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DEVELOPING A DIGITALIZATION STRATEGY BASED ON HUMAN–ARTIFICIAL INTELLIGENCE COLLABORATION AND INTEGRATING IT INTO INDUSTRIAL MANAGEMENT

Rashidov Hasan Shirinboyevich
Senior Lecturer, Department of Digital Economics
Tashkent State University of Economics

Abstract

This article develops a digitalization strategy for industrial management grounded in human–artificial intelligence collaboration, treating AI not as a standalone automation layer but as a socio-technical capability embedded across planning, operations, quality, maintenance, logistics, finance, and risk management. The proposed approach frames digital transformation as an institutional redesign problem: value is created when human managerial judgment, domain expertise, and ethical accountability are systematically integrated with machine learning, optimization, and decision-support systems. The study conceptualizes collaboration through complementary roles: humans define objectives, constraints, and governance; AI provides pattern discovery, forecasting, anomaly detection, and scenario simulation; and joint workflows translate insights into controllable managerial actions. A strategy architecture is presented that links business goals to data stewardship, interoperable platforms, workforce upskilling, and process reengineering, with measurable key performance indicators for productivity, quality, energy efficiency, and resilience. The article also outlines a maturity pathway for industrial organizations, moving from digitization of records to data-driven operations and, ultimately, adaptive management supported by continuous learning loops. Special attention is given to practical implementation conditions in emerging industrial ecosystems, including legacy equipment, uneven data quality, cybersecurity exposure, and skills gaps. The expected contribution is a coherent, implementable framework that enables industrial firms and public stakeholders to coordinate investments, manage risks, and scale AI-enabled productivity improvements while preserving transparency, accountability, and human oversight in managerial decision-making.

Keywords: Digitalization strategy; human–AI collaboration; industrial management; decision support systems; data governance; process mining; predictive maintenance; demand forecasting; intelligent operations; cybersecurity; organizational learning; change management; KPI architecture; interoperability; responsible AI.

INSON VA SUN'IY INTELLEKT HAMKORLIGIGA ASOSLANGAN RAQAMLASHTIRISH STRATEGIYASINI ISHLAB CHIQISH VA UNI SANOAT BOSHQARUVIGA INTEGRATSIYA QILISH

Rashidov Hasan Shirinboyevich
Toshkent davlat iqtisodiyot universiteti
"Raqamli iqtisodiyot" kafedrasi katta o'qituvchisi

Annotatsiya

Ushbu maqolada sanoat boshqaruvi uchun inson–sun'iy intellekt hamkorligiga tayangan raqamlashtirish strategiyasi ishlab chiqiladi; bunda sun'iy intellekt alohida "avtomatlashtirish qatlami" sifatida emas, balki rejalashtirish, operatsiyalar, sifat nazorati, texnik xizmat ko'rsatish, logistika, moliya va risk-menejment bo'ylab singdiriladigan sotsiotexnik salohiyat sifatida talqin etiladi. Taklif etilayotgan yondashuv raqamli transformatsiyani institutsional qayta loyihalash muammosi sifatida ko'radi: qiymat shunda yuzaga keladiki, insonning boshqaruviy hukmi, sohaga xos ekspertiza va axloqiy javobgarlik mashinaviy o'rganish, optimallashtirish hamda qarorlarni qo'llab-quvvatlash tizimlari bilan tizimli ravishda uyg'unlashtiriladi. Tadqiqot hamkorlikni bir-birini to'ldiruvchi rollar orqali konseptuallashtiradi: insonlar maqsadlar, cheklovlar va boshqaruv (governance) qoidalarini belgilaydi; sun'iy intellekt esa andozalarni aniqlash, prognozlash, anomaliyalarni topish va ssenariy modellashtirishni ta’minlaydi; qo‘shma ish oqimlari esa olingan tahliliy natijalarni boshqariladigan amaliy harakatlarga aylantiradi. Maqolada biznes maqsadlarini ma’lumotlarni boshqarish (data stewardship), o‘zaro mos platformalar (interoperable platforms), kadrlar salohiyatini oshirish va jarayonlarni qayta muhandislashtirish bilan bog‘laydigan strategik arxitektura taklif etiladi hamda unumdorlik, sifat, energiya samaradorligi va barqarorlik uchun o‘lchanadigan asosiy ko‘rsatkichlar tizimi asoslanadi. Shuningdek, sanoat tashkilotlari uchun yetuklik yo‘li tasvirlanadi: yozuvlarni raqamlashtirishdan ma’lumotlarga tayangan operatsiyalarga, undan esa uzluksiz o‘rganish sikllari bilan qo‘llab-quvvatlanadigan moslashuvchan boshqaruvga o‘tish. Rivojlanayotgan sanoat ekotizimlarida uchraydigan amaliy joriy etish sharoitlari, jumladan, eskirgan uskunalar, ma’lumotlar sifati notekisligi, kiberxavfsizlikka ta’sirchanlik va ko‘nikmalar yetishmovchiligi masalalariga alohida e’tibor qaratiladi. Kutilayotgan ilmiy-amaliy hissa shundan iboratki, taklif etilgan yondashuv sanoat korxonalari va davlat manfaatdor tomonlariga investitsiyalarni muvofiqlashtirish, xatarlarni boshqarish hamda sun’iy intellekt asosidagi unumdorlik oshishini keng ko‘lamda joriy etishga imkon beruvchi, shu bilan birga shaffoflik, javobgarlik va qaror qabul qilishda inson nazoratini saqlab qoladigan izchil va amaliy tatbiq etiladigan konseptual asosni taqdim etadi.

