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INTEGRATION OF ARTIFICIAL INTELLIGENCE METHODS INTO PROJECT QUALITY MANAGEMENT: REAL-TIME CONTROL OF COMPLIANCE WITH STANDARDS

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Abstract. The subject of the present study is the processes, tools and technological solutions that ensure the use of artificial intelligence to automate and increase the accuracy of quality control in projects, as well as the factors that affect the success of their implementation. The purpose of the study is to analyse and generalise approaches to the integration of artificial intelligence (AI) methods into project quality management, with a particular focus on real-time control of compliance with standards. The objective of the research is to ascertain the economic, organisational and technological viability of implementing AI, in addition to identifying risks and barriers that may impede the effectiveness of the project. Methodology. The study is grounded in a comprehensive analysis of international and industry cases (Ocado, Siemens, Nissan), a meticulous review of reports from leading consulting companies (Accenture, Deloitte, PMI), and a systematic summary of practical recommendations for the stages of AI implementation: data preparation, understanding stage, modelling, implementation, scaling and support. Four financial models were considered to assess economic efficiency: ROI, TCO, NPV and IRR. Additionally, typical integration issues were analysed, including a lack of qualified personnel, inconsistent data, staff resistance, and an absence of a clear strategy. Results. Implementing AI in quality control reduces the proportion of defects by an average of 5.2%, cuts readjustment costs by up to 70%, cuts the need for inspection personnel by 40%, and achieves an ROI of 45% in the first year. In manufacturing processes, (ML), (CNN), (RNN), (NLP) algorithms and expert systems automate routine checks, accelerate defect detection and increase accuracy to 99.995%. Practical examples demonstrate that comprehensive implementation can pay for itself within 1–3 years. Practical significance. The results and recommendations obtained can be used by enterprises to create effective digital transformation strategies, to optimise quality control processes, to reduce costs and to increase competitiveness. The developed approaches to the phasing of implementation and assessment of economic efficiency allow for the minimisation of risks associated with the integration of AI. Research value / Novelty. The study offers a systematic approach to implementing AI in project quality management, taking into account technological, organisational and economic factors. Its novelty lies in its comprehensive consideration of practical cases and the risks that impede the effective implementation of AI, while providing tools to overcome these risks. This promotes more informed decision-making in the field of digital modernisation and increases trust in innovative technologies within the business environment.

Keywords: artificial intelligence, project quality management, process automation, digital transformation.

JEL Classification: O33, O22, P41

1. Introduction

In the digital economy, artificial intelligence (AI) is increasingly regarded as a pivotal technology for enhancing the efficiency of business processes, including project management. The roles of AI are central to modern industry, which is currently grappling with the promises of advanced digitalisation, big data and artificial intelligence. In this context, emphasis

is placed on the role these technologies can play in addressing new, emergent requirements in the industrial, societal and environmental landscape. This involves using data and AI to increase production flexibility during periods of disruption and make value chains more robust. It also involves deploying technology that adapts to the worker rather than the other way around, and using technology to promote

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circularity and sustainability (Directorate-General for Research and Innovation (European Commission), 2021). According to Accenture's research, when AI is implemented effectively within a company's operations, key performance indicators can increase by at least 6.5 times. Furthermore, 69% of projects can achieve 95% of the expected business benefits and ROI indicators can exceed previous expectations in 64% of cases (Project Management Institute, 2019). In general, a certain level of team involvement and awareness can dramatically improve business scalability and contribute to steeper growth in profitability (Yansiti, Lakhani, 2021).

Introducing AI into project quality management processes can significantly improve efficiency by optimizing work, in particular:

- Automation of labour-intensive operations. Inspection tasks, such as visual product inspection, documentation audits and incoming data monitoring, are often highly repetitive. AI-based systems can inspect large volumes of data 24/7, thereby minimising the human factor. "... Building a modern AI factory with a well-designed data processing platform gives the enterprise more opportunities to focus on key challenges related to data management and security." (Yansiti, Lakhani, 2021)
- Increased accuracy and speed of defect detection.
 Machine learning and computer vision algorithms enable the detection of hidden patterns and anomalies, which may not be possible through conventional visual inspection.
- Improved economic performance. The implementation of AI-based systems in conjunction with the development of databases designed to facilitate the operation of AI can lead to a reduction in the probability of errors, an enhancement in the likelihood of the timely elimination of inconsistencies, and a positive impact on the quality and outcome of the project. Furthermore, optimised resource utilisation, encompassing both material and human resources, can contribute to enhanced financial outcomes.

