Degree project

UNIVERSITY OF SKÖVDE

Title: Enhancing Quotation Efficiency in Precision Engineering through Digital Tools and Data-Driven Approaches

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Abstract

Precision engineering companies face increasing demands to improve efficiency, reduce environmental impact, and retain expert knowledge in an increasingly digitalized industrial landscape. This master's thesis explores how digital technologies—specifically Business Intelligence (BI), Artificial Intelligence (AI), and voice recognition—can be effectively integrated into small and medium-sized precision engineering firms to enhance cost estimation, process monitoring, and decision support.

Adopting a mixed-methods approach, the study combines field observations in two industrial SMEs with the design and implementation of tailored digital tools. Three main solutions were developed: (1) **Power BI dashboards** for real-time monitoring of production and energy efficiency; (2) a **quotation support tool in Excel**, embedding the reasoning process of an expert estimator through structured formulas and engineering abacuses; and (3) a **voice-assisted input system**, allowing users to verbally specify part features, which are then processed to estimate machining time automatically.

Although a fully autonomous AI-based quotation system could not be deployed due to technical and data limitations, exploratory work was carried out on **OCR-enhanced part classification from 2D technical drawings** and the **leveraging of historical ERP data** to support semi-automated quoting. Feedback from company stakeholders confirmed that the implemented tools significantly improved operational transparency, reduced manual workload, and contributed to knowledge formalization.

The thesis concludes that **small-scale, user-focused digital solutions** can create immediate value for precision engineering SMEs while laying the foundation for future integration of advanced AI and data analytics. It provides recommendations for further research in areas such as AI model training with domain-specific datasets, ERP system integration, and the development of sustainability-oriented performance indicators.

Keywords: Precision Engineering, Digital Transformation, Business Intelligence, Quotation Automation, Voice Recognition, Industry 4.0, Sustainable Manufacturing, Document Intelligence

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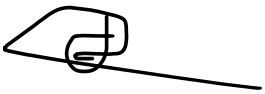
Signature: 

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1 Introduction

1.1 Background

Precision engineering plays a foundational role in sectors where failure is not an option: aerospace, automotive, medical devices, and microelectronics. In these industries, production requires extremely tight tolerances, high-reliability components, and advanced manufacturing expertise. The economic and safety risks associated with deviations or delays are considerable, making precision a core value and competitive necessity.

Despite their central importance, many precision engineering companies—especially small and medium-sized enterprises (SMEs)—struggle to adopt digital technologies at scale. These firms are often constrained by limited financial resources, fragmented IT systems, and a high reliance on human expertise accumulated over decades (Kamble et al., 2020). Recent studies of digital transformation in SMEs highlight similar barriers, including insufficient digital skills, organizational resistance to change, and concerns over data infrastructure (Omowole et al., 2024).

One of the most underexplored pain points in this sector is the quotation process. Preparing a manufacturing quotation for one-off parts or small batches involves evaluating technical drawings, interpreting customer specifications, selecting appropriate materials and operations, and estimating machining times and costs. This process depends heavily on the intuition and tacit knowledge of a few expert estimators—making it time-consuming, error-prone, and highly variable. Tacit knowledge is particularly critical in small technology enterprises, serving as a cornerstone of their innovation and operational capability (Koskinen & Vanharanta, 2002).

Furthermore, because the data used for quotations is often unstructured (e.g., 2D PDF drawings, handwritten notes, or verbal input), traditional IT systems are poorly equipped to handle it. As a result, there is a bottleneck in operations: slow turnaround times for offers, inconsistent pricing, poor traceability, and risks to business continuity when expert estimators retire or leave. Moreover, disconnected quotation workflows make it difficult to monitor historical performance, optimize pricing strategies, or improve accuracy over time. While large enterprises may address this through integrated ERP and PLM systems, SMEs lack the scale or resources to implement such comprehensive solutions.

This thesis focuses on exploring how digital technologies—starting from low-code tools like Excel and Power BI, and extending toward artificial intelligence (AI) and voice recognition—can support the formalization and partial automation of the quotation process in SME contexts. Recent advances in large language models (LLMs), voice-to-text APIs, and 2D document parsing open up promising avenues for digitizing unstructured engineering data (Bommasani et al., 2021). At the same time, business intelligence (BI) platforms like Power BI offer affordable ways to track performance, feedback loops, and operational metrics without complex infrastructure.

By focusing on the quotation process as a strategic entry point for digitalization, this study proposes a phased and iterative approach: starting with the formalization of expert knowledge into an Excel-based estimation tool, evolving toward real-time monitoring dashboards, and experimenting with AI-based extraction and voice input systems—

drawing on AI adoption frameworks tailored for SMEs (Hussain & Rizwan, 2024). This path reflects the realities of SME environments, where pragmatic, incremental improvements often provide the most value.

The aim is to demonstrate that precision engineering firms can benefit from targeted, user-centric digital tools to reduce manual workload, improve traceability, and prepare for more advanced automation—without requiring large-scale IT overhauls. In doing so, the thesis contributes to bridging the gap between tacit operational expertise and structured, scalable digital workflows.

1.2 Problem Statement

The quotation process in precision engineering SMEs represents a critical but often overlooked barrier to operational efficiency, scalability, and digital transformation. While large firms may integrate ERP, CAD, and PLM tools to manage cost estimation, SMEs frequently rely on informal methods and undocumented expertise. As a result, generating a reliable quotation becomes a time-intensive, person-dependent activity with little room for automation or traceability.

This creates a paradox: precision engineering firms, which rely on exactitude and optimization in production, often begin their business process with an informal and inconsistent quotation step. The lack of formalization limits process improvement, knowledge transfer, and responsiveness to customer demands.

At the same time, the push for Industry 4.0 adoption places pressure on these firms to modernize. Technologies such as Business Intelligence, AI-based document analysis, and voice interfaces promise improvements, but their adoption is constrained by fragmented IT environments, lack of technical expertise, and the absence of structured historical data (Mittal et al., 2018; Xu et al., 2018). Moreover, the increasing complexity of parts, variation in orders, and customer-specific requirements make full automation unfeasible in the short term.

Drawing on insights from the literature (Koskinen & Vanharanta, 2002; Mittal et al., 2018; Stock & Seliger, 2016; Xu et al., 2018), this thesis synthesizes the challenges into four categories that structure the analysis:

1.2.1 Formalization vs. Tacit Knowledge

The core expertise behind quotations is rarely documented. Estimators often rely on mental models, past experiences, and intuitive judgments. Capturing this into digital tools requires both structured modeling (via rules, equations, or templates) and flexible inputs (e.g., voice or drawing interpretation) (Koskinen & Vanharanta, 2002).

1.2.2 Data Fragmentation and Unstructured Inputs

Quotation inputs arrive in diverse formats—technical drawings, emails, phone calls—which are difficult to parse or process digitally. Integrating AI tools capable of extracting structured data from 2D PDFs or speech could provide a pathway forward but requires experimental validation (Xu et al., 2018).

1.2.3 Incremental vs. Transformative Approaches

For SMEs, a full digital transformation is rarely feasible. Instead, the opportunity lies in phased, incremental improvements—starting with an Excel-based system, integrating dashboards for feedback, and progressively exploring AI applications. This "scaffolded" approach aligns better with resource constraints and user learning curves (Mittal et al., 2018).

1.2.4 Sustainability and Regulatory Pressures

While operational improvement is the primary driver, sustainability has become a transversal concern across industrial decision-making. In the context of quotation processes, sustainability can be examined along three complementary dimensions:

• Environmental sustainability

Accurate quotations contribute to reduced material waste, fewer production reworks, and better resource allocation. However, digitalisation introduces trade-offs, including higher energy consumption from servers or potential electronic waste (Stock & Seliger, 2016).