Kalit so‘zlar. raqamlashtirish strategiyasi; inson–sun’iy intellekt hamkorligi; sanoat boshqaruvi; qarorlarni qo‘llab-quvvatlash tizimlari; ma’lumotlarni boshqarish; jarayonlarni qazib olish (process mining); prognozli texnik xizmat (predictive maintenance); talabni prognozlash; intellektual operatsiyalar; kiberxavfsizlik; tashkiliy o‘rganish; o‘zgarishlarni boshqarish; KPI arxitekturasi; o‘zaro moslik; mas’uliyatli sun’iy intellekt.

Introduction

Industrial enterprises increasingly treat digitalization as a strategic imperative rather than an IT modernization project. Yet many initiatives fail to produce stable managerial value because technology is deployed without redesigning the decision processes through which organizations plan, coordinate, and control production. In industrial management, the core bottleneck is not the lack of data or algorithms, but the weak integration between human expertise and computational intelligence. Managers and engineers hold tacit knowledge about constraints, safety, and operational trade-offs, while AI systems excel at discovering patterns, forecasting dynamics, and optimizing under large-scale complexity. A credible digitalization strategy must therefore be built on human–AI collaboration, where the organization explicitly defines which managerial decisions are augmented by AI, which remain human-dominant due to accountability or ethical risk, and how the joint workflow is governed.

Human–AI collaboration in industrial management can be understood as a structured division of cognitive labor. Humans formulate objectives, interpret context, validate assumptions, and take responsibility for final decisions. AI contributes by processing high-velocity operational data, modeling non-linear relationships, detecting anomalies, and generating scenario-based recommendations. The collaboration becomes productive only when it is operationalized through governance rules, data pipelines, and interfaces that translate model outputs into actions that fit industrial routines. Without this alignment, organizations face common failure modes: dashboards that do not change decisions, predictive models that cannot be acted upon, automation that increases risk due to opaque logic, and fragmented "pilot projects" that do not scale.

In the context of industrial transformation, digitalization strategy should be defined as a portfolio of coordinated changes that connect business goals to digital capabilities. This includes data governance, platform interoperability, workforce development, process reengineering, cybersecurity, and performance management. Importantly, strategy must address the full socio-technical stack: equipment and sensors, enterprise systems, analytics and AI models, and the human roles that make decisions using these tools. Human–AI collaboration becomes the organizing principle that ties these layers together. Instead of asking "Which AI tools should we buy?", the strategic question becomes "Which decision loops should we improve, and what combination of human competence and AI capability is required to do so safely and effectively?"

