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A Combined Function-Structure-Behaviour and Return on Investment Framework for Improved Decision-Making in Zero-Defect Manufacturing

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Abstract

Zero-Defect Manufacturing (ZDM) is a complex challenge that requires not only advanced technologies but also sound decision-making tools to ensure successful implementation. This paper proposes a novel approach that combines Function-Structure-Behaviour (FSB) analysis with Return on Investment (ROI) calculations to support more accurate and holistic investment decisions in ZDM. The combined framework aims to reduce the reliance on gut feelings and subjective judgement, making ZDM investment decisions more transparent, rational, and ultimately more successful. It allows decision-makers to explore trade-offs, validate strategy performance, and implement ZDM in a scalable, digitally supported way. Simulation results demonstrate the feasibility and practical value of the proposed approach, and a critical analysis reveals that the two strategies embody fundamentally different philosophies of quality management and carry distinct implications for scalability, human factors, and operational robustness.

Keywords: Zero-Defect Manufacturing (ZDM); Return on Investment (ROI); Human Factors & Ergonomics (HF&E); Function-Structure-Behaviour analysis (FSB); Quality Management;

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1. Introduction

Zero-Defect Manufacturing (ZDM) has emerged as a critical paradigm in contemporary manufacturing, representing the ultimate goal of eliminating defects throughout the production process [1]. As interest in ZDM grows, particularly within the context of Industry 4.0 and the transition toward Industry 5.0 [2, 3], manufacturers are increasingly recognising the need for sophisticated approaches that integrate advanced technologies with robust decision-making frameworks [4, 5]. The complexity of achieving zero defects extends beyond mere technological implementation, requiring a comprehensive understanding of the interplay between technical systems, human factors, and organisational capabilities [6, 7, 8]. This challenge is further compounded by the ironies of automation, where increased automation paradoxically heightens the importance of human operators in ensuring system reliability and managing unexpected failures [9]. The evaluation of ZDM initiatives presents significant challenges, particularly in the financial justification of investments [10, 11]. Return on Investment (ROI) analysis has become the most widely used tool for assessing the feasibility and effectiveness of ZDM implementations using both technical and economic criteria [12, 13]. However, while ROI is often treated as a straightforward financial calculation, its effectiveness as a decision-making tool depends heavily on the quality of input assumptions, particularly the estimation of future benefits [12]. In practice, this is where most errors occur, with even large, experienced companies struggling to make reliable forecasts when evaluating new technologies [10, 13]. A fundamental issue lies in the frequent confusion between profit and cash flow concepts, where the latter provides a more realistic view of costs and returns for investment decisions [12]. Furthermore, conventional methods for calculating ROI frequently fall short of fully elucidating the intricate interactions among machine efficiency, human labour, and the adaptability of systems [1, 5, 14]. These are critical factors necessary for a thorough comprehension of automation's overall influence on manufacturing performance outcomes [2].

Current approaches to ZDM investment evaluation are further limited by their inability to account for the complex technical and organisational dimensions that influence manufacturing outcomes [6, 7]. The ironies of automation complicate this picture significantly: as systems become more automated, human operators gain greater importance in ensuring reliability and managing unexpected failures [9]. If critical tools or interfaces become unavailable, entire production systems can halt regardless of technological sophistication [14]. This highlights the critical need to integrate human factors into ROI analysis for ZDM [6, 7]. Additionally, it is important to recognise that not all ZDM investments require cutting-edge digital infrastructure. Historical examples, such as the Toyota Production System and visual management techniques like the 'Ohno Circle,' demonstrate that significant improvements in quality and productivity can be achieved through simple, human-centred methods [1]. These examples suggest that Industry 4.0 technologies, while beneficial, are not prerequisites for ZDM success; rather, they serve as complementary tools that enhance already robust human-centric practices [2, 3].

This paper proposes a novel approach that combines Function-Structure-Behaviour (FSB) analysis with ROI calculations to support more accurate and holistic investment decisions in ZDM. By linking technical performance with economic outcomes and accounting for the often-overlooked human and organisational dimensions [7, 8], this combined framework aims to reduce reliance on subjective judgement and gut feelings, making ZDM investment decisions more transparent, rational, and ultimately more successful. The FSB framework provides a systematic method for analysing the functional requirements, structural components, and behavioural characteristics of manufacturing systems [7], while ROI analysis offers quantitative financial evaluation [12, 13]. Together, they create a comprehensive decision-making tool that addresses the complexity and ironies of automation inherent in modern manufacturing environments [9, 14].