• Social sustainability

Digital tools can reduce cognitive load and stress for estimators by providing structured support and reducing dependence on tacit memory. This helps maintain workforce well-being and facilitates the integration of junior staff (Stock & Seliger, 2016).

• Business and organisational sustainability

Encoding quotation knowledge can strengthen resilience against staff turnover and enables institutional memory. Structured quotation data supports long-term decision-making, pricing stability, and strategic planning (Stock & Seliger, 2016).

To synthesise these implications, Table 1 links sustainability dimensions to key components of the quotation workflow.

Table 1. Sustainability impacts across quotation workflow components

Quotation Component	**Environmental Impact**	**Social Impact**	**Business/Organisational Impact**
Input reception (drawings, RFQs)	Reduced rework; risk of digital storage load	Less stress from ambiguous inputs	Improved traceability
Knowledge extraction	Less scrap due to better estimates	Supports junior workers	Preserves expertise despite turnover
Digital processing (OCR, AI, BI)	Higher energy use; potential e-waste	Reduces cognitive burden	Scalable and repeatable processes

Cost/process modeling	More accurate resource use	Better decision transparency	Stable pricing and competitiveness
Feedback loops	Long-term waste reduction	Supports continuous learning	Institutionalised improvement

These sustainability considerations act as cross-cutting factors rather than process stages. The next section introduces the pipeline that structures the quotation process itself.

1.2.5 The Quotation Pipeline in Precision Engineering SMEs

The challenges outlined above can be conceptualised as a pipeline representing the transformation of unstructured inputs into reliable quotations (Figure 1). The pipeline includes:

- Knowledge encoding
- Digital processing
- Cost and process modelling
- Feedback integration

Although some operations occur sequentially, others—such as drawing interpretation and machining time estimation—may proceed in parallel depending on tooling and expertise availability. This framework maps the creation of quotations (input → estimate) and their execution (validation → reinforcement of the knowledge base).

Sustainability concerns discussed in Section 1.2.4 operate transversally across all stages: improved estimates reduce waste, digitalisation reshapes workloads, and structured knowledge enhances long-term organisational resilience.

In this thesis, particular focus is placed on the stages of knowledge encoding, digital processing, and feedback integration, as these represent both the major bottlenecks in SMEs and the areas where digital tools can realistically provide incremental improvements.

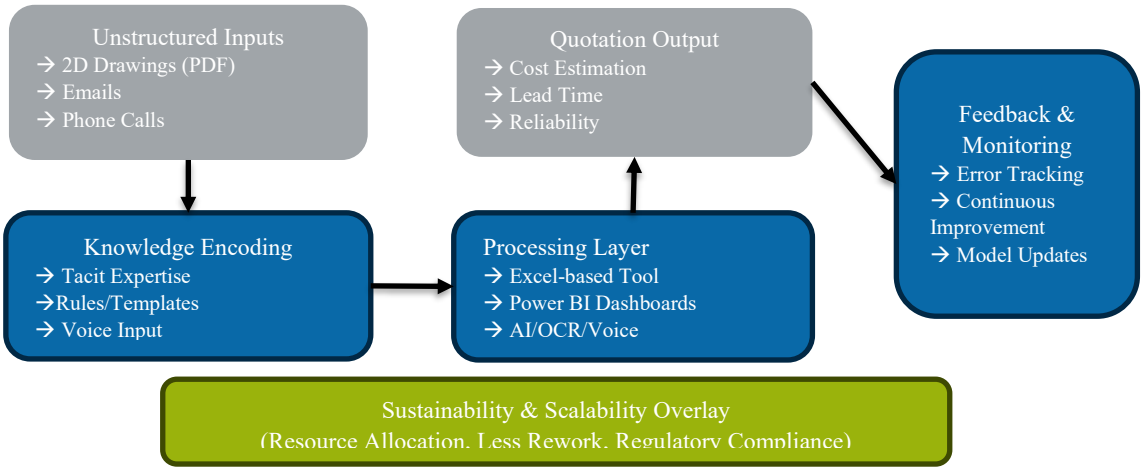

Figure 1. Quotation process pipeline in precision engineering SMEs, highlighting the stages addressed in this thesis.

1.3 Research Objectives

The overarching objective of this research is twofold. On the one hand, it seeks to contribute to the broader question of how SMEs in precision engineering can progressively adopt scalable pathways to digitalization, balancing structured models with exploratory prototypes (Müller et al., 2018; Brous et al., 2020). On the other hand, it grounds this ambition in a specific case study: the digitization of the quotation process for custom-manufactured parts. This process is both essential and frequently under-digitized, making it a compelling focus for applied research. Using a Design Science Research (DSR) methodology (Hevner et al., 2004), the research iteratively develops, evaluates, and refines tools that act on different components of the quotation pipeline (Fig. 1), particularly the knowledge encoding layer, the processing layer, and the feedback & monitoring layer, while considering the transversal sustainability and scalability overlay.

1.3.1 Formalize Expert Knowledge in Quotation Practices

Pipeline components addressed:

- Knowledge Encoding (fully addressed)
- Unstructured Inputs → Knowledge Encoding transition (partially addressed)

A first objective is to formalize the tacit expertise of estimators, which often resides in the minds of a few senior employees and is therefore vulnerable to turnover and difficult to scale. The research aims to document and model the logic used to price parts, including experiential heuristics and geometric parameters, and encode this knowledge into a structured Excel-based tool using regression models, empirical abacuses, and parametric rules. In doing so, the objective is to provide traceable and reproducible structures that enable iterative refinement and knowledge retention, echoing the importance of knowledge formalization in organizational learning.

1.3.2 Monitor Quotation Performance through Business Intelligence

Pipeline components addressed:

- Feedback & Monitoring (fully addressed)
- Quotation Output → Feedback Loop (fully addressed)
- Processing Layer (partially addressed)

The second objective is to establish a feedback loop that strengthens the reliability of the quotation process. By developing Power BI dashboards, the research seeks to analyze past quotations, monitor KPIs such as accuracy and time-to-quote, and visualize company-specific trends. This focus responds to the growing role of business intelligence in enhancing decision-making and traceability, as emphasized in the literature on data-driven management in SMEs (Wamba et al., 2017). Through comparative analyses across

companies, this objective also contributes to identifying common patterns or divergences that inform tool generalization.

1.3.3 Explore the Use of AI/OCR for Unstructured Input Processing

Pipeline components addressed:

- Unstructured Inputs (fully addressed)
- Unstructured Inputs → Knowledge Encoding (exploratory)
- Processing Layer (exploratory)

The third objective is to explore how AI can be leveraged to process unstructured inputs that are common in quotation workflows, such as 2D PDF drawings and verbal communication. This includes investigating the potential of OCR, voice-to-text, and large language models to extract structured information that can feed into the quotation process. Such exploration aligns with recent advances in applying AI to technical documentation and communication (Khan et al., 2025), while also critically assessing the feasibility, accuracy, and integration opportunities of these approaches within SME environments.

1.3.4 Evaluate SME Adoption Conditions and Constraints

Pipeline components addressed:

- Entire pipeline (contextual, not technical)
- Sustainability & Scalability Overlay (fully addressed)

A fourth objective addresses the organizational and technical conditions that determine whether digital tools for quotation can be effectively adopted in SMEs. Factors such as limited infrastructure, workforce capacity, and organizational culture often play a decisive role. By capturing user feedback in industrial contexts, this research evaluates adoption barriers and enablers in line with findings from digital transformation studies in SMEs (Kamble et al., 2020). The objective is therefore not only to design digital tools but also to ensure that they are aligned with the real-world constraints of SME operations.

