2*, 100013. https://doi.org/10.1016/j.dte.2024.100013 and Figure 1

HMI, human–machine interface; CSF, critical success factor; WSN, wireless sensor network; IoT, Internet of Things; HCSM, human-centric smart manufacturing; MES, manufacturing execution systems; HCI, human-computer interaction; CPS, cyber-physical systems; BCI, brain–computer interfacing; AI, artificial intelligence; I5.0, industry 5.0.

**TABLE 3:** Human, culture and technology critical success factors for Industry 5.0 in smart manufacture.

| Critical success factor extraction | Expansion of critical success factors | I(1–15) | U(1–15) | I × U Rank |
|---|---|---|---|---|
| **Sustainability human CSFs** | **Sustainable smart manufacture I5.0 human and culture** | | | |
| 1. Organisational readiness for I4.0 to I5.0 transition (L), (B) | Ensure the level of state-of-the-art technology and cultural adaptation is in place. | - | - | - |
| 2. Digital leadership (L), (B) | Executive commitment driving strategic direction for smart manufacturing capability improvements. | - | - | - |
| 3. Workforce DTx development and acceptance (H), (L), (B) | Employee training in essential digital skills to ensure acceptance for migration from I4.0 to I5.0. Personalised training recommended. | - | - | - |
| 4. Security and privacy for effective DTx (L), (D) | Review and ensure security procedures being simpler and objective therefore easier to quantify while privacy is more subjective. | - | - | - |
| 5. Legal and ethical concerns in transition to I5.0 (L), (B), (H) | Regulations and a protocol need to be developed, which is of concern as none exist. | - | - | - |
| 6. Upskilling, reskilling, talent retention (L), (H) | I5.0 requires training by upskilling, reskilling, learning and unlearning essential to align the employee skills with new technologies for increased productivity. | - | - | - |
| 7. Cultural economic advantages, (L), (H) | Cultural collaboration developing these at the micro and macro level with new technology introductions in formal scientific and professional trust could lead to economic benefit. | - | - | - |
| **Sustainability technological CSFs** | **Sustainable smart manufacture I5.0 technology** | | | |
| 8. Scalability design to ensure HCSM system (L), (B), (T) | In I4.0 to I5.0 migration in smart manufacturing systems, scalability refers to a system's ability to absorb increased workload by adding resources. | - | - | - |
| 9. I4.0 to I5.0 sustainable investment costs (L), (B) | Capital costs in migration require accurate budgeting with investment payback determined up front. Government initiatives sought for supporting sustainability in marginal profit businesses. | - | - | - |
| 10. High-powered analytical ability for smart manufacturing. (L), (B), (D) | Value creation in I5.0 requires individuals to have strong analytical and digital capabilities. Internally businesses must create flat, agile organisational structures with analytical and IT functional capabilities. | - | - | - |
| 11. Environmental sustainability and performance measurement (L), (B), (T) | Environmental issues such as greenhouse gas emissions, global warming, climate change, garbage disposal, recycling and reworking should receive equal focus and attention aligned to global standards.<br>Implement holistic metrics beyond financial KPIs. | - | - | - |
| 12. Adoption of advanced technology to create value in I5.0 (L), (T) | Top management must articulate and communicate what it expects from value creation through digital transformation for I5.0 and be aware of the advantages, challenges and dangers with its introduction. | - | - | - |
| 13. Process automation for DTx in smart manufacturing (B), (T) | Ensure automation of complex business processes leverages technology across three tasks: centralising information, automating operation and diminishing human input. | - | - | - |
| 14. IndAI sensitisation towards sustainability in transition to I5.0 (L), (B), (T) | DTx includes adaptation of technologies such as VR/AR, IIoT and ML/AI to provide sustainable solutions in pollution control, sustainable production and smart manufacturing which play an important role in the transformation phase and leveraging these for operational efficiency. | - | - | - |

*Source*: Author interpretation from Sarkar, B.D., Shardeo, V., Dwivedi, A., & Pamucar, D. (2024). Digital transition from industry 4.0 to industry 5.0 in smart manufacturing: A framework for sustainable future. *Technology in Society, 78*, 102649. https://doi.org/10.1016/j.techsoc.2024.102649

VR, virtual reality; AR, augmented reality; IIoT, Industrial Internet of Things; ML, machine learning; AI, artificial intelligence; HCSM, human-centric smart manufacturing; DTx, digital transformation; IndAI, industrial artificial intelligence; I5.0, industry 5.0; I4.0, industry 4.0.