The structure of the paper is as follows. Section 2 outlines the proposed methodology, combining FSB analysis with a cash-flow-based ROI model to assess ZDM strategies. Section 3 presents a simulation study applied to a gear manufacturing line, comparing two ZDM scenarios: defect detection via robot-mounted cameras and defect prediction via basket scanning. Section 4 reports the results, highlighting the technical and financial impacts of each approach. Section 5 discusses the findings in the context of automation, human factors, and organisational readiness. Section 6 concludes with key insights and directions for future research.

2. Method and Material

This section presents the integrated approach used to evaluate ZDM investments by combining FSB analysis with ROI assessment. It begins with a detailed explanation of how FSB principles are applied to manufacturing systems to map functional goals, structural components, and system behaviours, thereby uncovering critical design and operational dependencies. The section then outlines the ROI calculation method, emphasising cash flow analysis over profit-based metrics to provide a more realistic picture of investment performance. Relevant tools, models, or frameworks employed in the analysis are described, along with the data sources and criteria used for selecting case studies or industrial examples. Finally, the section clarifies key assumptions underlying the approach and acknowledges its current limitations in terms of generalisability and data availability.

2.1. *Function-Structure-Behaviour in manufacturing systems*

The FSB framework is employed to model and understand the internal logic of manufacturing systems targeted for ZDM. A dedicated FSB framework for ZDM was previously introduced by Psarommatis et al. [6], as shown in Figure 1. The process begins by identifying the primary functions that the system is intended to fulfil, such as defect detection, real-time process control, or autonomous reconfiguration. These functions are then mapped onto the physical and organisational structures responsible for delivering them, including machinery, human operators, and digital infrastructure. Finally, system behaviours are analysed, capturing dynamic responses to internal or external stimuli, such as a failure in a sensor or a variation in material quality. The FSB framework helps uncover misalignments between intent (function), implementation (structure), and outcome (behaviour), allowing for targeted improvements that support zero-defect objectives. This structured approach also aids in identifying which components most influence performance and which should be prioritised in investment decisions.

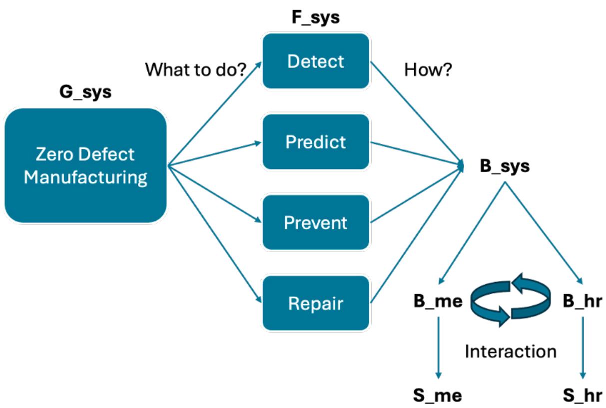

Fig. 1. Function-Structure-Behaviour framework for Zero-Defect Manufacturing [6]

2.2. *Return on Investment*

This part details the approach to ROI assessment. It presents the financial rationale behind this choice and outlines the specific formula and metrics used to estimate investment performance in a manufacturing context. The economic dimension of the proposed method focuses on calculating the ROI with a specific emphasis on cash flow rather than conventional profit figures. While profit is often used in investment justification, it can mislead decision-making due to its inclusion of non-cash accounting elements such as depreciation or future income projections. Instead, this approach uses net cash flow projections over a defined investment horizon to assess viability. The basic ROI is calculated using equation 1.

$$ROI = \frac{Net\ Cash\ Flow\ from\ Investment - Initial\ Investment}{Initial\ Investment} \times 100 \quad (1)$$

To improve accuracy, cash flows are adjusted for cost savings from defect reduction, productivity gains from improved processes, and any operational disruptions avoided. Costs include capital expenditures, labour required to operate or maintain the ZDM-related system, and potential training or reconfiguration efforts. Scenarios with and without automation, or with different levels of human intervention, are also compared to capture the 'ironies of automation,' where reducing human oversight can introduce hidden risks and downtime costs.