1.3.5 Provide Actionable Recommendations for Implementation

Pipeline components addressed:

- Pipeline as a whole (synthesis)
- Sustainability & Scalability Overlay (fully addressed)
- Processing Layer & Feedback Layer (practical emphasis)

The final objective is to bridge the gap between research and practice by delivering concrete recommendations for implementation. These include tailoring advice to companies at different levels of digital maturity, proposing step-by-step roadmaps for initiating and scaling quotation digitalization, and highlighting best practices and pitfalls

observed during field evaluations. This pragmatic orientation ensures that the research does not remain theoretical but instead contributes actionable guidance to support future implementations in industrial contexts.

1.3.6 Alignment Between Research Questions and Research Objectives

The research objectives are designed to directly address the research questions. This table maps each research question to its corresponding objective, ensuring clarity and alignment between the guiding questions and the practical aims of the thesis.

Table 2. Alignment between Research Questions (RQ) and Research Objectives (RO)

Research Question (RQ)	**Research Objective (RO)**	**Pipeline Components Addressed**
RQ1. How can expert knowledge be encoded into digital tools to improve quotation accuracy and speed?	RO1. Formalize tacit estimator expertise into structured models (Excel rules, parametric models, abacuses).	Knowledge Encoding (full); Input → Encoding transition (partial)
RQ2. What are the opportunities and limitations of AI tools for processing unstructured technical data?	RO3. Experiment with AI/OCR/voice to extract structured data from drawings and speech.	Unstructured Inputs (full); Input → Encoding (exploratory); Processing Layer (exploratory)
RQ3. What would an effective framework for incremental adoption of digital tools in SMEs look like?	RO4. Evaluate adoption conditions and SME constraints.	Entire pipeline (contextual); Sustainability & Scalability overlay
RQ4. What is the role of feedback and monitoring in reinforcing quotation reliability and improvement?	RO2. Implement BI dashboards and feedback mechanisms.	Feedback & Monitoring (full); Output → Feedback loop (full)
RQ5. How can research findings be translated into actionable recommendations for SMEs at different digital maturity levels?	RO5. Provide implementation roadmaps and best practices.	Whole pipeline (synthesis); Sustainability & Scalability overlay

1.3.7 Conclusion

By addressing these five objectives, the thesis contributes to the broader debate on how SMEs can adopt scalable and incremental digitalization pathways, a debate that contrasts structured transformation models with more flexible, step-by-step approaches (Müller et al., 2018; Brous et al., 2020; Kamble et al., 2020). Together, these objectives operationalize the different stages of the quotation pipeline introduced earlier, while contributing to broader reflections on scalable digitalization in SMEs. Within this context, the specific case of quotation process digitalization in precision engineering

illustrates how tacit knowledge can be formalized, how feedback loops strengthen reliability, and how AI can be explored for unstructured inputs. The findings suggest that targeted interventions can preserve expertise, reduce time-to-quote, and provide actionable guidance for SMEs, while also opening avenues for future automation and sustainability-oriented practices.

2 Theoretical Framework

2.1 Knowledge Capture and Formalization in SMEs

Knowledge management is a fundamental concern for small and medium-sized enterprises (SMEs), particularly those operating in technically demanding sectors such as precision engineering. These firms rely extensively on tacit knowledge—the experiential know-how, intuitions, and insights held by employees—which is rarely documented and often acquired through years of practice on the shop floor or in the estimation office (Adesina et al., 2024).

The distinction between tacit and explicit knowledge originates from Polanyi's foundational work — notably *Personal Knowledge* (1958) and *The Tacit Dimension* (1966) — where tacit knowledge is conceptualized as personal, embodied, and inherently difficult to articulate ("we know more than we can tell"). While Polanyi establishes the epistemological basis, Nonaka and Takeuchi (1995) operationalized this distinction through the SECI model, a dynamic framework describing how organizations convert individual tacit know-how into collective, explicit knowledge structures.

The SECI model consists of four modes of knowledge conversion:

- Socialization (Tacit → Tacit): knowledge is transferred through shared experience, observation, and apprenticeship, without formal codification (e.g., learning machining strategies by watching a senior operator).
- Externalization (Tacit → Explicit): tacit insights are articulated into rules, templates, or models, making them communicable (e.g., translating estimation heuristics into cost formulas or decision criteria).
- Combination (Explicit → Explicit): multiple explicit sources are reorganized or integrated into new structured knowledge (e.g., merging ERP data, historical quotations, and machining time tables).
- Internalization (Explicit → Tacit): individuals absorb explicit knowledge and transform it into personal expertise through practice (e.g., using documented estimation rules until they become intuitive).

In precision engineering, this framework clarifies how tacit expertise—such as intuitive understanding of tolerances, material behavior, machining constraints, or negotiation practices—can be progressively formalized. Conversely, explicit knowledge refers to codified information captured through manuals, cost databases, process sheets, or software systems (Chevalier et al., 2013). The SECI model thus provides the conceptual bridge between Polanyi's epistemology and contemporary organizational practices, illustrating how SMEs might transform undocumented estimation know-how into scalable, digitalizable processes.

For precision engineering SMEs, the conversion of tacit knowledge into explicit knowledge is not merely an academic concern—it is a matter of operational survival. When expert estimators, programmers, or machinists retire or change jobs, they often take with them years of expertise that has never been documented. This knowledge loss leads to inconsistencies in quotation, errors in production, and delays in onboarding new staff. Such risks are also identified in studies of knowledge-based manufacturing SMEs, where structured knowledge capture and formalization practices significantly reduce

performance variation and error rates in complex machining tasks (Wittenborg et al., 2025; Wang et al., 2021).

2.1.1 Techniques for Capturing Tacit Knowledge

Capturing tacit knowledge is one of the central challenges in knowledge management, since it is embedded in the experiences, intuitions, and heuristics of experts rather than in formal documentation (Nonaka & Takeuchi, 1995; Gavrilova & Andreeva, 2012). Several techniques have been developed to externalize this knowledge and support its transfer within organizations.

One widely applied approach is the structured or semi-structured interview, where experts are systematically questioned to uncover the reasoning behind their decision-making processes. Such interviews are effective in surfacing implicit rules and heuristics, particularly in complex problem-solving contexts (Kothari et al., 2012; Gavrilova & Andreeva, 2012).

Another commonly used technique is direct observation or shadowing, in which analysts follow experts during their daily activities to document how decisions are made in real time. This method is particularly valuable for identifying context-specific routines that experts themselves may find difficult to articulate (Kothari et al., 2012; Gavrilova & Andreeva, 2012).

The think-aloud protocol is also well established: experts verbalize their thought process while performing a task, allowing implicit reasoning patterns to become explicit. In quotation processes, for instance, an estimator might describe how machining times are estimated or how past cases influence current decisions, providing access to otherwise hidden cognitive heuristics (Kothari et al., 2012).

More formalized approaches use knowledge elicitation tools such as concept mapping, rule-extraction software, or cognitive modeling. These methods help structure tacit knowledge into reusable representations, turning experiential expertise into assets that can be stored, refined, and transferred across the organization (Gavrilova & Andreeva, 2012).

Finally, storytelling has been identified as an effective way of eliciting tacit knowledge, especially in SMEs or in contexts where retiring experts hold critical expertise. Structured storytelling sessions can generate rich taxonomies of tacit constructs, helping to codify experiential know-how into organizational knowledge bases (Whyte & Classen, 2012; Gavrilova & Andreeva, 2012).

In the context of precision engineering SMEs, these techniques are particularly relevant for quotation processes, where experienced staff often rely on mental heuristics, analogies with past jobs, and informal decision rules. By systematically applying elicitation methods, firms can externalize valuable expertise, reduce dependence on a small group of individuals, and improve the consistency and traceability of cost estimations (Whyte & Classen, 2012; Gavrilova & Andreeva, 2012).

2.1.2 From Knowledge Capture to Knowledge Formalization

Once tacit knowledge has been captured, it must be formalized into structured and operational formats that can be stored, shared, and applied consistently. This stage falls

within the domain of knowledge engineering, which provides systematic methods for building knowledge-based systems (Studer, Benjamins, & Fensel, 1998).