It is evident that the utilisation of artificial intelligence is congruent with the principle of continual improvement and the identification of opportunities for enhancement within the ambit of ISO 9001:2015 standards (regarding the requirements to the quality of management systems) (ISO 9001, 2015). AI-based systems have the capacity to continuously learn from the data provided and promptly signal any deviations from quality standards. The importance of the self-learning element of AI is also noted by the researchers Marco Iansiti and Karim R. Lakhani, who argue the following: "The learning function is essential in the operating model to enable continual improvement, enhancing production results over time, and developing new products and services. From the impact of Bell Labs' R&D to Toyota's never-ending process of improvement, modern corporations have constantly sought opportunities to innovate and learn in order to remain viable and competitive. Recently, the focus on innovation and learning has grown across all industries, seeking ways to overcome threats and capitalize on their own opportunities" (Yansiti, Lakhani, 2021).

2. Results

As the need to improve business processes to remain competitive grows, companies are increasingly incorporating AI-based systems at various stages, including real-time quality control. According to the Project Management Institute's (2023) report, approximately 21% of respondents used AI in their work processes. These figures provide an opportunity to consider and evaluate different approaches to using AI and the results of implementing modern technologies in quality control.

As an example, a system developed by Ocado serves as an illustration. "By performing thousands of route calculations per second, AI provides the company with a highly predictable delivery model, optimizing its entire fleet of thousands of delivery trucks, delivering orders in all weather and traffic conditions across the UK. Algorithms optimize truck routes in real time, ensuring that delivered products are fresh.

In addition to optimizing routes, AI predicts when consumers are more likely to order products, usually several days before they need them. Using unusually detailed information about consumer preferences, the algorithms cross-check with possible constraints from farmers in Ocado's network of suppliers <...>" (Yansiti, Lakhani, 2021). This approach enables the company to evaluate the quality of its own capabilities and the quality of the products supplied to customers, thereby mitigating the risk of delivery delays and customers refusing services and switching to competitors due to poor service.

Siemens has implemented analogous technology in its own manufacturing systems. The Siemens Industrial Copilot, equipped with advanced Senseye Predictive Maintenance functionalities, facilitates visual oversight of conveyors at "every stage of the maintenance cycle, from repair and prevention to prediction and optimization" (Siemens, 2025). The system has already been instrumental in reducing "save on average 25% reactive maintenance time" (Siemens, 2025).

In addition, Deloitte's research shows that introducing AI technologies into production, particularly on conveyors, can increase safety and sustainable development by 10%, improve the efficiency of work processes by 20%, enhance product quality by 30%, and save up to 30% on annual costs. A survey of companies revealed that 92% of respondents noted an increase of 12% in several indicators after the introduction of

traditional artificial intelligence systems (Coykendall, Hardin, Morehouse, 2023).

Nissan is also making active use of AI technologies in its assembly processes. The main applications are the detection of microdefects and the acceleration of car assembly. During the assembly process, AI assists in selecting the correct buttons for the control panel and the appropriate mirror dimming, as well as determining the optimal door bend angles for different models. Using these technologies has increased assembly accuracy to 99.995% (Nissan Global, 2022). Nissan also employs artificial intelligence to regulate the standard of car painting. The implementation of AUTIS technologies has been demonstrated to enhance defect detection by 7%, as indicated by the available indicators. The AI system has been demonstrated to achieve a 98% success rate in identifying non-conformities, while human observers typically achieve rates ranging from 85% to 95%. Furthermore, the inspection time has been reduced, with AUTIS scanning 0.2 mm of the surface in 22.5 seconds, in contrast to the previous laser system, which scanned 0.3 mm of the surface in 45 seconds (Nissan Stories USA, 2024).

Consequently, Nissan has achieved a 100% rate of uniformity, thereby ensuring that equivalent quality standards and comparable indicators are present across the entirety of its manufacturing facilities. It is also expected to increase customer trust and reduce complaints after a drop in sales in 2024 (Singh S., 2024).