2.3. Simulation tool

To support the application of the combined FSB and ROI framework, a simulation and scheduling tool was developed to model, analyse, and optimise various ZDM strategies under realistic operating conditions. The simulation component is designed around a modular architecture that captures the interdependencies between technical functions (e.g., defect detection, basket handling), system structures (robots, cameras, operators), and dynamic behaviours (failures, adaptations, rework). Inspired by prior research [4, 5], the simulation integrates discrete-event and system dynamics modelling to capture both time-sensitive operations and long-term behavioural patterns, including equipment degradation, learning curves, and feedback from human interventions.

Each ZDM scenario—whether based on detection (robot-mounted cameras), prediction (3D fixture scanning), or prevention (standardisation and lean practices)—is represented as a distinct module within the simulation. Inputs include real-world data on equipment failure rates, repair costs, cycle times, labour hours, and investment needs. The outputs are both technical (defect rate, downtime, throughput) and economic (net cash flow, ROI over time), enabling comparative analysis across different implementation strategies. Notably, the tool supports evaluation of the 'ironies of automation,' where high-tech solutions may introduce hidden vulnerabilities if not complemented by robust human and organisational structures.

Complementing the simulation engine is an integrated scheduling tool, grounded in lean and data-driven principles, which dynamically adjusts production sequences based on real-time system feedback. The scheduler incorporates Multi-Criteria Decision-Making (MCDM) logic to balance competing objectives, e.g., due date adherence, defect risk minimisation, energy efficiency, and resource availability. Drawing from Psarommatis et al.'s earlier work [1, 6], this scheduling layer is not static but adaptive, responding to disruptions detected by sensors or operators by re-sequencing jobs or reassigning resources. It supports hybrid decision-making modes: automated optimisation via heuristic or evolutionary algorithms, and human-in-the-loop adjustments through visual dashboards.

Together, the simulation and scheduling tools provide a unified platform for evaluating ZDM investments not only in terms of system performance but also in terms of their financial and operational sustainability. They allow for scenario comparison (e.g., high-tech detection vs. low-tech behavioural standardisation), timeline-sensitive ROI forecasting, and adaptive job shop control, thus, making the approach both practical and forward-compatible with Industry 4.0.

3. Simulation study

To demonstrate the feasibility and practical value of the proposed approach, a simulation study was conducted using a hypothetical manufacturing scenario yet industry-representative gear manufacturing facility serving the automotive sector. The scenario is inspired by real-world practices observed at GKN Driveline, in Köping, Sweden, which supply high-precision gears for transmissions and drivetrains. These components must meet stringent tolerances and reliability standards due to their critical role in vehicle performance and safety. Achieving zero-defect outcomes in such a context is not just desirable but it is imperative, driven by customer demands and just-in-time production constraints. The baseline scenario reflects manufacturing practices typical of legacy systems in the automotive sector, characterised by repetitive high-volume operations with minimal digital integration. The production line employs hard automation with limited sensorisation, and coordination is heavily based on operator experience and manual inspection. Robots are not equipped with vision or feedback systems and operate in open-loop control, which means that any deviation, such as misaligned baskets or wear-induced mechanical tolerances, must be corrected by human intervention. Maintenance is predominantly reactive, with repairs triggered post-failure rather than predicted. This setup, while robust for standardised production, lacks flexibility and responsiveness, making it vulnerable to defects and inefficiencies as production variability increases.

As presented in Table 1, the single unidirectional line is compound by several machines and human resources. On one hand, in terms of machines, the line is compound by 1 washing station, 50 robots used for material handling and several value-added machines such as cutting or heat treatment. In this simulation it is assumed that the yield of the value-added machines is 100%, thus not considered. On the other hand, in terms of human resources, by 1 overarching manager, 1 team leader, 1 maintenance operator, 1 repair operator for all damaged goods (including baskets), and 10 cell operators that are responsible for operating the cells, feeding the cells with material from the previous cell by pushing an array of baskets inside the cell, and perform low level maintenance when needed.

Table 1. Description of the simulation scenario.