Common formalization tools include:

- Ontologies, which define domain concepts and their relationships (e.g., materials, tolerances, machining operations). Ontologies have been widely used in engineering design and manufacturing to structure domain-specific knowledge and enable interoperability between systems (Uschold & Gruninger, 1996).

- Decision trees, which represent alternative choices and outcomes (e.g., material + shape + tolerance → process route). This technique has been applied in engineering contexts for process planning and fault diagnosis (Quinlan, 1993).

- Rule-based systems, which codify expert reasoning into sets of conditional statements. Early AI research demonstrated their power in expert systems such as MYCIN (Buchanan & Shortliffe, 1982), and similar approaches have since been adapted to engineering knowledge for quotation and process planning.

2.1.3 Benefits of Formalizing Knowledge in Quotation

Formalizing knowledge in quotation processes provides multiple organizational benefits. Codifying expert assumptions into structured systems ensures greater standardization, reducing variability and human error while supporting accurate and consistent cost estimations. It also enables scalability, as less experienced employees can rely on embedded rules and guidance, while allowing continuous improvement through iterative refinement based on feedback from production data. Moreover, formalized knowledge facilitates integration with digital systems such as ERP or business intelligence platforms, enhancing traceability and enabling data-driven decision-making. These advantages are consistent with evidence showing that knowledge codification transforms tacit insights into reusable assets, thereby improving organizational performance and continuity (Kimble, 2013).

2.1.4 Challenges of Knowledge Formalization in SMEs

Despite its advantages, the formalization of knowledge remains particularly challenging in small and medium-sized enterprises (SMEs). Barriers often include limited financial and human resources, as well as the absence of a formal culture of knowledge management, where documenting and sharing expertise is not considered a strategic priority (Durst & Edvardsson, 2012).

Studies show that many SMEs lack explicit policies or structures to support knowledge formalization, and employees may not recognize informal practices as contributing to long-term knowledge retention. This reduces the incentive to externalize expertise and increases the risk of knowledge loss when key individuals leave the organization (Durst & Edvardsson, 2012).

Other recurring obstacles include short-term business pressures, managerial unawareness of the strategic value of knowledge, and competing operational priorities that push documentation and transfer of expertise to the background (Durst & Edvardsson, 2012).

More recent research confirms that these challenges persist. Koivisto and Taipalus (2023) highlight that SMEs continue to struggle with the transfer of tacit knowledge due to limited time, scarce resources, and the lack of structured processes for capturing and sharing expertise.

2.2 Digital Transformation in Precision Engineering

Digital transformation refers to the strategic integration of digital technologies into all aspects of a company's operations, with the aim of improving performance, increasing flexibility, and enabling innovation (Vial, 2019). In the context of precision engineering SMEs, digital transformation is both a challenge and an opportunity—one that reshapes business models, quotation systems, production processes, and customer interactions.

This section explores the drivers, barriers, and tangible impacts of digital transformation within the precision engineering sector, with a specific focus on its role in quotation and planning workflows.

2.2.1 Strategic Drivers and Opportunities

Digital transformation in precision engineering SMEs is increasingly seen not as an option but as a strategic imperative. Global competition, shorter product life cycles, and rising customer expectations are forcing companies to rethink how they operate and deliver value. In this context, digitalization offers a set of powerful drivers that motivate SMEs to engage in transformation efforts.

Efficiency gains arise from the automation of repetitive administrative and production tasks, which reduces manual workload, minimizes human error, and increases overall process reliability. For SMEs with limited human resources, even modest efficiency improvements can create significant competitive advantages (Faisal et al., 2023).

Responsiveness and agility are enhanced through real-time data collection and analysis, allowing firms to react faster to market fluctuations, urgent customer requests, or unexpected disruptions. This is particularly important in make-to-order environments, where precision engineering companies must adapt quickly to highly customized demands (Ciampi et al., 2021).

Traceability and compliance improve as digital records provide a transparent audit trail across design, production, and quality control stages. Enhanced traceability not only strengthens compliance with industry standards but also builds customer trust, especially in sectors such as aerospace, automotive, and medical devices, where tolerances are extremely tight (OECD, 2021).

Scalability and modularity are enabled by digital systems that can be deployed in a stepwise manner, allowing SMEs to expand capabilities progressively without committing to a full-scale transformation upfront. This modular approach aligns investments with growth and reduces financial risk (Gonzalez et al., 2024).

As emphasized by Kane et al. (2015), digital transformation is driven less by the adoption of specific technologies than by the ability of firms to leverage them for agility, efficiency, and new value creation. In the context of precision engineering SMEs, this can be interpreted as placing particular emphasis on the capability to generate fast, reliable, and cost-competitive quotations. Because quotation accuracy and lead time are often decisive factors in winning contracts, digital tools that support data-driven costing, scenario

simulation, and integration with production planning can therefore act not only as operational improvements but also as strategic differentiators in increasingly competitive markets.

2.2.2 Barriers to Adoption in SMEs

While digital transformation is gaining momentum, small and medium-sized enterprises (SMEs) often face systemic obstacles that slow down adoption compared to larger firms.

According to Müller et al. (2018), common barriers include:

- Financial constraints: High upfront investment costs and limited ROI visibility
- Skills gap: Lack of internal digital competencies and limited access to specialized talent
- Legacy infrastructure: Inflexible software, outdated machines, and fragmented data systems
- Cultural resistance: Change management challenges and fear of automation among staff

These barriers create a digital divide within the industry, where innovative potential exists but is difficult to unlock without external support, pilot projects, or customized low-cost solutions.

2.2.3 Industry 4.0 as a Framework for Digitalization

The concept of Industry 4.0 provides the theoretical and technological foundation for digital transformation in manufacturing. It encompasses a wide range of technologies that work together to create intelligent, connected, and adaptive production systems, enabling a shift from reactive to proactive operations. The strategic initiative of Industry 4.0 was first outlined by Kagermann et al. (2013), emphasizing the integration of digital and physical processes to enhance manufacturing capabilities.

Key technological components include Cyber-Physical Systems (CPS), which integrate digital control with physical machinery, and the Internet of Things (IoT), which enables real-time data collection from sensors, machines, and products (Hermann et al., 2016). Cloud computing provides scalable storage and processing of industrial data, while big data analytics supports advanced decision-making. Artificial intelligence (AI) further enables prediction, pattern recognition, and intelligent automation, transforming how processes are monitored and optimized (Lasi et al., 2014).

In the context of precision engineering, where small margins, tight tolerances, and short delivery times are critical, these capabilities are particularly valuable. By leveraging Industry 4.0 technologies, SMEs can enhance operational efficiency, improve quality control, and respond more rapidly to customer demands, laying the groundwork for both incremental and transformative digitalization initiatives.

2.2.4 Introduction Digital Transformation in Quotation and Planning Workflows

One of the most tangible applications of digital transformation in precision engineering lies in the modernization of quotation and planning workflows. Traditionally manual, experience-driven, and prone to inconsistency, these processes are increasingly targeted by digital tools aimed at improving speed, accuracy, and strategic value. For instance, Mandolini et al. (2011) present *LeanCost*, a knowledge-based tool designed specifically for early cost estimation in manufacturing by analyzing product design data and automatically generating estimations—demonstrating that quotation processes have indeed been focal points for digitalization efforts within engineering contexts.

a) IoT-Enabled Shop Floor Monitoring

The deployment of IoT technologies allows machines to transmit real-time data about their status, energy usage, and cycle times. According to Kusiak (2018), sensor-equipped machines can significantly improve the accuracy of cost estimation by providing dynamic data on machine availability and operational efficiency. This real-time monitoring also supports predictive maintenance and leaner scheduling, which are critical for SMEs with limited production capacity.