For industrial organizations, the most valuable decision loops typically include production planning and scheduling, quality control, maintenance, inventory and logistics, energy management, and financial control. Each loop has a distinct risk profile and requires different collaboration patterns. For example, predictive maintenance relies on AI for anomaly detection and remaining useful life estimation, but requires human validation, root-cause reasoning, and planning of interventions in line with safety regulations. Demand forecasting can be strongly AI-driven, yet the translation of forecast uncertainty into inventory policy requires managerial judgment about service levels, working capital, and supplier risk. Quality management benefits from computer vision and statistical learning, while corrective actions depend on human-led process redesign and accountability for compliance.

A further challenge is that digitalization in industry increasingly depends on cross-functional coordination. Data needed for AI use cases often spans production, procurement, sales, and finance. If the enterprise lacks common data standards, master data discipline, and interoperability between systems, AI models become brittle and context-blind. Therefore, a strategy centered on human–AI collaboration must institutionalize data stewardship roles, ensure traceability of model inputs and outputs, and align incentives so that units contribute to shared digital assets rather than optimizing local metrics.

This article addresses these issues by proposing a practical framework for developing a digitalization strategy that embeds human–AI collaboration into industrial management. The framework is designed for economic and managerial audiences concerned with productivity growth, operational resilience, and responsible innovation. It outlines a maturity pathway, defines governance mechanisms for AI-enabled decisions, and proposes measurable KPIs to evaluate transformation outcomes. The focus is on creating an implementable strategic logic that organizations can use to prioritize use cases, allocate investments, and scale solutions beyond pilot stages, while maintaining transparency, cybersecurity, and human accountability.

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Methods

The study applies a design-oriented, mixed-method approach to construct a strategic framework for industrial digitalization based on human–AI collaboration. The methodological logic follows four stages: problem structuring, strategic architecture design, operationalization into decision-loop interventions, and evaluation through performance and governance criteria. This approach is suitable for managerial settings where causal inference is constrained by organizational heterogeneity and where the primary output is an implementable strategy model rather than a single predictive artifact.

At the problem structuring stage, the industrial organization is modeled as a network of decision loops that transform inputs into outputs under constraints of capacity, quality, safety, cost, and time. Decision loops are defined as recurring managerial cycles such as plan–execute–monitor–adjust in production planning, maintenance, quality control, inventory replenishment, and energy optimization. For each loop, the method identifies decision owners, information dependencies, latency requirements, and risk levels. This produces a decision map that becomes the baseline for determining where AI augmentation yields the highest marginal value. The mapping also distinguishes between structured decisions suitable for algorithmic support and unstructured decisions that require human deliberation, negotiation, or ethical judgment.

At the strategic architecture design stage, the method uses a capability-based planning perspective. Digitalization is decomposed into capabilities across data, technology, process, and people. Data capabilities include data governance, master data management, metadata, data quality controls, and access policies. Technology capabilities include interoperability (APIs and integration), industrial IoT, data platforms (data lakehouse or enterprise data warehouse), analytics tooling, and model deployment infrastructure (MLOps). Process capabilities include standardized workflows for how insights become actions, exception management, and feedback loops that capture outcomes for learning. People capabilities include literacy in data and AI, role redesign, and training for supervisors, planners, and engineers. A core methodological step is aligning these capabilities with business objectives using a strategy-to-KPI chain: each strategic objective (e.g., reduce downtime, improve yield, lower energy

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intensity) is linked to decision loops, required data assets, AI functions, human responsibilities, and measurable indicators.

Operationalization is performed through the development of human–AI collaboration patterns for each prioritized decision loop. Collaboration patterns are defined as explicit interaction protocols: advisory mode (AI suggests, human decides), co-pilot mode (AI simulates and ranks options, human selects and justifies), constrained automation (AI executes within predefined limits, human monitors), and human override (mandatory for safety-critical exceptions). For each pattern, the method specifies interfaces, explanation requirements, escalation rules, and accountability assignments. To reduce implementation risk, the method recommends building minimum viable decision support for each loop, where the first release focuses on stable data integration and interpretable outputs rather than maximizing algorithmic complexity.