Variable	**Quantity**
Robots	50
Robot operators	10
Robots per operator	5
Maintenance operator (overarching)	1
Repair operator	1
Repair fixtures per month	2000
Cost of fixture per unit	€ 100
Cost of robot grippers	€ 100
Cost of average salary operator	€ 50.000/year
Cost of average salary maintenance	€ 50.000/year
Cost of average salary repair operator	€ 50.000/year

The issue faced by the company relates to its mechanical handling equipment, which is used for the movement, storage, and protection of products during manufacturing. Commonly referred to as ‘baskets,’ these fixtures serve as the primary coordinate system for the machines. Damage or wear to the baskets can lead to machine breakdowns and part damage due to collisions. When a cell is not connected to a conveyor system, the operator is responsible for manually feeding it with new baskets. The production line in question was designed and built in the 1990s, during a period when product variation was minimised. As a result, the robotic system lacks integrated sensors and is considered a form of hard automation, i.e. ‘blind.’ Each cell, composed of five robots, was commissioned by an external company, although not necessarily the same one for all cells.

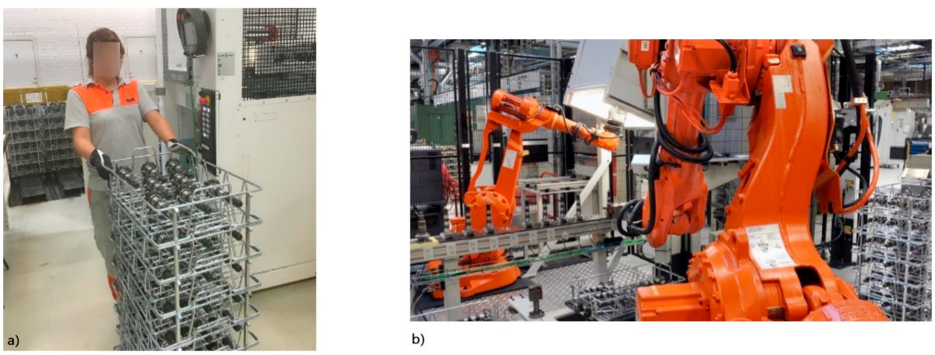

Fig. 2. Real world pictures of the material handling system: (a) baskets transported by operators (b) baskets used by robots in a fixed position or placed in conveyor.

The ROI analysis was conducted using two financial models: a traditional profit-based projection and a cash-flow-based method aligned with the framework proposed in this study. The conventional model estimated returns based on annualised profit gains from improved yield and reduced rework. However, it did not account for the actual timing and scale of expenditures, particularly initial costs related to operator training, sensor integration, and downtime during system commissioning. In contrast, the cash-flow-focused model included monthly operational cost reductions (e.g., fewer scrap parts, lower labour hours for rework) and staggered capital investments throughout the first year.

3.1. Simulation scenario 1 – ZDM Detection

In this ZDM scenario, the focus is on detecting defects through the use of cameras installed on each robot. The aim is to identify issues during operation, such as part misalignment or handling errors, before they propagate downstream. Each robot cell is fitted with a camera system integrated into the robot's controller, and these systems require calibration, maintenance, and synchronisation with existing reference frames. While the detection approach provides real-time feedback and can reduce scrap and rework, it also introduces complexity. For example, inconsistencies in coordinate systems between cells, reliance on operator intuition during adjustments, and uncoordinated maintenance actions can reduce the overall effectiveness of the system. The return on investment must account for both the hardware and integration costs and the gains from fewer defects, more stable cycle times, and fewer customer complaints. This strategy emphasises visibility of failure, i.e., seeing problems as they happen, to enable timely intervention.

- The main function of Scenario 1 is to "ensure 100% detection of defects during production";
- The structure of Scenario 1 is compound by: cameras integrated on robot arms, lighting systems, real-time image processing units, and additional human roles (e.g., robotics engineer for setup, repair technician, operator for validation);
- The behaviour of Scenario 1 is based on the sequence of (i) the camera triggers defect classification, (ii) the operator interprets or verifies ambiguous defects, (iii) a robotics engineer refines the detection algorithm, (iv) a maintenance operator adjusts hardware based on feedback, and (v) the system may autonomously halt or re-route parts.

The benefits of this ZDM approach include the reduction of scrap and rework, with fewer downstream failures or recalls, reduced need for inspection, and thus inspection bottlenecks, and more predictable cycle times with fewer customer complaints due to manufacturing quality. For it, system and implementation costs consist of the camera hardware, engineering and operator labour hours, downtime during deployment and learning, and maintenance and calibration.