IoT-driven manufacturing enables accurate lead time and cost predictions by capturing live machine data and integrating it into production planning systems (Kusiak, 2018).

b) ERP and Inventory Integration

Modern ERP systems play a central role in unifying operational data relevant for quotations. As demonstrated by Sebayang et al. (2021), ERP compatibility facilitates internal integration of inventory systems across departments, providing shared digital access to real-time stock information and enabling more efficient and error-resistant operations. This integration supports more accurate and data-driven quotations by reducing manual inventory mismatches and enabling quick comparison with previous cost structures.

c) Predictive Analytics and Simulation

The use of AI-powered analytics can simulate different production scenarios, assess risk levels, and generate cost forecasts. As illustrated in contemporary smart manufacturing frameworks (Welland, C. (2023); CostItRight. (2025)), predictive analytics enable manufacturers to anticipate future bottlenecks—whether from machine downtime, material fluctuations, or process disruptions—and incorporate these insights into cost estimation models. Such predictive models facilitate dynamic cost simulation based on evolving production parameters, supporting smarter and more robust decision-making in quotation workflows

Taken together, IoT monitoring, ERP integration, and predictive analytics can be viewed as complementary enablers of more intelligent and responsive quotation workflows. In the context of precision engineering SMEs, these approaches provide practical entry points toward greater digitalization of cost estimation and planning processes. They may also open pathways for more advanced applications, such as AI-assisted cost estimation from technical drawings or dynamic pricing strategies, which are increasingly discussed in recent studies on digital manufacturing.

2.2.5 Digital Transformation as a Strategic Enabler

While digital tools can enhance operational efficiency, their impact extends beyond technical improvements. Digital transformation should be understood as a strategic enabler that reshapes how small and medium-sized enterprises (SMEs) create, deliver, and capture value. Frank et al. (2019) emphasize that digitalization is not merely about adopting new technologies, but about rethinking business models to support adaptability, customer orientation, and sustainability.

In precision engineering SMEs, this strategic dimension becomes visible in several ways. On the one hand, digitally enabled production systems allow for greater customization and modularity, enabling firms to provide tailored solutions at scale while maintaining efficiency (Frank et al., 2019). On the other hand, digital servitization extends the value proposition by combining products with complementary services such as monitoring, predictive maintenance, or collaborative design. This evolution toward product-service systems (PSS) creates new revenue streams and strengthens customer relationships (Coreynen et al., 2017).

These two perspectives—business model transformation through digitalization (Frank et al., 2019) and the expansion of value through servitization (Coreynen et al., 2017)—illustrate that digital transformation in SMEs is not a simple technology upgrade. Rather, it is a strategic enabler that redefines competitive positioning and long-term growth opportunities.

2.2.6 Summary

The quotation workflow is undergoing a paradigm shift. IoT-driven monitoring tools and predictive analytics enable firms to move from static, experience-based quotations toward dynamic, data-enriched systems. Yet, realizing this vision requires not only technical innovation but also organizational readiness and strategic alignment (Kane et al., 2015; Kusiak, 2018).

The integration of IoT, ERP systems, and predictive analytics into quotation and planning workflows allows SMEs to modernize their operations, reduce costs, and improve customer responsiveness. More importantly, these tools lay the foundation for broader strategic shifts toward customization, servitization, and sustainability.

2.3 The Role of Business Intelligence (BI) in Precision Engineering

2.3.1 Introduction to BI

BI refers to the technologies, strategies, and practices used to collect, analyze, and visualize business data to support decision-making (Chaudhuri et al., 2011). In precision engineering, where accuracy, efficiency, and real-time monitoring are crucial, modern BI tools such as Power BI, Tableau, and Qlik Sense enable companies to track key performance indicators (KPIs), optimize operations, and enhance sustainability efforts.

The integration of BI into precision engineering provides several key benefits. Recent studies highlight that BI enhances decision-making by enabling data-driven insights in real time, improves operational efficiency by identifying bottlenecks and reducing

downtime, supports sustainability monitoring by tracking energy use and emissions, and strengthens predictive capabilities by anticipating equipment failures and maintenance needs (Trieu, 2017).

As emphasized by Malawani et al. (2025), BI should not be seen merely as a set of technological tools but as an analytical infrastructure that builds organizational agility and strategic responsiveness in dynamic environments. This reinforces its role as a cornerstone for SMEs aiming to improve competitiveness while advancing sustainability.

2.3.2 BI for Sustainable Manufacturing

BI tools play a critical role in advancing sustainable manufacturing by enabling firms to monitor and optimize environmental performance. As demonstrated by Al-Hyassat and Ghasemi (2025), BI capabilities enhance green supply chain management and operational integration, which in turn significantly elevate environmental outcomes. These platforms synthesize data from diverse sources—such as IoT sensors and production systems—to track energy use, material inefficiencies, and waste generation; by visualizing such metrics, organizations can identify improvement areas, automate environmental reporting, and align with sustainability standards like ISO 14001 and the Global Reporting Initiative (GRI).

However, despite these capabilities, the integration of BI platforms with corporate management systems has been lacking, even among leaders in sustainability. Bergh et al. (2024) highlight that while BI enables manufacturing companies to gain insights and make environmentally friendly choices, its full potential remains underutilized due to insufficient integration with existing management systems. This underutilization hinders the adoption of more sustainable practices and the realization of the strategic benefits that BI can offer in the context of sustainable manufacturing.

By addressing these integration challenges and leveraging BI alongside AI and Industry 4.0 technologies, manufacturers can transition towards data-driven, sustainable production models that reduce environmental impact while enhancing operational resilience.

2.3.3 Challenges in Implementing BI in Precision Engineering

Despite its advantages, BI adoption in precision engineering comes with several challenges. Prior studies have consistently highlighted issues of data integration—since legacy systems are often incompatible with modern BI tools—alongside skill gaps, where employees lack the analytical and technical expertise to fully exploit advanced functionalities (Chaudhuri et al., 2011; Popovič et al., 2012). In addition, high implementation costs related to infrastructure upgrades, cloud storage, and cybersecurity remain significant barriers, particularly for SMEs with limited resources (Isik et al., 2013).

To address these obstacles, progressive implementation strategies have been proposed, emphasizing phased deployment, employee training, and system upgrades. As noted by Wixom and Watson (2010), a stepwise approach increases the chances of successful BI adoption by aligning technological change with organizational learning and capacity building.

2.3.4 Future of BI in Precision Engineering

As Industry 4.0 continues to evolve, Business Intelligence (BI) is expected to increasingly integrate AI-driven analytics, edge computing, and immersive data visualization techniques. Studies emphasize that BI—and particularly BI combined with advanced analytics—serves as a foundational enabler of strategic value in smart manufacturing, strengthening decision-making and adaptive operations (Bordeleau et al., 2020).

Future-oriented developments include AI-powered BI systems capable of providing predictive recommendations for real-time process optimization, edge analytics enabling decentralized low-latency decisions, and sustainability-driven BI innovations incorporating emissions forecasting and real-time energy optimization (AtScale, 2025). By combining BI with AI and sustainability-focused strategies, precision engineering companies are expected to progress toward next-generation, eco-efficient, and adaptive manufacturing systems (AtScale, 2025).

In practice, concrete solutions such as Microsoft's Power BI demonstrate how these trends are already being applied. Power BI enables real-time data visualization, predictive analytics, and sustainability monitoring within manufacturing workflows. For instance, it can track machine utilization, defect rates, and throughput efficiency, while integrating AI models to anticipate maintenance needs and reduce unplanned downtime. Its supply chain analytics functions support the monitoring of material consumption, supplier performance, and inventory fluctuations, contributing to waste reduction and improved logistics. On the sustainability side, Power BI provides reporting features that dynamically measure carbon footprints, energy use, and compliance with environmental regulations. A recent case study in the heavy manufacturing sector illustrates these benefits, showing that Power BI implementation improved equipment performance, reduced downtime, and enhanced operational efficiency (Beyond Digital, 2024).