The method also incorporates process mining and value-stream analysis to diagnose where digitalization will generate measurable impact. Event logs from ERP, MES, and maintenance systems are used to identify bottlenecks, rework cycles, queue times, and compliance deviations. These diagnostics inform use-case selection by revealing high-cost variability and controllable delays. In parallel, the method applies risk assessment for AI adoption, including cybersecurity threat modeling, data privacy classification, model risk management, and operational safety considerations. Each AI-enabled loop is evaluated for failure consequences, detectability, and mitigation options, producing a risk-weighted prioritization of projects.

Evaluation criteria are defined across three dimensions: economic performance, operational reliability, and governance maturity. Economic performance is assessed through KPIs such as OEE improvement, scrap reduction, forecast accuracy gains translated into inventory turns, and maintenance cost per unit of output. Reliability is assessed through stability of model performance, robustness to data drift, and continuity of operations under system faults. Governance maturity is assessed through auditability, transparency of decision rationales, compliance with internal policies, and evidence of human oversight. The overall methodological output is a strategy blueprint with a prioritized roadmap, capability build-out plan, and a measurement system that supports iterative scaling and institutional learning.

Results

The proposed framework yields a structured digitalization strategy model that can be directly embedded into industrial management through decision-loop redesign and capability build-out. The main result is an integrated strategy blueprint consisting of a decision-loop portfolio, a human–AI collaboration operating model, a data and platform architecture, and a staged implementation roadmap with measurable KPIs. Instead of organizing transformation around isolated technologies, the framework organizes it around managerial control cycles and clarifies how AI outputs become accountable actions.

The decision-loop portfolio identifies five high-impact loops for industrial enterprises: production planning and scheduling, quality management, maintenance management, inventory and logistics, and energy and resource efficiency. For each loop, the framework specifies a target performance objective, the AI functions required, the human roles responsible, and the feedback signals needed to learn from outcomes. In production planning, the strategy emphasizes forecasting and optimization to reduce schedule instability, changeover losses, and late deliveries. AI contributes demand prediction, constraint-aware scheduling suggestions, and scenario simulation under capacity and supplier uncertainty. Human planners remain responsible for objective setting, constraint validation, and final approval because plans often involve trade-offs not visible in data, such as contractual priorities, labor constraints, or safety requirements.

In quality management, the strategy operationalizes collaboration as a combination of AI-based defect detection and human-led root-cause analysis. AI functions include computer vision inspection, anomaly detection in process parameters, and early warning dashboards for drift in quality indicators. Humans perform containment actions, interpret causal plausibility, and redesign processes or training protocols. The framework defines a closed-loop mechanism: every quality incident triggers a structured data capture of

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conditions and corrective actions, which becomes training and validation material to improve detection models and refine control limits.

In maintenance management, the framework produces a predictive maintenance module integrated with work-order planning. AI functions include remaining useful life estimation, failure mode classification, and prioritization of interventions based on risk and production impact. Human maintenance engineers validate recommendations, confirm failure modes, and plan interventions aligned with safety and spare parts availability. A measurable result is a maturity pathway from reactive maintenance to condition-based maintenance, then to predictive and prescriptive maintenance, where the organization learns which interventions reduce downtime most effectively.

In inventory and logistics, the strategy integrates AI forecasting with policy design. AI provides probabilistic demand forecasts, lead-time risk estimation, and anomaly detection for supplier performance. Human managers translate uncertainty into replenishment policies, service-level targets, and contractual strategies. The result is a governance-ready mechanism for balancing working capital against service reliability, supported by KPI linkages such as inventory turnover, stockout rate, and forecast bias.

In energy and resource efficiency, the framework embeds AI into operational energy management. AI functions include load forecasting, anomaly detection for energy waste, and optimization of equipment settings under quality constraints. Humans set acceptable ranges, ensure compliance with technical regulations, and verify that optimization does not create hidden quality degradation. The result is a measurable mechanism to reduce energy intensity per unit output while preserving process stability.