3.2. Simulation scenario 2 – ZDM Prediction

In this ZDM strategy, the goal is to prevent defects before they occur by identifying potential failure sources early in the process. Rather than adding sensors to every robot, the focus is placed on the washing station, where every part must pass through before entering robotic cells. Here, a 3D camera array is used to scan the baskets that hold the parts, since basket deformation is a known cause of robotic collision or part misplacement. By analysing these baskets and detecting damage patterns, the system can flag or remove problematic units before they cause any disruption. This preventive approach eliminates failure sources upstream, i.e., before the part reaches the critical robot interaction. It reduces equipment wear, minimises unplanned downtime, and improves process consistency without increasing the complexity of downstream automation. The return on investment is achieved through cost-effective, centralised inspection and early intervention, supported by maintenance action when deformation thresholds are exceeded.

- The main function of Scenario 2 is to "Predict and prevent downstream defects or collisions by identifying deformed or problematic baskets before parts re-enter robotic cells";
- The structure of Scenario 2 is compound by: 3D camera array installed at the washing station, high-speed image processing system, decision logic (pass/block/re-route), updated basket handling SOP;

- The behaviour of Scenario 2 is based on the sequence of (i) baskets are scanned, deformation detected (ii) flagged by system (iii) maintenance is notified (iv) defective baskets removed or repaired (v) clean, conforming baskets continue in production.

The benefits of this ZDM approach include (i) quality improvements with a reduced scrap and rework due to early detection of basket deformation (ii) operational efficiency, fewer downstream defects or robotic collisions and reduced need for end-of-line inspection and (iii) improved delivery consistency, fewer warranty claims or late deliveries from missed defects.

4. Results

The simulation results highlight the practical and economic implications of deploying different ZDM strategies in a gear manufacturing environment, particularly when addressing recurrent part-handling failures caused by fixture degradation. The baseline, or current situation, leads to significant quality-related losses: 2,000 annual robot crashes result in approximately 3,600 scrapped parts, totalling €738,999 in yearly losses when including downtime and material costs. This figure underscores the urgency and potential value of implementing targeted defect mitigation strategies. The results form the simulation can be observed in Table 2.

Table 2. Results from the simulation.

	Current situation	Scenario 1	Scenario 2
Crushes	2000	600	200
Parts recoverability factor	0.95	0.95	0.95
Current situation scraped parts	3600	1080	360
Parts Losses	€ 693,000.00	€ 207,900.00	€ 69,300.00
Downtime losses due to crash	€ 45,037.50	€ 13,500.00	€ 4,500.00
Downtime losses due ZDM	–	€ 42,000.00	€ 67,500.00
Total losses for a year	€ 738,999.04	€ 263,400.00	€ 141,300.00
Total save per year	–	€ 475,599.04	€ 597,699.04
Total investment	–	€ 80,000.00	€ 200,000.00
ROI	–	**5.94**	**2.99**

Scenario 1, which introduces robot-mounted vision systems for real-time defect detection, yields a significant reduction in equipment crashes (from 2,000 to 600), thereby decreasing scrap rates and related losses. Annual losses fall to €263,400, delivering a yearly savings of €475,599.04. With an initial investment of €80,000, this detection-based strategy achieves a robust ROI of 5.94, indicating high capital efficiency. However, it also introduces €42,000 in new downtime costs attributed to system calibration, maintenance, and the learning curve associated with integrating real-time detection technology. This suggests that while detection enhances visibility and responsiveness, it may temporarily increase system complexity and operational overhead.

Scenario 2, focused on predictive inspection through centralised 3D scanning at the washing station, delivers even greater loss reduction—cutting crashes down to 200 annually and decreasing scrap to 360 parts. Despite a higher initial investment of €200,000 and increased downtime during deployment (€67,500), this approach results in the lowest total losses (€141,300/year) and the highest absolute savings (€597,699.04/year). The calculated ROI of 2.99, although lower than in Scenario 1, reflects a trade-off between cost-effectiveness and performance impact. Scenario 2 is particularly effective at addressing root causes upstream, thereby minimising disruptions downstream and improving process stability.