2.4 AI and Document Intelligence for Technical Drawings in SMEs

In the context of digital transformation for precision engineering SMEs, Artificial Intelligence (AI) is becoming a practical tool to unlock value from previously untapped resources: unstructured data. This includes technical documents, scanned drawings, handwritten notes, voice memos, and free-form email exchanges that traditionally resisted automation.

Engineering-specific challenges arise because technical drawings and engineering plans contain symbols, geometric annotations, and domain-specific notations that make them difficult for AI and Optical Character Recognition (OCR) systems to interpret. These challenges make precision engineering an especially relevant context for Document Intelligence (Cutting et al., 2021). Recognizing this, OCR-based processing of technical drawings becomes a core example of how AI can support SMEs, bridging the gap between unstructured input and actionable data.

Recent advances in Document Intelligence, powered by Large Language Models (LLMs), OCR, and voice recognition, are transforming how such data can be understood, structured, and exploited. For instance, domain-adapted LLMs have shown strong capabilities in interpreting specialized engineering text and annotations (Naveed et al., 2023). OCR systems continue to improve in extracting structured information from complex technical drawings (Schlagenhauf et al., 2022), while AI-powered voice

recognition allows engineers to input data verbally, reducing manual entry and accelerating documentation processes (Beňo et al., 2023). This section highlights their relevance in the SME industrial context and presents use cases that bridge current capabilities and future potential, with OCR for engineering drawings serving as a central illustration.

2.4.1 From Structured to Unstructured: The Data Challenge in SMEs

While many digital initiatives in SMEs focus on structured data—such as ERP databases, CAD models, or production logs—these organizations often rely heavily on informal or legacy data formats for critical business processes, particularly in quotation, planning, and communication. Examples of such unstructured data include:

- PDFs of customer drawings with annotated specifications
- Handwritten estimates or workshop notes
- Emails containing client requirements or feedback
- Oral explanations during internal reviews or client calls

This unstructured data contains a wealth of operational and strategic information but often remains underutilized due to the lack of tools capable of interpreting it at scale. AlKendi et al. (2024) highlight that SMEs face significant challenges in managing and leveraging unstructured data, including limited resources, lack of technical expertise, and the absence of structured frameworks for data utilization. Their research emphasizes the need for SMEs to develop systematic approaches to identify problems, develop solutions, and resolve issues related to unstructured data, in order to effectively harness its potential for business improvement.

2.4.2 Optical Character Recognition (OCR): Unlocking Information from Technical Drawings

In precision engineering SMEs, one of the key tasks is to extract structured information from technical drawings for quotations, production planning, and quality control. This includes dimensions, tolerances, material types, and surface treatments. Currently, this process is largely manual, time-consuming, and error-prone, due to the complexity of engineering drawings. Standard OCR engines struggle to handle non-standardized layouts, special symbols such as tolerances or geometric notations, rotated or vertical text, and the noise or shading often present in scanned documents (Schlagenhauf et al., 2022).

Recent advances in deep learning-based OCR methods have started to address these challenges. Convolutional neural networks (CNNs) and attention-based Transformers can learn complex layout and symbol patterns, significantly outperforming traditional OCR approaches in technical contexts (Li et al., 2021). Lightweight OCR pipelines optimized for industrial applications, such as PP-OCR, have also demonstrated robust performance on multi-format documents and engineering diagrams (Du et al., 2020).

By leveraging these advanced OCR technologies, SMEs can progressively automate the extraction of critical information from PDF plans and scanned drawings, enabling the

storage of data in structured formats for quotations, production planning, and historical analysis. OCR thus acts as a bridge between legacy documentation and modern digital workflows, transforming previously unstructured engineering knowledge into actionable data (Schlagenhauf et al., 2022).

2.4.3 Large Language Models (LLMs): Understanding Technical Language

Large Language Models (LLMs), such as OpenAI's GPT-4, Google's Gemini, and Meta's LLaMA3, represent a major step forward in natural language processing, offering advanced capabilities in text comprehension and generation. These foundation models are trained on large-scale datasets and can be adapted to specific tasks with limited fine-tuning, making them relevant for SMEs in precision engineering where structured and unstructured technical information needs to be processed efficiently (Bommasani et al., 2021).

In this context, LLMs can support practical applications such as extracting key information from free-text documents (e.g., materials, machining operations, deadlines, or standards), classifying the intent of communications, or summarizing long email chains into concise insights. They may also assist through conversational interfaces that guide quotation or documentation tasks, and help engineers compare technical specifications across document versions. These applications suggest that LLMs can reduce cognitive workload for estimators and engineers, while improving the consistency of knowledge handling (Bommasani et al., 2021).

Nevertheless, the reliability of LLMs in engineering contexts remains an open question. A recent evaluation of GPT-4, Gemini, and LLaMA3 across multiple language processing benchmarks highlighted both their strengths in general reasoning and their limitations in domain-specific precision. Performance was shown to vary depending on task complexity, technical vocabulary, and contextual requirements, indicating that outputs should be validated before use in tasks demanding engineering-level accuracy (Du et al., 2025).

Despite these constraints, LLMs hold potential to transform unstructured technical inputs into actionable data for SMEs. When combined with complementary technologies such as optical character recognition (OCR) and voice recognition, they can play a role in accelerating quotation, planning, and documentation processes within precision engineering firm.

2.4.4 Voice Recognition: Enabling Hands-Free and Context-Aware Input

In industrial environments, particularly on the shop floor or during inspections, manual data entry is often impractical and time-consuming. Voice recognition technologies provide a natural and ergonomic alternative, enabling hands-free interaction with digital systems. Modern voice-based interfaces can transcribe spoken input into text, including domain-specific terminology relevant to precision engineering, and interpret simple voice commands to access information or initiate processes. When integrated with other AI tools such as OCR and LLMs, voice recognition may support multi-modal understanding, for example by linking spoken instructions with visual content on technical drawings (Radford et al., 2022).

One potential application is in quotation workflows: estimators could dictate part specifications while reviewing drawings, with the system assisting in structuring the information and referencing historical data. Such use may improve operational efficiency, enhance traceability, and support less experienced staff by providing AI-assisted guidance (Radford et al., 2022).

2.5 Integrated Document Intelligence in the Quotation Workflow

2.5.1 Conceptual Overview of the Document Intelligence Workflow

The integration of OCR, Large Language Models (LLMs), and voice recognition enables SMEs to develop a fully digitized, intelligent quotation pipeline. This workflow directly addresses the challenges outlined in Section 1.2 (Problem Statement), such as reliance on unstructured inputs, tacit knowledge dependence, and limited automation. It also operationalizes the research objectives defined in Section 1.3, combining formalized expertise, AI-based data extraction, and feedback mechanisms into a coherent, semi-automated quotation process (Khan et al., 2025).

The workflow can be conceptualized as follows:

Step 1: Input

- Customer sends a PDF drawing and provides a verbal description of requirements.
- Unstructured inputs include technical symbols, annotations, and spoken instructions.

Step 2: Processing

- OCR extracts dimensions, tolerances, materials, and other relevant parameters from technical drawings.
- LLMs interpret specifications, classify semantic content, and link features to previous cases.
- Voice recognition converts spoken information into structured data for integration.

Step 3: Knowledge Integration

- The system compares extracted features with historical quotations and expert rules.
- It applies formalized logic (as developed in the Excel-based tool, Section 4.3.1) to estimate costs and production time.

Step 4: Output and Feedback

- Generates a draft quotation including justification and delivery estimate.

- Supports human validation, allowing adjustments and knowledge refinement.
- Data can feed back into dashboards for monitoring performance (Section 1.3.2) and continuous improvement.