It is evident that companies have the capacity to utilise a variety of AI algorithms, or indeed to combine them with each other. Table 1 presents a comprehensive overview of the predominant AI algorithms, along with illustrative instances of their implementation in the domain of quality management.

Despite the success of certain AI-based technologies, a proportion of initiatives have been unsuccessful.

A significant contributing factor to the suboptimal performance of AI systems is the dearth of personnel with the requisite expertise to implement AI effectively. According to surveys, 56% of companies noted this as a significant obstacle to working with AI (Garther, 2019).

Another obstacle to companies using AI effectively is the lack of high-quality, prepared data with which to train models. "Data often contains a variety of systematic errors of assessment and even common mistakes, so significant investments must be made to ensure thorough checking of information for discrepancies and inconsistencies. Moreover, when different data streams are combined into one stream for comprehensive analysis, different types of data must be organized. ... For example, records must be consistent, duplicates must be excluded, and all variables must match" (Yansiti, Lakhani, 2021). Due to data inconsistency, AI may generalise poorly, miss "unfamiliar" defects, or make incorrect predictions. Reconciliation of data stored in different departments also incurs significant time and personnel costs, meaning that not all companies are able to implement AI successfully in their work.

Implementation is sometimes hindered by inflated expectations of AI, a lack of clear strategy for introducing new technologies into existing projects and staff resistance and lack of qualifications. To address these issues, training programmes and workshops can be introduced to explain the benefits, such as reducing routine tasks and enabling staff to focus on more complex ones. Staff can also be involved in testing pilot solutions and forming "focus groups" of leading users. It is also worth paying attention to the factors that can harm the project and lead to inefficiency, despite the predicted economic benefits. These factors are actually the main challenges when it comes to integrating AI into projects.

Table 1 **Basic AI algorithms and application scenarios in quality management**

Algorithm	Application area	Advantages	Example
ML (Machine Learning)	General tasks: classification "fit/unfit", defect prediction, analysis of text data (reviews, reports)	Flexibility, ability to work with different types of data	ML model for estimating the probability of defects in automotive components
CNN (Convolutional	Automatic visual control: detection of	High accuracy and speed in	Quality control on the assembly
Neural Network)	scratches, deformations, foreign objects	image recognition	line with high-resolution cameras
RNN (Recurrent Neural Network)	Forecasting parameters, dynamic indicators, time series (temperature, vibration)	Accounting for sequences and trends over time	Determining the optimal time for equipment maintenance
NLP (Natural Language Processing)	Analysis of text documentation, specifications, requirements, automatic report generation, customer feedback processing	Automatisation of routine text checks, search for hidden problems	Audit of ISO 9001, search for discrepancies in technical documentation
Expert systems and indistinct logics	Formalisation of "rigid" rules of standards (ISO, FDA), decision-making according to the "if-then" scheme	Transparency and reproducibility of rules	Assessment system for the alignment with the FDA or CMMI requirements

A primary challenge in this field is to ensure data security. The principal threats are as follows: data leakage and cyberattacks on systems with the objective of seizing data. Researchers at the AI Security Centre have identified two categories of AI data breaches: the intentional misappropriation of technology for the purpose of causing further harm, and organisational risks.

To prevent intentional misappropriation of project data, they suggest taking the following steps:

- Establish limited access to the AI model;
- constantly monitor the program and software for anomalous behavior;
- sign contracts with AI developers that state their legal responsibility for the security of the system.

To avoid organisational risks, which can also lead to data leakage, errors in the AI system, etc., it is proposed to:

- Periodically increase the security culture within the company;
- create a special group that would periodically check the security of processes;
- test the AI model before a wider launch, as well as familiarise the project team with the work of AI in order to avoid further failures in the programme due to employee ignorance;
- regularly conduct security audits;
- use data encryption and multi-level authentication (Hendrycks, Mazeika, Woodside, 2023).

As previously referenced, a number of obstacles exist which hinder the successful integration of the AI system. These include the incompatibility of existing data formats, their imperfection, lack of completeness of data and dispersion of data across different departments. This results in failures in the operation of the AI system and unreliable results that the model will display based on the available incomplete data.