In summary, both ZDM scenarios demonstrate clear economic and operational advantages over the current state, but they vary in their balance between investment, complexity, and effectiveness. Scenario 1 is more agile and cost-efficient, making it attractive for near-term returns, while Scenario 2 offers a more sustainable and preventive solution with broader long-term benefits. These findings support the value of scenario-based evaluation using an FSB-ROI simulation framework, which enables manufacturers to align technical improvements with economic priorities in a structured and evidence-driven manner.

5. Discussions

The observed fragmentation characteristic of the so-called ‘normal accidents,’ which refer to the failures resulting from the intricate interactions among system components rather than from the malfunctions of individual components, is noteworthy. Each robotic cell’s semi-autonomous functionality introduces numerous potential failure points, where issues such as calibration drift, sensor deterioration, or communication delays may undermine the overall efficacy of the system. This architectural intricacy stands in contrast to the core principle of simplicity and predictability upheld by ZDM. Employing the FSB framework in ZDM systems signifies a groundbreaking method for systematic analysis and comparison of quality management strategies. The FSB framework offers a structured methodology to decompose complex manufacturing systems into their constituent components and to comprehend the relationships among the intended functions, emergent behaviours, and underlying structures. The analysis reveals that identical quality management functions can be executed through fundamentally divergent structural methodologies, each producing unique behavioural patterns with variable levels of effectiveness. To facilitate a clearer comparison of the advantages and limitations of each scenario, Table 3 provides a schematic summary of the key differences between the detection-based and prediction-based strategies, complementing the numerical results in Table 2.

Table 3. Schematic comparison of Detection-based (Scenario 1) and Prediction-based (Scenario 2) ZDM strategies.

Category	**Scenario 1: Detection**	**Scenario 2: Prediction**
Core philosophy	reactive, detect defects during operation	proactive, prevent defects before they occur
ROI	5.94 (higher capital efficiency)	2.99 (higher savings, lower efficiency)
Initial investment	€80,000	€200,000
Total yearly savings	€475,599	€597,699
Downtime impact	€42,000 (due to calibration, learning)	€67,500 (deployment disruption)
Organizational maturity needed	medium, moderate structure and established maintenance routines	high, requires strict operation procedures
Complexity	distributed: per robot cell	centralized: single scanning station
Operator role	interpret ambiguous defects; fine-tune calibration	act on early warnings
Key risk	calibration drift; fragmented implementation	underutilization of system

The simulation results demonstrate that both Scenario 1 (detection via robot-mounted cameras) and Scenario 2 (prediction via fixture scanning) can substantially reduce defect-related losses in the production line. However, a critical analysis reveals that the two strategies embody fundamentally different philosophies of quality management—reactive versus proactive—and carry distinct implications for scalability, human factors, and operational robustness. Scenario 1, while showing an impressive ROI of 5.94, is rooted in local visibility and reaction. It enables the system to identify defects as they occur, thus acting as a safety net. However, the solution is inherently fragmented; each robotic cell operates semi-autonomously, and the system’s effectiveness depends on consistent calibration, synchronisation, and operator response to detected anomalies. The €42,000/year downtime attributed to calibration and intervention suggests a hidden cost of complexity, where the solution itself introduces fragility. This raises questions about long-term maintainability, especially in older lines with legacy automation and inconsistent reference frames. Furthermore, the reliance on operators to validate defects reveals a continued dependency on tacit knowledge, challenging the assumption that automation alone guarantees zero-defect outcomes. Scenario 2, by contrast, offers a centralised and preventive approach. It addresses root causes upstream—deformed fixtures—thus decoupling defect risk from the variability of downstream robot behaviour. Although its ROI is lower (2.99), this strategy achieves a higher systemic impact and reduces operator burden. Still, the initial investment is substantial (€200,000), and the benefits are contingent on consistent enforcement of preventive maintenance and SOP updates. There is also an implicit assumption of organisational maturity—that the company has the discipline to act on early warnings, maintain calibration, and sustain the supporting processes over time. Without this, the predictive system risks becoming another underutilised asset.

The FSB framework reveals that system behaviour is not merely the sum of individual component behaviours, but emerges from the interactions between structure and function. Both scenarios raise broader considerations related to the ironies of automation. As systems become more complex and reliant on sensors and software, the role of human operators does not diminish—it evolves. In Scenario 1, human insight is needed to interpret ambiguous signals; in Scenario 2, it is needed to translate early warnings into preventive action. ZDM, therefore, is not purely a technological challenge but an organisational one. The effectiveness of both strategies ultimately depends on how well technology is embedded within operational routines, human workflows, and maintenance culture.