**TABLE 4:** Industrial artificial intelligence critical success factors.

| Coded CSF | Description | I (1–15) | U(1–15) | I x U Rank |
|---|---|---|---|---|
| 1. Avoid overuse of excess code IndAI (B), (T) | Increases system complexity<br>Leads to potential system failure<br>Uncomplicated code and software development with focus on physical performance | 14 | 15 | 210 |
| 2. Avoid indiscriminate use of high-end intelligence (B), (T) | It is surplus, costly and leads to complication | - | - | - |
| 3. Avoid low-end IndAI to simplify complexity (B), (T) | Leads to incorrect decisions, returns unsatisfactory quality and increases yield loss | - | - | - |
| 4. Industrial systems (B), (T) | Ensure robust, non-brittle systems are selected | - | - | - |
| 5. Link I5.0 with IndAI (T), (D) | I5.0 fundamentals resilience, sustainability, human-centricity and link with IndAI opportunities collaborative, self-learning and crowd intelligence | - | - | - |
| 6. Apply 4 IndAI application layers (T) | Four layers include: Industrial applications, AI algorithms, computing engine and hardware infrastructure | - | - | - |
| 7. Empowering technologies of IndAI layers select and evaluate (L), (B) (T), (D), | Blockchain which relies on SMPC, cobots, VR/AR, Industrial Metaverse, digital twins with HCPS and CPSS enablers.<br>Ensure correct CPU and GPU arrangements<br>Need to manage heat generation from CPUs | - | - | - |
| 8. Manage barriers to IndAI (L), (B), (H) | Social and technological barriers and their computations | - | - | - |
| 9. Understand the Four future research considerations (L) | (a) Rapid response, reliable system with distributed deep learning, shared ledger, (b) security in distributed computing on privacy protecting data sharing, (c) system adaptability, flexibility with algorithms, hardware, software and model interaction, (d) interoperability and robustness man-machine integration progressive technological mechanisms | - | - | - |

*Source*: Author interpretation from Leng, J., Zhu, X., Huang, Z., Li, X., Zheng, P., Zhou, X., Mourtzis, D., Wang, B., Qi, Q., Shao, H., Wan, J., Chen, X., Wangm, L., & Liu, Q. (2024). Unlocking the power of industrial artificial intelligence towards industry 5.0: Insights, pathways, and challenges. *Journal of Manufacturing Systems, 73*, 349–363. https://doi.org/10.1016/j.jmsy.2024.02.010 from Figure 2 and Figure 3

SMPC, secure-multiparty computation; CSF, critical success factor; AI, artificial intelligence; CPSS, cyber-physical – social systems; HCPS, human-cyber-physical systems; CPU, central processing unit; GPU, general processing unit; IndAI, industrial artificial intelligence; I5.0, industry 5.0.

requirements of resilience and sustainability for migration to I5.0. These are grouped into human and technological categories (Table 3).

## Industrial artificial intelligence in Industry 5.0

From section 'Levels and grades of industrial artificial intelligence' to section 'Manufacturing and sustainability for industry 5.0' on IndAI implementation, an additional nine CSFs are extracted (Table 4).

These 37 CSFs pertinent to migration to I5.0 require inclusion, enabling a more robust I5.0 DTx strategy formulation process detailed in section 'A digital transformation strategy model for leadership adaptation to industry 5.0 smart manufacturing implementation'.

# A digital transformation strategy model for leadership adaptation to industry 5.0 smart manufacturing implementation

Building on previous research findings, Gaffley and Pelser (2021), we propose an enhanced seven-step model, Figure 3, guiding manufacturing leadership through effective implementation strategies transitioning towards I5.0 enabled by HMI, HCSM and IndAI with their empowering technologies.

## The revised digital transformation model towards industry 5.0 implementation

The first prerequisite is the appointment of a cross-functional DTx project team, drawn from mechatronics, engineering, IT, supply chain and services (human resources and finance).

STEP 1: The first team priority is to determine the baseline DTx gap. The outcome is benchmarked against a set industry standard or internal business objective. The original research has a DTx conversion of 47.7% in the South African manufacturing sector (Gaffley, 2022; Gaffley & Pelser, 2021).

Alternatively, four data parameters (analytics, storage, management and data decision-making) and four technological parameters (IIoT connectivity, digital twin with CPS, cybersecurity with blockchain and new future technologies) are evaluated on a scale 1 (least progress) to 10 (most relevance) for each parameter. These coordinates are linked across eight axes with scores aligned and joined in a spider web configuration (Kayali et al., 2023). The resultant set of lines visually has their spacings as before (blue) and after (red) depicting the broad DTx gap as STEP 1. The gap is then evaluated against 37 CSFs from Table 2, Table 3 and Table 4 coded for inclusion in Steps 2 to 6 in Figure 3:

- leadership (L)
- business (B)
- technology (T)
- data (D)
- human capital (H).