As indicated by research undertaken by the PMI, one of the significant steps on the way to unifying existing data and organising it for further implementation in AI systems is communication between all departments involved in the project (Project Management Institute, 2020). It is generally proposed that the integration of the AI model with the existing systems should be implemented in a phased manner (see Fig. 1).

Subsequent to the implementation of an AI model, the following step is to scale and provide further support for the system. However, the transition from Proof-of-Concept (PoC) to industrial-scale operation is often delayed, because in order to spread the model to other processes, even with successful implementation, it requires adaptation for other types of work or regarding other products.

In order to achieve this objective, it is possible to prepare implementation instructions and guidelines (knowledge transfer) for other teams. Consequently, a team that has previously executed a successful launch of an AI model will possess the capability to expedite the process and circumvent errors and delays for those who will implement this solution in their work. Moreover, it is imperative to undertake periodic retraining of personnel, as it may be feasible to enhance the efficacy of the existing model through the incorporation of additional functionalities or technological updates. It is also imperative to continue to monitor the performance of the model (Model Drift Monitoring) to avoid failure in the operation of algorithms.

In addition to internal training, it is important that AI work remains transparent and accessible to external consumers, clients, partners and auditors (Explainable AI, or XAI). XAI should enable the system's competencies and understanding to be explained, as well as its past actions, current processes and future steps. It should also disclose the information on which its actions are based (Bernardo, 2023).

Transparency in AI decision-making is crucial in high-risk sectors such as pharmaceuticals, medicine, aviation and defence. XAI can help explain why a model has rejected a certain product, thereby helping companies to avoid additional risks, such as lawsuits, reduced customer trust and reputational damage.

The sequential process of implementing and further operating AI in the quality control system can be time-consuming and require significant investments and costs. As previously stated, the integration of artificial intelligence into occupational projects does not always result in success, despite substantial financial investments.

The ability to assess the effectiveness of implementing AI in project quality management is an important stage that can prevent the aforementioned mistakes, which can result in significant losses of investment and time. These mistakes can put the project at risk or even lead to its closure.

Therefore, before integrating AI into work and projects, it is necessary to assess the feasibility of doing so. The authors have identified the following as the main economic evaluation models: ROI (return on investment), TCO (total cost of ownership), NPV (net present value) and IRR (internal rate of return). These models can quickly demonstrate the economic benefits and potential of an AI model.

ROI simply determines the 'cost/benefit' ratio. For example, the initial cost of an AI system is 100,000 USD, with annual savings planned at 150,000 USD. Thus, the ROI is equal to $((150,000-100,000)/100,000)\times100\%$, which is 50%. This AI model will therefore lead to an economic benefit of 50% from implementing AI. The only thing ROI does not take into account is the time factor: when will this 50% benefit be obtained?

The TCO model will help to close this gap to some extent, as it estimates direct and indirect costs over the

entire duration of the project. TCO takes into account capital expenditure (CAPEX), including the purchase of equipment and licences, as well as the installation of computer and security systems. It also considers operational expenditure (OPEX), including support, updates and the modernisation of software, as well as personnel training. Hidden costs include possible downtime during the implementation of AI and the time required for specialists to adapt to the new work model.

For example, when implementing an AI-based visual quality control system with an initial capital investment of 100,000 USD, the system can be justified from a TCO perspective if the expected savings exceed 240,000 USD in five years.

The following two models estimate the profit from implementing AI models in a project, rather than savings. NPV is calculated as the difference between the present value of future cash flows and the initial investment. This model considers the discount

DATA
PREPARATION
AND
MODELLING

Iterations with predefined time frames and scope according to system requirements. With a defined time limit and scope of tasks, these iterations allow for freedom in the experimental search for solutions. These non-unified iterations ensure that the team does not burn out during the preparatory phase, striking a balance between routine tasks and advanced research.

The time frame for the entire phase should be defined and the scope of tasks limited to avoid exceeding the specified time frames. Such constraints are very important for meeting deadlines at this stage, regardless of the number of repeated cycles, but this practice is severely limited by the dependence of the time frame on the team's experience and the complexity of the problem.

The Spike Story method can also be applied at this stage to adapt agile practices to the needs of research in AI projects.



