Innovations in industrial enterprises: the role of AI, IOT, and automation in enhancing competitiveness

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***Abstract**: Industrial enterprises are entering a phase in which competitiveness is increasingly shaped by advanced digital technologies and the organizational capabilities that transform them into measurable outcomes. This paper analyzes how Artificial Intelligence (AI), Internet of Things (IoT), and automation influence operational excellence and how their effects are mediated by leadership, knowledge management capabilities, digitalization maturity and e-HRM systems. Based on the resource-based view and dynamic capability theory, a capability-mediated framework is proposed. Evidence from Tata Steel, Freeport-McMoRan and Siemens demonstrates that technology alone does not ensure competitiveness; value emerges when digital systems are embedded into organizational routines, governance mechanisms and workforce development processes.*

***Keywords**: AI; IOT; AUTOMATION; INDUSTRIAL COMPETITIVENESS; DIGITAL TRANSFORMATION; KNOWLEDGE-ORIENTED LEADERSHIP; E-HRM; HR ANALYTICS; DYNAMIC CAPABILITIES*

1. Introduction

Industrial enterprises are undergoing structural transformation driven by AI, IoT, and automation—technologies increasingly embedded across the industrial value chain, from engineering and manufacturing to operations, supply chains, and workforce systems [32, 23]. While earlier digital initiatives often emphasized automation or IT modernization, the current wave is characterized by AI-enabled decision systems, real-time cyber-physical connectivity, and continuous optimization through learning loops [17, 23].

From a competitiveness standpoint, firms able to sense, interpret, and act on operational data faster can reduce downtime, increase throughput, improve yield, and shorten time-to-market—advantages that accumulate into sustained performance differences when digitalization is managed as an organizational capability rather than a one-time technology investment [1, 10, 24, 33]. Evidence consistently shows that digital transformation is rarely an automatic driver of performance; instead, benefits depend on complementary organizational capabilities, governance, and digitalization management maturity [10, 24, 33].

Research in SMEs and MSMEs emphasizes that digital technologies often work through mediating mechanisms: leadership orientation, knowledge sharing quality, organizational agility, and dynamic capabilities determine whether digital adoption becomes performance improvement [10, 19, 20, 21, 33]. Extending these insights to industrial enterprises, AI/IoT/automation should be treated as strategic resources whose performance impact is contingent on organizational readiness and human systems alignment [1, 27, 33].

A further context is Bulgaria's digital transformation trajectory. Despite relatively strong connectivity, Bulgarian industrial sectors remain below EU averages in digital maturity, with limited integration of Industry 4.0 technologies and persistent capability gaps [2, 3, 7]. This reinforces the need to analyze competitiveness not only through technology adoption but through systemic capability building, ecosystem development, and change management [4, 5, 6].

This paper contributes by integrating:

(1) operational impacts of AI/IoT/automation;

(2) capability-based theories (resource-based view; dynamic capabilities);

(3) leadership and HR digitalization mechanisms (KOL, e-HRM, HR analytics).

The argument is strengthened using industrial cases across steel, mining, and industrial software ecosystems [15, 8, 23].

2. Prerequisites and means for solving the problem

2.1. Conceptual framing: RBV and strategic digital assets

According to the resource-based view (RBV), sustained competitive advantage stems from resources that are valuable, rare, difficult to imitate, and non-substitutable [1]. In industrial enterprises, AI models, IoT sensor networks, industrial data platforms, and automation systems can meet these criteria when they are deeply integrated into production routines and continuously improved through learning cycles via digitalization management and structured capability ownership [33]. Importantly, the "resource" is not only the technology artifact but also embedded know-how: data pipelines, domain-specific feature engineering, model retraining, and decision governance [8, 15].

This explains why similar technology investments can yield different outcomes across firms: performance differences emerge from the capability to convert digital tools into repeatable routines under operational complexity (e.g., mining and steelmaking environments) [15, 8].

2.2. Dynamic capabilities: sensing, seizing, and reconfiguration

Dynamic capability logic complements RBV by emphasizing a firm's ability to sense opportunities, seize them through coordinated action, and reconfigure assets as environments shift [33]. In industrial contexts, this includes iterative deployment, operational experimentation within safe boundaries, and rapid process reconfiguration based on data feedback [8]. Evidence also indicates that agility and digital process maturity act as key enablers and barriers—particularly where digital processes are fragmented, readiness is uneven, and governance is weak [21, 27, 33].