STEP 2 – Leadership Digital Strategy (L): Considers and identifies visionary external uncontrollable variables impacting DTx strategy development for leadership evaluation, as these are factors over which the business has little or no control.

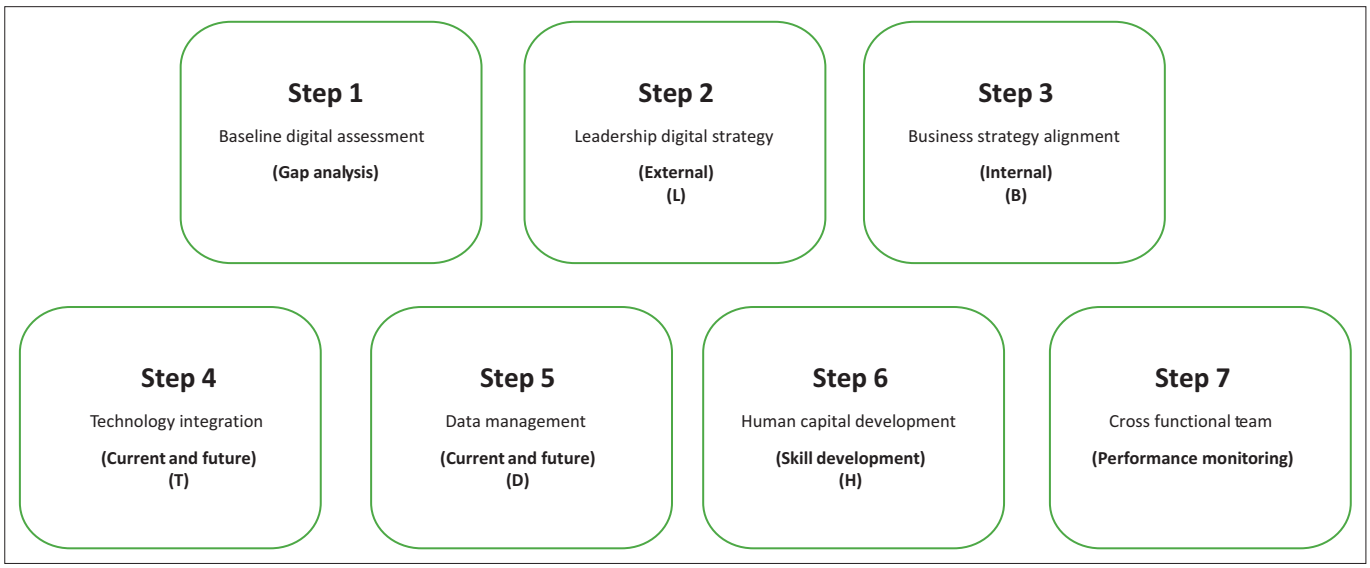
STEP 3 – Business Strategy Alignment (B): Defines the internal controllable dependent DTx variables relevant to goals which leadership has control over.

STEP 4 – Technology Implementation (T): Considers all technologies that expand and prioritise digital assets analysis outcomes.

STEP 5 – Data Management (D): Considers all aspects of data management covered in the literature review.