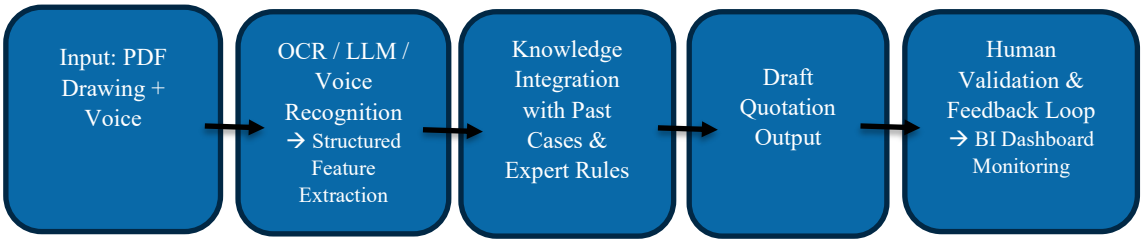

Figure 2: Integrated Document Intelligence Workflow for SME Quotation Process

This conceptual pipeline illustrates how Document Intelligence operationalizes the research objectives by:

- Formalizing tacit expert knowledge,
- Processing unstructured inputs, and
- Enabling traceable, repeatable, and semi-automated quotation decisions.

2.5.2 Risks, Limitations, and Human Oversight

The integration of AI tools into quotation processes offers substantial potential for improving efficiency and decision-making; however, it must be approached with careful consideration of the associated technical, ethical, environmental, and organizational risks. AI systems are inherently fallible: they may misinterpret ambiguous texts or drawings, generate "hallucinations" (particularly in large language models), or induce quality drift if over-relied upon. In precision engineering quotation contexts, even minor misinterpretations can propagate through the process, resulting in cost overruns, delivery delays, or reduced competitiveness (Binns, 2018; Jaekel et al., 2022).

Beyond technical limitations, AI deployment introduces significant ethical and societal considerations. One primary risk is inbuilt bias: language and vision models are trained on large datasets that may contain structural biases or blind spots. Such biases can influence classification, text interpretation, or decision-support outputs, potentially constraining rather than enhancing human judgment. For instance, biased training data could distort the interpretation of machining tolerances or material properties, producing unsafe or suboptimal recommendations (Mehrabi et al., 2021; Sun et al., 2019).

Another critical concern is the risk of over-delegation. Automation may inadvertently shift responsibility from skilled human operators to opaque AI systems. Without clear oversight and accountability mechanisms, SMEs may adopt AI tools that appear authoritative but lack contextual awareness—particularly hazardous in precision engineering, where expert judgment remains central (Leitão et al., 2022; Victores, 2024).

Data privacy and confidentiality constitute additional key risks. Transmitting customer drawings, RFQs, or internal cost models to external AI platforms can expose sensitive intellectual property, which is especially critical in aerospace, medical device, and defense sectors. SMEs must ensure compliance with contractual obligations and data protection regulations to mitigate these risks (European Commission, 2021).

From an environmental perspective, while AI can facilitate sustainability by reducing rework or optimizing quotations, it also introduces substantial environmental burdens. Large AI models require significant computational resources during both training and inference, generating a non-negligible carbon footprint. For SMEs, inefficient or excessive use of cloud-based AI may conflict with sustainability objectives, especially when simpler low-code or rule-based systems could suffice (Strubell et al., 2019). Additionally, frequent hardware upgrades, GPU demands, and cloud-provider dependencies increase e-waste and resource consumption (Hilty & Aebischer, 2015).

The literature consistently emphasizes that AI should augment rather than replace human expertise. Human-in-the-loop approaches are critical for ensuring safe and reliable outcomes, particularly in high-stakes technical contexts. AI deployment often relies on "loopholes"—misalignments between prescribed rules and real-world human-AI interaction—which necessitate systematic oversight (Victores, 2024). Multi-layered human oversight frameworks are indispensable for mitigating hallucinations and errors in LLMs or vision-based systems, ensuring contextualized, accurate decision support (Leitão et al., 2022).

For precision engineering SMEs, these considerations imply that AI should function strictly as a controlled assistant, not an autonomous estimator. Human validation remains essential to safeguard quality, ensure contextual interpretation, and maintain reliability, particularly when handling complex geometries, unstructured inputs, or client-specific requirements.

2.5.3 Strategic Value for SMEs

For SMEs in the precision engineering sector, the adoption of AI-driven document intelligence tools holds significant operational, strategic, and sustainability value. These tools streamline quotation and documentation processes by enhancing speed, consistency, and accuracy, thereby reducing the margin for human error and accelerating response times. More importantly, they enable firms to retain and reuse expert knowledge that would otherwise be lost—addressing critical challenges in knowledge management for SMEs.

From a strategic risk management perspective, recent literature underscores how AI integration can strengthen resilience and competitive positioning for SMEs. Sotamaa, et al. (2024) illustrate that AI-enhanced technologies are essential components in SME risk management frameworks, helping these firms build adaptive capacities and respond to disruptive events more effectively. Incorporating document intelligence solutions aligns with this trend by providing a structured means to mitigate risks tied to knowledge loss and process variability.

Sustainability also emerges as a key benefit. Document intelligence reduces rework, improves quotation accuracy, and supports predictive planning—all of which contribute to efficient use of resources and lower carbon emissions. In resource-constrained

industrial settings rich in data but limited in manpower, such tools are not optional extras but strategic levers that enhance both competitiveness and long-term viability.

In summary, the theoretical framework highlights the central challenges of digitalizing quotation processes in precision engineering SMEs, particularly regarding tacit knowledge, fragmented data, and adoption constraints. Since this thesis not only analyzes these challenges but also seeks to design and evaluate digital solutions, a design-oriented research methodology is required. The specific methodological framework chosen for this purpose will be presented in Chapter 4, while the next chapter reviews the relevant literature on quotation processes, digital tools, and sustainability in SMEs.

3 Literature Review

In the context of Industry 4.0, the quotation process in precision engineering SMEs can be interpreted as increasingly complex and knowledge-intensive. Estimating the feasibility, cost, and production time of custom parts often relies on incomplete technical data, oral instructions, or unstructured drawings, which in practice depends heavily on the tacit knowledge of experienced operators. As pressures for flexibility, traceability, and speed increase, these informal practices may show limitations in terms of reliability, scalability, and sustainability.

This literature review aims to explore how digital technologies—ranging from data analytics and AI to OCR and low-code tools—can be leveraged to modernize and formalize the quotation process in precision engineering SMEs. More specifically, it investigates the intersection of three dimensions:

- the technical and cognitive complexity of quotation in high-variability, low-volume contexts;
- the digital strategies and tools (both academic and commercial) proposed to support or automate these tasks;
- the sustainability goals (resource efficiency, circularity, carbon reduction) that are increasingly shaping industrial estimation practices.

This review also serves a dual purpose: it positions the research within an emerging field of interest at the convergence of operational excellence and digital transition, and it identifies the scientific and practical gaps that the thesis seeks to address. Most of the reviewed studies focus on either large-scale industries or specific subproblems such as feature recognition or cost modeling. Very few tackle the quotation process as a whole, especially in contexts where limited digital infrastructure, informal practices, and multidisciplinary constraints coexist—precisely the reality faced by many precision engineering SMEs.

To structure this literature review, we organize it into five major sections:

- **Section 3.1** presents the quotation process in precision engineering SMEs, focusing on its specific challenges and reliance on tacit knowledge.
- **Section 3.2** explores how artificial intelligence, OCR technologies, hybrid systems, and low-code tools (such as Excel and Power BI) can support the automation of quotation processes, the extraction of technical knowledge, and the formalization of decision-making workflows.
- **Section 3.3** links quotation to sustainability objectives, showing how digital estimation can contribute to energy efficiency, resource optimization, and circularity.
- **Section 3.4** reviews concrete examples from both industry and academic research, comparing their applicability to SME contexts.
- **Finally, section 3.5** synthesizes the insights gained and highlights the gaps and opportunities that justify the proposed methodological approach of this thesis.