Use checklists and SOPs (standard operating procedures). Although SOPs are usually employed during the implementation stage, when practices are highly structured, they can also be useful during the understanding stage. This allows optimal expectations and realistic metrics to be set for measuring project success. Competency mapping helps to identify training and resource requirements. The result will be a competency matrix to help assess the necessary skills at all stages of the AI project, serving as a kind of roadmap for its implementation. This, along with the appropriate training of the team, will help avoid over-reliance on a few specialists with the necessary expertise.



Collaboration between businesses, teams and clients for data collection. To facilitate effective interdisciplinary collaboration, it is recommended that a six-dimensional model is used (Dimension 1: Processes, practices and tools; Dimension 2: Organisational environment; Dimension 3: Competencies of participants; Dimension 4: Contextual factors; Dimension 5: Effective integration of the first four dimensions; Dimension 6: Programmatic implementation following effective integration).

Communicate with the business team about any changes to the timeframe or expected business results. Whether this practice is used during the preparation stage depends on the business team's availability and how regularly they provide feedback, as well as the research team's ability to implement changes in real time. Depending on these two factors, one option is to inform the business team regularly and process their feedback immediately. Another option is to implement ongoing changes after the previous iteration cycle is completed. If an organisation is implementing two or more AI projects, it is good practice

If an organisation is implementing two or more AI projects, it is good practice to invest in automated data management tools to increase the efficiency of data collection, processing and modelling.

Figure 1. Stages of AI implementation into the existing systems

Source: Project Management Institute, 2020

MODELLING STAGE In Champion-Challenger modelling, multiple models are tested simultaneously before settling on the one that best meets the business needs. The reason for spending extra time creating several "challenger" models is to ensure that customer requirements are met as effectively as possible.



Engage the IT team sustainably throughout the project. Ideally, the IT team will be involved from the outset rather than at the implementation stage. This will enable risks relating to scaling to be identified early on. However, it is worth considering the time and cost implications of such engagement.

Using MLOps (machine learning operations) increases the likelihood of operationalising the model, allowing the research team to focus on developing new models and reducing the time taken to implement them.

Using MLOps to extend CI/CD (continuous integration/continuous deployment).

Using pure agile practices for implementation, as experimentation is already decreasing at this stage.



The 3E method is used to measure success. The three metrics used to determine the success of the project implementation are effectiveness (whether the right things are done), efficiency (whether they are done in the right way) and experience (customer experience).

Surveys and other methods of collecting feedback from the business team, customers and users are used to understand ways to improve project practices (where possible).

Figure 1. Stages of AI implementation into the existing systems

Source: Project Management Institute, 2020

rate and project duration, calculating the annual cash flow.

For instance, the preliminary financial commitment for the AI model component of the project amounted to 2 million USD. The expected annual cash flows (savings/income increase) were estimated at 0.8 million USD (year 1), 1 million USD (year 2), 1.2 million USD (year 3), etc. Therefore, the discount rate was set at 10%. Consequently, within a period of three years, revenue had surpassed 2 million USD, and the NPV was found to be greater than zero. Based on these estimates, it is recommended that the project be implemented.

The final model that is put forward for the evaluation of the implementation of AI is IRR. The IRR is the discount rate at which the NPV is equal to zero. To illustrate this, consider a capital rate of 10% and a conditional IRR of 15% for an AI project. In this scenario, the project would be deemed attractive for investment, as the IRR would exceed the cost of capital and generate additional value.

3. Conclusions

In general, with the right assessment and implementation, AI can not only multiply investments, but also:

- 1. Reduce costs for defects and readjustment. Early warnings about defects minimise the risk of releasing low-quality products and recalls from the market.
- 2. Increase personnel productivity. AI will perform routine tasks, while employees can focus on more complex conceptual solutions, including innovative ones.
- 3. **Improve and simplify decision-making processes**. AI can generate real-time analytics and dashboards for managers, which increases process transparency.
- 4. **Stimulate innovation**. To integrate AI, IT infrastructures are often updated, cloud computing, IoT sensors, and digital twins are introduced, which in turn improves all areas of the company's work, even those in which AI is not involved.