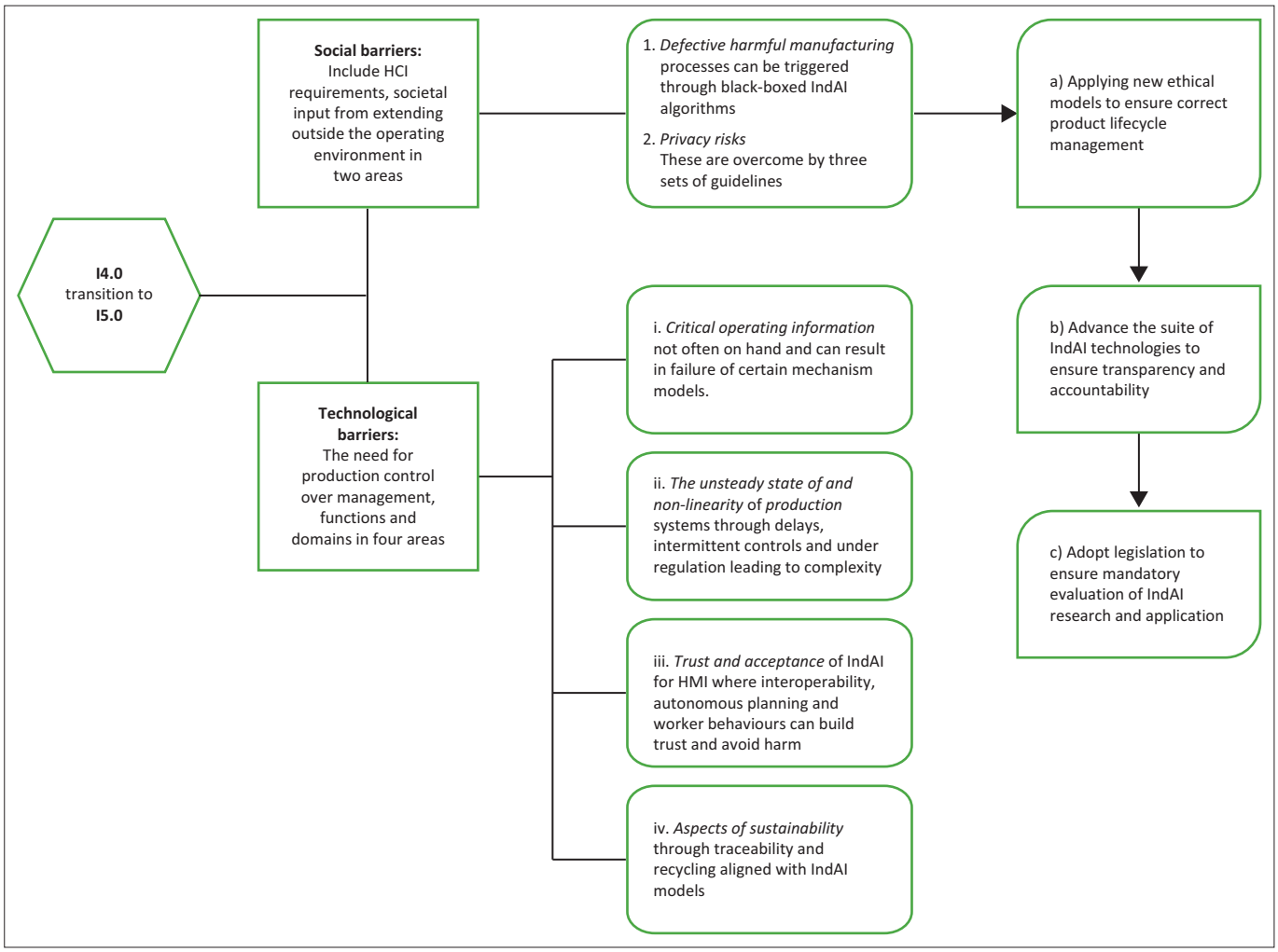
STEP 6 – Human Capital Development (H): Considers all aspects of human 'back in the loop' for HMI, BCI, HCSM and skills requirements.

STEP 7 – Performance monitoring review with cross-functional teams assigned clearly defined roles and responsibilities with aligned KPIs.




*Source*: Gaffley, G., & Pelser, T. (2021). Developing a digital transformation model to enhance the strategy development process for leadership in the South African manufacturing sector. *South African Journal of Business Management, 52*(1), a2357. https://doi.org/10.4102/sajbm.v52i1.2357; Gaffley, G. (2022). *A digital transformation model to enhance the strategy development process for leadership in the South African manufacturing sector*. Published Doctoral dissertation. University of KwaZulu Natal.; Leng, J., Zhu, X., Huang, Z., Li, X., Zheng, P., Zhou, X., Mourtzis, D., Wang, B., Qi, Q., Shao, H., Wan, J., Chen, X., Wangm, L., & Liu, Q. (2024). Unlocking the power of industrial artificial intelligence towards industry 5.0: Insights, pathways, and challenges. *Journal of Manufacturing Systems, 73*, 349–363. https://doi.org/10.1016/j.jmsy.2024.02.010; Yang, J., Liu, T., Liu, Y., & Morgan, P.L. (2024). Human-machine interaction towards industry 5.0: Human-centric smart manufacturing. *Digital Engineering, 2*, 100013. https://doi.org/10.1016/j.dte.2024.100013 and supporting authors

**FIGURE 3:** The seven-step model for digital transformation.




*Source*: Adapted from technological barriers Leng, J., Zhu, X., Huang, Z., Li, X., Zheng, P., Zhou, X., Mourtzis, D., Wang, B., Qi, Q., Shao, H., Wan, J., Chen, X., Wangm, L., & Liu, Q. (2024). Unlocking the power of industrial artificial intelligence towards industry 5.0: Insights, pathways, and challenges. *Journal of Manufacturing Systems, 73*, 349–363. https://doi.org/10.1016/j.jmsy.2024.02.010 and social barriers Huang, C., Zang, Z., Mao, B., & Yao, X., (2023). An overview of artificial intelligence ethics. Transactions on artificial intelligence. *IEEE Transactions on Artificial Intelligence, 4*(4), 799–819. https://doi.org/10.1109/TAI.2022.3194503

HMI, human–machine interface; IndAI, industrial artificial intelligence; AI, artificial intelligence; HCI, human-computer interaction.