2.3. Knowledge-oriented leadership and knowledge management capabilities

Technology-driven competitiveness depends heavily on leadership systems that cultivate knowledge flow, experimentation, and high-quality knowledge sharing. Knowledge-oriented leadership (KOL) is linked to performance through mechanisms such as knowledge sharing quality, service innovation, and ambidextrous innovation—especially under technological turbulence [20, 19]. In fast-evolving environments, leaders who institutionalize learning loops and protect constructive experimentation are more likely to extract value from digital investments [10, 19].

2.4. Human systems: e-HRM, HR analytics, and adoption readiness

Industrial digitalization requires workforce readiness: skills, engagement, role clarity, and behavioral adoption. Evidence shows that e-HRM tools can improve employee engagement and HRM system effectiveness, thereby supporting organizational effectiveness [25, 31]. HR analytics contributes to organizational effectiveness by enabling evidence-based workforce decisions [34, 29]. Adoption and scaling are shaped by contextual enablers, culture, and readiness [28, 30], and readiness assessment models emphasize that industrial digitalization requires multi-dimensional preparation (process, people, technology, governance)—not merely installing tools [27].

2.5. Bulgarian industrial context: digital transformation and resistance

Studies on Bulgarian industrial enterprises emphasize gaps in readiness, ecosystem development, and change management [2, 3, 5, 7]. Resistance to change and insufficient capabilities for reengineering projects are reported barriers that can prevent industrial digital initiatives from generating measurable performance outcomes [4]. This supports the capability-mediated perspective adopted in this paper.

3. Solution of the examined problem

3.1. Capability-mediated model

This paper applies an integrative synthesis: peer-reviewed evidence on leadership, digital transformation, and HR digitalization is combined with practitioner case studies on AI deployment in industrial operations. The core proposition is:

AI, IoT, and automation improve competitiveness primarily through capability pathways—digital transformation maturity, leadership orientation, knowledge management capability, and HR digitalization readiness—rather than through adoption alone [10, 24, 33].

Key mediators and enablers include:
• KOL and knowledge sharing quality [20, 19];
• Digitalization management and agile/dynamic capabilities [21, 27, 33];
• HR digitalization readiness and analytics [29, 27, 34];
• Organizational culture and contextual barriers [28, 30].

Table 1: *Capability-mediated competitiveness mechanisms in industrial digital transformation*

No.	Technology	Capability mediator	Competitiveness outcome
1	AI	Data governance; model retraining routines; agile execution; KOL	Higher throughput; lower downtime; better yield and cost efficiency
2	IoT	Real-time monitoring capability; cybersecurity governance; data backbone maturity	Faster detection of drift; fewer failures; improved resilience
3	Automation	Standardized workflows; reskilling and adoption management; e-HRM support	Stable quality; higher consistency; reduced cost of poor quality
4	Digital twins	Simulation + real-time data integration; decision validation routines	Reduced CapEx risk; faster change validation; capacity optimization
5	e-HRM / HR analytics	Workforce readiness; engagement; evidence-based HR decisions	Sustained adoption; faster upskilling; higher organizational effectiveness

3.2. AI, IoT, and automation as operational competitiveness levers

3.2.1. AI: predictive and prescriptive value

AI creates value through prediction (failures, yield, energy consumption) and optimization (recommended control settings, scheduling, resource allocation). Predictive maintenance is a documented use case in industrial environments [14]. At scale, AI improves decision quality by detecting patterns and anomalies in complex process data [17]. The highest value often comes from prescriptive optimization combined with iterative improvement cycles and adoption routines embedded into daily work [8, 15].

3.2.2. IoT: real-time monitoring and risk governance

IoT enables continuous data flows across equipment, processes, and environments. In smart manufacturing, sensor infrastructures support monitoring of equipment condition, process drift, energy waste, and quality deviations [16]. Industry tracking also highlights that IoT adoption is accelerating across industrial operations, reinforcing its role as a baseline enabler for efficiency and data-driven management [11]. These data streams become the backbone for analytics, optimization, and digital twins [23]. IoT connectivity also expands cyber risk exposure, meaning cybersecurity capability is necessary for protecting competitiveness and operational integrity [12].

3.2.3. Automation: quality stability and throughput consistency

Automation improves consistency, throughput, and quality by reducing process variability and human error. In automotive manufacturing, robotics and automation are widely linked to throughput and operational performance improvement [13]. Automated inspection and feedback loops support quality performance and reduce cost of poor quality [18]. Yet automation also intensifies workforce transition requirements, making reskilling and adoption management central to sustained outcomes [22, 25].