A pivotal aspect of this study involves the assessment and conceptualisation of ROI, particularly in the context of predictive and preventive strategies. Traditional ROI metrics often fail to capture strategic, qualitative benefits such as increased process resilience, improved workforce trust, and reduced pressure on inspection teams. Although these advantages are difficult to quantify, they can exert a significant cascading influence on organisational performance, culture, and long-term competitiveness. The cash-flow-based ROI model employed here addresses part of this gap; however, further development could include the valuation of risk reduction and scenario-based projections of failure costs. The integrated FSB and ROI framework rests on several assumptions, including the premise that system functions can be clearly identified and mapped to structures and behaviours. This assumption may not hold in highly complex or poorly documented environments. Moreover, ROI estimations depend on relatively stable market conditions and accurate forecasts of cost savings and performance improvements, both of which are often subject to uncertainty. The current model primarily considers direct costs and measurable gains, omitting intangible but influential factors such as workforce morale or long-term innovation capacity. As such, the framework is best suited for mid to large-scale industrial applications where baseline data and system transparency are available. To address current limitations in generalisability, future work will expand case coverage and refine estimation methodologies. Additionally, ROI must be evaluated across multiple behavioural scenarios, since behaviour is emergent and not necessarily optimal. For example, in one facility, the disregard of operator feedback may lead to suboptimal system performance and low ROI, while in another, effective collaboration may enable rapid adaptation of detection algorithms and result in high ROI. Future work should focus on validating the proposed framework in real-world industrial settings, extending the current analysis beyond simulated data alone. Such validation would allow for the assessment of the framework's applicability under actual operational constraints and organisational dynamics.

6. Conclusions

This paper has introduced an integrated framework for ZDM investment evaluation, combining FSB analysis with cash-flow-based ROI calculations. The framework addresses key shortcomings in traditional ROI assessments by incorporating the complex interdependencies between technical performance, human interaction, and organisational structure that characterise modern manufacturing systems. It offers a structured means of understanding not only how quality objectives are met, but also how different implementation strategies shape system behaviour and long-term effectiveness.

The simulation study conducted on a gear manufacturing line demonstrated the practical application of the proposed method. Two ZDM strategies were analysed: a detection-based approach using robot-mounted cameras, and a prediction-based approach using basket scanning at the washing station. Both scenarios yielded significant economic gains when compared to the baseline, with annual savings of €475,599 and €597,699, respectively. However, FSB analysis revealed that the two strategies were based on fundamentally different design philosophies. The detection-based approach showed high capital efficiency with a localised, reactive structure and a calculated ROI of 5.94. In contrast, the prediction-based approach offered centralised, proactive defect prevention with an ROI of 2.99, emphasising long-term stability. These distinctions, which are critical for strategic planning, would not have emerged through ROI analysis alone.

The combined FSB-ROI framework also proved effective in uncovering the systemic trade-offs involved in increasing automation. While advanced technologies reduce manual inspection, they also increase the demand for skilled human oversight in diagnostics, algorithm tuning, and maintenance. The framework highlights that ZDM effectiveness depends not only on technological investment but also on the alignment of system functions, structures, and behaviours with the specific capabilities of the organisation. Importantly, the study showed that substantial quality improvements can be achieved without relying exclusively on high-end Industry 4.0 technologies. Instead, targeted interventions, informed by system-level understanding, can produce measurable results with lower implementation risk.

Despite its advantages, the framework has certain limitations. It primarily addresses direct, quantifiable costs and benefits, potentially underestimating the strategic value of factors such as workforce engagement, operational resilience, and cultural readiness for change. Moreover, it assumes that system functions can be clearly mapped to behaviours and structures, which may not hold in highly complex or undocumented environments. Future research will seek to extend the model by incorporating intangible benefits and adapting it for less formalised industrial settings. The proposed Scenario 3, focusing on behavioural and human-centred interventions such as the 'Ohno Circle', will further explore non-technological pathways to achieving zero defects. Overall, the integrated FSB-ROI framework offers a transparent and comprehensive foundation for evaluating ZDM investments, providing actionable insights for decision-makers aiming to balance performance, cost, and long-term viability.

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