**FIGURE 4:** Challenges with implementing industrial artificial intelligence.

Review the process every 3–6 six months as DTx is a moving target with frequent technology, data innovations and improvements.

## The revised digital transformation model determining weighted and prioritised critical success factor implementation

- The CSFs are scored on impact to the business (1–15) and urgency with which they need implementation (1–15). An example in Table 4, point 1, (I[14] × U[15] = 210).
- The weighted scores are ranked highest to lowest for all CSFs, selected and prioritised for implementation.
- Budgets, responsibilities and timelines for each CSF are assigned for project approval.
- Critical success factors can be applied to more than one of the steps in the model as shown in the coding Table 2 to Table 4.
- Performance criteria, objectives, KPIs and financial returns are applied to each CSF for the cross-functional project team, leadership and workforce.
- Review Steps 2 to 6 regularly ensuring continual alignment and adaptation to new technological and data management developments.

The structured approach enables leadership in manufacturing to effectively bridge gaps leveraging emerging I5.0 opportunities inherent within industry transitions.

## Limitations and future research directions

Future research directions aligned with migration from I4.0 to I5.0 implementing IndAI have two sets of future challenges, social and technological barriers, as depicted in Figure 4 (Leng et al., 2024).

Figure 4 shows social and technological barriers with social barriers having two ethical considerations and three supporting sets of guidelines for HMI in I5.0 (Huang et al., 2023). Similarly, the technological barriers are characterised by the need for production control over various professions,

domains and functions in four key areas of operation (Leng et al., 2024). Leng et al. (2024) advise that a systematic understanding of IndAI technologies is recommended for leadership to evaluate the correct technology application to unlock IndAI as an integral part of the DTx processes they lead.

Future research directions would include the aspect of sustainability and its impact on HCSM in I5.0, migration of I5.0 to I6.0, 6G connectivity, the industrial metaverse, digital twins, blockchain for personal data, operational security and supply chain, advanced cyber optic systems and IndAI advances in smart manufacturing. Authors in the literature review highlight that some of these technologies are in incubation and experimental stages with outcomes yet to be defined. These need constant evaluation before progressing their implementation.

# Conclusion

The systematic literature findings focus on the transition of I4.0–I5.0. These are synthesised into actionable insights in strategy development guiding leadership encountering complex transitions between industrial paradigms emphasising human-centricity, worker safety, personal data, security, health and protection alongside technological advancements.

The proposed seven-step DTx model offers practical navigation for leadership tailored specifically towards addressing identified technological and data management gaps in the development of DTx strategy formulation. Simultaneously, leveraging emerging technological opportunities inherent within I5.0 ergonomic worker inclusion in manufacturing through synchroperation, sustainability and resilience in its implementation strategies requires understanding by leadership.

Practically, the future growth of IndAI is seen in the four-layer IndAI reference framework drawing on collaborative, self-learning and crowd intelligence inextricably linked to I5.0 and the anticipated I6.0 paradigm through advanced technological integration and human-centric approaches. Within this framework, it will continue to develop empowered by technological opportunities with future developments in IndAI, BCI, industrial metaverse, digital twins, HCPS, SMPC, blockchain and shared computing, executable executors, GPU and CPU development.

This article contributes a strategic roadmap for DTx leadership in I5.0, offering both theoretical insight and actionable guidance for manufacturers navigating technological and human-centric complicity.

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## Competing interests

The authors declare that they have no financial or personal relationships that may have inappropriately influenced them in writing this article. The author, Theuns G. Pelser serves as an editorial board member of this journal. The peer review process for this submission was handled independently, and the author had no involvement in the editorial decision-making process for this article. The authors have no other competing interests to declare.

## CRediT authorship contribution

Garth R. Gaffley: Conceptualisation, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Visualisation, Writing – original draft, Writing – review & editing. Theuns G. Pelser: Conceptualisation, Supervision, Writing – review & editing. All authors reviewed the article, contributed to the discussion of results, approved the final version for submission and publication, and take responsibility for the integrity of its findings.

## Ethical considerations

This article does not contain any studies involving human participants or animals performed by any of the authors. The research is based on secondary data derived from literature and does not require ethical clearance.

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## Data availability

The authors confirm that the data supporting the findings of this study are available within the article.

## Disclaimer

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