A second major result is the human–AI collaboration operating model. The framework defines standardized collaboration patterns and assigns them to decision loops according to risk. Advisory and co-pilot modes dominate planning, quality, and logistics, while constrained automation is recommended only for low-risk, high-frequency control adjustments with clear guardrails. For safety-critical domains, the model mandates human override and escalations, with documented decision rationales. This operating model translates

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responsible AI principles into concrete managerial procedures rather than abstract policy statements.

A third result is the data and platform architecture aligned with industrial realities. The strategy specifies an interoperability layer connecting ERP, MES, SCADA/IoT, quality systems, and maintenance systems, supported by a governed data layer with master data discipline and metadata. It proposes MLOps practices for model deployment, monitoring, and retraining, including drift detection and performance auditing. This architecture is paired with organizational roles: data owner, data steward, model owner, and process owner, each with explicit accountability for data quality, model risk, and operational adoption.

Finally, the framework yields a staged roadmap with measurable outcomes. Stage one focuses on data readiness and quick-win decision support: standardized data capture, KPI baselining, and interpretable dashboards tied to specific decisions. Stage two scales targeted AI use cases with human-in-the-loop workflows and formal governance. Stage three institutionalizes continuous improvement through learning loops, where decision outcomes feed back into model refinement and process redesign. Across stages, the strategy provides a KPI system that links digital investments to economic value, enabling management to track productivity, quality, resilience, and risk reduction in a coherent measurement structure.

Discussion

The results indicate that the central leverage point in industrial digitalization is not algorithm selection but the redesign of managerial decision loops so that human expertise and AI capabilities operate as a coupled system. This shifts digitalization strategy from a technology procurement narrative to an operating model narrative. For economic and management audiences, the implication is straightforward: the return on digitalization depends on whether the organization can convert data and models into disciplined decisions that change operational behavior at scale. When AI is introduced without a clear decision-rights structure, organizations often accumulate analytics outputs that are informative but non-operative. In contrast, a collaboration-centered strategy makes the

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adoption challenge explicit by specifying who uses the output, in what workflow, under what constraints, and with what accountability.

A key insight is that human–AI collaboration reduces two structural risks common in industrial management. The first is the "automation trap," where optimization or predictive systems are deployed in ways that erode situational awareness, leading to brittle operations when conditions change. The collaboration model mitigates this by enforcing interpretability requirements, escalation rules, and human override in high-consequence contexts. The second is the "pilot trap," where individual departments run isolated AI projects that cannot be scaled due to inconsistent data, incompatible platforms, or unresolved governance. The strategy addresses this by making data stewardship, interoperability, and model lifecycle management first-order strategic components. In other words, the framework treats scaling capacity as a capability, not as a side effect.

From the standpoint of industrial economics, the proposed KPI chain matters because it translates digitalization into measurable productivity channels. Improvements in OEE, scrap rates, downtime, energy intensity, and inventory turns are not merely operational indicators; they represent cost functions and value drivers that affect competitiveness, export potential, and investment efficiency. In settings where capital is constrained and modernization occurs unevenly, a decision-loop approach helps prioritize projects with high economic elasticity. It also supports rational sequencing: without data quality and process discipline, advanced AI will not stabilize, and the organization will experience model drift, false alarms, and loss of trust. Therefore, early-stage transformation should emphasize data capture, standardization, and interpretable decision support, even if this seems less "advanced" than deploying deep learning systems.

The collaboration patterns also clarify how to align responsible AI with industrial governance. Responsible AI is often discussed in general ethical terms, but industrial management requires actionable controls: auditability of recommendations, traceability from input data to decision, and documented reasons for overrides. The operating model provides these controls by assigning model ownership, defining acceptable error boundaries, and institutionalizing

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monitoring for drift and bias. This is particularly relevant in industrial contexts where AI decisions can affect worker safety, environmental outcomes, and compliance with technical regulations. By embedding governance into decision workflows, the strategy reduces compliance risk while preserving the speed benefits of digital tools.