Table 2 **Results before and after AI integration into auto parts production**

Indicator	Before AI	After AI
Share of defectives, %	7,5%	2,3%
Readjustments costs, \$ annually	300 000	132 000
Personnel efficiency in 9 months, %	-%	67%
ROI for the first year, %	-	45%

Source: Notional data summarised on the basis of real cases from industry reports by Project Management Institute, 2019; Kodithyala, 2025

This effect lends support to the argument that the implementation of AI in quality management, with adequate risk management and planning, is a profitable venture on average within a timeframe of 1-3 years. The potential of AI to transform formal quality control

into a driving force for improving products and processes is significant. AI methods and algorithms, such as ML, CNN, RNN, NLP, as well as expert systems, offer the opportunity to perform a wide range of tasks, from the visual inspection of products to the automated analysis of text documentation, while ensuring that only the necessary control processes are automated.

It is evident that the integration of artificial intelligence within the framework of project quality management engenders tangible economic and operational advantages. A systematic approach to planning, evaluation (ROI, TCO, NPV, IRR) and scaling will provide the opportunity to avoid typical pitfalls and maximise the potential of artificial intelligence for continual improvement of quality, competitiveness and innovativeness.

References:

Bernardo, V. (2023). Explainable Artificial Intelligence. *EDPS TechDispatch*. Available at: https://www.edps.europa.eu/system/files/2023-11/23-11-16 techdispatch xai en.pdf

Coykendall, J., Hardin, K., & Morehouse, J. (2023). 2024 manufacturing industry outlook. Available at: https://www2.deloitte.com/us/en/insights/industry/manufacturing/manufacturing-industry-outlook-2024

Directorate-General for Research and Innovation (European Commission), Breque M, De Nul L., Petridis A. (2021). Industry 5.0: Towards a sustainable, human-centric and resilient European industry. Available at: https://op.europa.eu/en/publication-detail/-/publication/468a892a-5097-11eb-b59f-01aa75ed71a1/

European Commission: Directorate-General for Research and Innovation, Breque, M., De Nul, L. and Petridis, A. (2021). Industry 5.0 – Towards a sustainable, human-centric and resilient European industry. *Publications Office of the European Union*. Available at: https://data.europa.eu/doi/10.2777/308407

Garther (2019). Survey Analysis: AI and ML Development Strategies, Motivators and Adoption Challenges. Available at: https://www.gartner.com/en/documents/3940005

Hendrycks, D., Mazeika, M., & Woodside, T. (2023). An Overview of Catastrophic AI Risks. *Center for AI Safety*. Available at: https://safe.ai/ai-risk

ISO 9001 (2015). Quality management systems – Requirements. Available at: https://ontu.edu.ua/download/pubinfo/dcc/standard-ISO-9001-2015-en.pdf

Kodithyala, K. S. (2025). Synergy of AI and human expertise: The new paradigm in platform engineering quality assurance. World Journal of Advanced Engineering Technology and Sciences, 15(02), 811–818.

Nissan Global (2022). AI technology brings excitement to Nissan Japan. Available at: https://www.nissan-global.com/EN/STORIES/RELEASES/nissan-ai-technology/

Nissan Stories USA (2024). How AI is driving Nissan's cutting-edge paint process toward perfection. Available at: https://usa.nissanstories.com/en-US/releases/how-ai-is-driving-nissans-cutting-edge-paint-process-toward-perfection

Project Management Institute (2019). AI Innovators: Cracking the Code on Project Performance. Available at: https://www.pmi.org/learning/thought-leadership/pulse/ai-innovators

Project Management Institute (2020). Playbook for Project Management in Data Science and Artificial Intelligence Projects. 66 p.

Project Management Institute (2023). Shaping the Future of Project Management With AI. 26 p.

Siemens (2025). Siemens expands Industrial Copilot with New generative AI-powered Maintenance Offering. Available at: https://press.siemens.com/global/en/pressrelease/siemens-expands-industrial-copilot-new-generative-ai-powered-maintenance-offering

Singh, S. (2024). Nissan Global Production Cuts Imperil CEO's Recovery Plan. *Bloomberg*. Available at: https://www.bloomberg.com/news/articles/2024-07-25/nissan-global-production-cuts-imperil-ceo-s-recovery-plan

Yansiti, M., & Lakhani, K. (2021). Competition in the era of artificial intelligence. Kyiv: Fors Ukraina, 304 p.

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