3.2.4. Ecosystems and platformization

Competitiveness increasingly depends on participation in digital business ecosystems where platforms enable coordination, co-creation, and scaling across networks [5]. This aligns with Siemens' ecosystem framing of Industrial AI as an integrated operating layer across lifecycle functions [23].

4. Results and discussion

4.1. Case evidence: what works in practice

4.1.1. Tata Steel (Kalinganagar): analytics as a capability system

Tata Steel's Kalinganagar plant illustrates analytics transformation in a high-variance steel process. Analytics models were used to improve control of a critical thermal stage in production, and the transformation required not only model development but workforce capability building, adoption management, and continuous model updating as conditions shifted [15]. The case demonstrates a core lesson: early model success can degrade when input conditions change, requiring retraining, governance, and internal ownership [15]. The plant's capability development contributed to recognition as an advanced Industry 4.0 adopter [15, 32].

4.1.2. Freeport-McMoRan (Bagdad): AI optimization combined with agile execution

Freeport-McMoRan's Bagdad mine demonstrates how AI can unlock gains by challenging entrenched assumptions and turning prediction into optimization. The case highlights cross-functional teamwork, iterative deployment (MVP logic), and operational experimentation within safety boundaries—an organizational design aligned with dynamic capabilities and agility [8]. The competitiveness mechanism is not the algorithm alone, but the ability to embed model recommendations into daily operational routines and continuously improve the system [8]. This aligns with the principle that organizations should prioritize measurable business improvements over technology novelty, supported by pragmatic change and governance practices [9].

4.1.3. Siemens at CES 2026: Industrial AI operating system, digital twins, and copilots

Siemens' CES 2026 announcements illustrate an ecosystem-scale strategy: Industrial AI as a lifecycle-integrated operating layer spanning design, simulation, manufacturing, and supply chain coordination [23]. Digital Twin Composer is positioned as infrastructure for connecting comprehensive digital twins with simulation and real-time engineering data, enabling virtual decision-making and validation at scale [23]. Siemens also announced industrial copilots embedded across engineering and manufacturing software to reduce workflow friction and accelerate adoption [23]. This supports the argument that competitiveness is reinforced when AI is operationalized into routines and human systems, consistent with evidence on engagement and HR digitalization mechanisms [25, 29].

4.2. Bulgaria: why capability mediation matters even more

Bulgarian enterprise studies highlight that connectivity alone is insufficient for industrial digital maturity. Transformation requires ecosystem strengthening, platform development, and structured change management [2, 3, 5, 7]. Resistance to change and lack of reengineering skills are reported barriers, reinforcing the need for KOL, learning routines, and HR digitalization as adoption infrastructure [4, 19, 20, 27].

4.3. Synthesis: what actually creates competitive advantage

Across literature and cases, three recurring patterns emerge:

•Technology is necessary but insufficient: adoption alone does not guarantee competitiveness [10, 24, 33].

•Embedding beats pilots: value compounds when AI/IoT/automation are institutionalized into daily routines, with governance and iterative improvement [8, 15].

•Leadership and human systems are multipliers: KOL supports innovation under turbulence through knowledge sharing quality and KM capability [20, 19], while e-HRM and HR analytics strengthen adoption, engagement, and workforce readiness [31, 25, 29, 34].

Additionally, the regulatory environment can influence digital transformation performance, particularly for SMEs and ecosystem-level digitalization [26].

5. Conclusion

Industrial competitiveness in the AI era is not determined by technology adoption alone but by the ability to build an integrated capability system: IoT-enabled data infrastructure, AI decision intelligence, automation-based stability and precision, and continuous improvement enabled by agile execution and workforce readiness. Evidence from steel and mining shows that measurable operational gains depend on internal capability ownership, adoption routines, and iterative model improvement—not one-time deployments [15, 8]. Siemens' ecosystem strategy further indicates that Industrial AI is moving toward lifecycle-integrated architectures where digital twins and copilots embed intelligence into daily workflows [23].

The reviewed literature reinforces that knowledge-oriented leadership and knowledge management capabilities enable organizations to convert digital tools into innovation and performance under technological turbulence [19, 20]. Digitalization management and agile/dynamic capabilities mediate outcomes [21, 27, 33], while e-HRM and HR analytics provide the human systems infrastructure required for scaling and sustaining advantage [31, 25, 29, 34]. Regulatory frameworks can further shape digital transformation capacity and outcomes, especially for smaller firms [26].

In sum, industrial enterprises that treat AI/IoT/automation as a strategic capability program—not a technology project—are more likely to achieve durable competitiveness in global markets [1, 10, 33].

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