Within the region-specific context of Uzbekistan's industrial modernization, several practical considerations become especially salient. Industrial enterprises may operate with mixed levels of equipment maturity, where legacy machinery coexists with newer lines. This creates heterogeneous data environments and complicates sensorization and integration. A collaboration-based strategy is advantageous here because it can deliver value even before full automation: advisory systems and co-pilot planning tools can use partial data to reduce variability, while parallel investments build the interoperability layer over time. Another constraint is human capital: the limiting resource is often the availability of managers, engineers, and analysts who can interpret AI outputs and sustain model governance. The framework's role design and upskilling emphasis addresses this by treating AI literacy as a managerial competency rather than a niche technical skill.

The discussion also highlights the organizational change problem. Digitalization redistributes decision authority, alters performance visibility, and can create resistance if perceived as surveillance or deskilling. The collaboration model mitigates resistance by framing AI as augmentation with preserved human accountability, and by involving decision owners in model design and validation. When operators and managers see that AI supports their objectives and that they retain control in exceptions, adoption is more likely to become durable. Nevertheless, the framework assumes active change management: communication of benefits, redesign of incentives, and continuous training.

Finally, there are methodological limits that shape interpretation. The framework is strategic and design-oriented; it does not claim that a single configuration fits all industries. Sector differences in process stability, safety criticality, and market volatility will influence which loops are prioritized and which collaboration patterns are acceptable. Future empirical work can test the framework through longitudinal case studies and quasi-experimental evaluations comparing plants that adopt decision-loop governance with those that pursue tool-centric digitalization. Even with these limits, the framework provides a coherent managerial logic for aligning AI with industrial performance, enabling economic universities and practitioners to teach, analyze, and implement digitalization as an accountable, value-driven transformation rather than a collection of disconnected technologies.

Conclusion

A viable digitalization strategy for industrial management emerges when human–artificial intelligence collaboration is treated as the core design principle rather than an add-on to technology deployment. The framework developed in this article demonstrates that the highest-value transformation moves through decision-loop redesign: organizations specify which managerial cycles will be improved, how AI will support them, what responsibilities humans retain, and how outcomes will be measured and fed back for learning. By structuring digitalization around production planning, quality, maintenance, logistics, and energy management, the strategy connects AI capabilities to operational economics, making productivity, reliability, and resilience explicit targets instead of indirect promises.

The proposed strategy blueprint integrates four elements into a single managerial system. First, it builds a decision-loop portfolio that clarifies where AI generates measurable value and where human judgment remains indispensable. Second, it defines standardized collaboration patterns—advisory, co-pilot, constrained automation, and human override—so that augmentation is governed by risk, accountability, and transparency requirements. Third, it aligns data governance and interoperability architecture with industrial realities, emphasizing master data discipline, traceability, and model lifecycle management as prerequisites for scale. Fourth, it establishes a staged roadmap that prioritizes data readiness and interpretable decision support before moving to advanced automation, thereby reducing pilot failure and adoption fatigue.

For industrial organizations and economic policymakers, the key implication is that digitalization succeeds when it institutionalizes learning. AI models will drift, processes will change, and markets will remain uncertain; therefore, sustainable advantage comes from building continuous feedback loops where decisions, results, and corrective actions become structured inputs for improvement. In this logic, human competence is not replaced but upgraded: managers and engineers develop the capacity to frame problems, validate model outputs, manage risk, and translate analytics into disciplined action. This is especially important in emerging industrial ecosystems, where uneven equipment maturity and skills gaps make tool-centric transformation brittle.

Overall, the article's contribution is a practical and governance-ready strategy model that can be used to prioritize investments, coordinate cross-functional digital assets, and scale AI-enabled productivity gains while preserving human oversight. Integrating human–AI collaboration into industrial management thus becomes a mechanism for responsible modernization: it increases the speed and quality of managerial decisions, strengthens operational resilience, and supports long-term competitiveness through measurable improvements in efficiency and reliability.

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