Through this literature review, we aim to build a strong theoretical foundation for the experimental and design-based contributions presented in the following chapters.

3.1 The Quotation Process in Precision Engineering SMEs: Specificities and Challenges

The quotation process lies at the core of business operations in precision engineering SMEs. It bridges the technical and economic dimensions of manufacturing, determining whether a company will secure a contract and whether that contract will be profitable. Despite its strategic importance, the quotation process remains under-digitalized, highly dependent on experience, and insufficiently studied in the context of small and medium-sized enterprises.

3.1.1 Strategic Importance of Quotation in Make-to-Order Contexts

In precision engineering, production is typically organized on a make-to-order (MTO) basis, with each order customized to specific client requirements. This approach means that the quotation process is not merely a pricing exercise but a strategic commitment that influences resource allocation, scheduling, and overall client satisfaction.

As Moodie et al. (1999) emphasize, the process of generating a quotation is clearly a key function in the management of the company and one that can make or break it. This underscores the critical role of accurate and timely quotations in determining the success of MTO operations.

Errors or inaccuracies at the quotation stage can have far-reaching consequences:

- Underpricing erodes already narrow profit margins, particularly critical for SMEs competing in high-precision markets.
- Overpricing reduces competitiveness and may cause customers to seek alternative suppliers.
- Unrealistic lead times damage client trust, leading to lost business and reputational risks.
- Misaligned production planning creates bottlenecks and inefficiencies, propagating delays throughout the value chain.

Beyond these immediate operational risks, the quotation phase also functions as a signal of reliability in the client–supplier relationship. In environments where customization is high and uncertainty significant, firms are judged not only on cost but also on the credibility of their lead-time commitments (Benioudakis et al., 2019). A quotation that balances customer expectations with realistic production capabilities strengthens long-term partnerships and builds trust, while systematic misestimations undermine the company's position in the supply chain.

Moreover, Benioudakis et al. (2019) show that in unobservable MTO systems, where customers lack full visibility into production processes, quotations play a dual role: they

provide information to customers while also shaping demand through perceived risk. For SMEs, this is particularly relevant, as strategic customers may adjust their ordering behavior depending on the firm's lead-time promises. This means that quotation management is not only about internal efficiency but also about managing customer perceptions and behaviors.

In this context, improving the quotation process becomes a powerful lever for competitiveness, especially for precision engineering SMEs operating with limited margins for error. A well-structured quotation system enables better risk management, aligns production with demand, and creates a foundation for data-driven performance improvements. Far from being an administrative step, the quotation process is therefore a strategic enabler, determining how effectively a company can position itself in increasingly dynamic and customer-driven markets.

3.1.2 The Central Role of Tacit Knowledge

In most precision engineering SMEs, the quotation process is predominantly carried out by senior staff—often the company owner, a production manager, or a senior technician—who rely heavily on tacit knowledge rather than formalized models or standardized procedures. This expertise encompasses an understanding of machining processes, equipment capabilities, supplier relationships, and the anticipation of potential manufacturing risks (Adesina & Ocholla, 2024; AlKendi et al., 2024). Such knowledge enables rapid decision-making, flexible adaptation to unusual orders, and nuanced judgment in complex or unforeseen situations.

However, this reliance on human expertise also introduces vulnerabilities. Quotation quality may vary between staff members, and the company becomes dependent on a limited number of individuals. Tacit knowledge is inherently personal, context-specific, and difficult to codify (Adesina & Ocholla, 2024; Tacit Knowledge Sharing, 2014), making its preservation and transfer particularly critical in SMEs where resources for formal knowledge management systems are limited.

Externalizing and formalizing this knowledge is essential to ensure continuity, scalability, and resilience, especially as experienced staff may retire, take leave, or become unavailable due to workload pressures. Failure to capture tacit knowledge can create operational bottlenecks, delaying responses to client requests and impacting overall efficiency (AlKendi et al., 2024).

Recent advances in document intelligence—including optical character recognition (OCR), AI-based extraction of technical information, and voice recognition—offer SMEs practical tools to partially formalize tacit knowledge embedded in drawings, handwritten notes, and verbal instructions. By converting previously unstructured information into structured formats, SMEs can retain critical expertise, improve traceability, and reduce dependency on individual staff members, without sacrificing flexibility or domain-specific judgment (Khan et al., 2025).

In conclusion, tacit knowledge is both a strategic asset and a potential risk. Its proper management—through partial formalization, digitization, and knowledge-sharing practices—enables SMEs to maintain high-quality quotations, support scalability, and mitigate operational risks in highly customized, make-to-order production environments.

3.1.3 Estimating Costs in a Context of Complexity and Uncertainty

The cost estimation process in precision engineering has long been recognized as highly complex and uncertain—particularly in make-to-order (MTO) environments. Traditional methods such as activity-based costing (ABC) or parametric models often lack sufficient granularity to capture the wide variety of technical, operational, and market variables that influence actual costs.

H'mida et al. (2006) introduced the Cost Entity approach, which connects product features with economic variables to create more structured and reliable cost models. Similarly, Niazi et al. (2006) provided a comprehensive review of cost estimation techniques, categorizing them into analytical, empirical, and hybrid approaches, and highlighting that no single method is universally sufficient across all manufacturing contexts. These works demonstrate that the challenges of cost estimation are not recent but have been a persistent issue in manufacturing for decades, especially as complexity and customization have increased.

In precision engineering SMEs, these challenges stem from multiple cost drivers: setup and changeover times influenced by machine states and part complexity; machine toolpath strategies and CNC capabilities; post-processing operations such as heat treatment or surface finishing; and highly variable quality control requirements. Uncertainty further compounds these difficulties, with fluctuations in raw material prices, supplier delays, and last-minute client design changes creating significant deviations between quotation and actual execution.

Recent advances, however, offer new solutions. Arıkan et al. (2025) show that AI-based predictive cost models using automated feature extraction from technical drawings, historical production data, and machine parameters can mitigate these risks. By dynamically combining technical, operational, and market dimensions, SMEs can improve quotation accuracy, optimize resource allocation, and enhance client trust in competitive markets.

In conclusion, cost estimation in precision engineering is inherently multi-dimensional and uncertain. Traditional research (H'mida et al., 2006; Niazi et al., 2006) laid the foundations by structuring and classifying cost estimation methods, while recent digital approaches (Arıkan et al., 2025) demonstrate the potential of AI and data-driven systems to transform quotation accuracy and reliability. The integration of these perspectives highlights the enduring challenge of cost estimation and the growing strategic value of digital tools in addressing it.

3.1.4 Tools Currently in Use: Strengths and Gaps

Despite the growing availability of digital solutions, many precision engineering SMEs continue to rely extensively on spreadsheets (e.g., Excel) or even pen-and-paper methods for quotation processes. A study of enterprises in the UK found that approximately 53 % of smaller SME employers used spreadsheets for record-keeping, with many still resorting to paper-based records in parallel (UK Government, 2023). This persistence of manual tools is driven by practical advantages: spreadsheets and paper offer flexibility that aligns with estimators' individual habits and established practices; they demand minimal licensing costs or specialized training, making them accessible in resource-constrained settings; and they operate independently of network connectivity or cloud infrastructure, providing autonomy in environments with limited IT support.

However, the reliance on these conventional tools introduces significant limitations in make-to-order manufacturing. Quotations may be based on outdated production or inventory data due to lack of integration; traceability and data security are often weak, increasing risks of errors, data loss, or non-compliance. These tools typically lack the ability to simulate alternative production scenarios, test assumptions, or create learning loops from past quotation deviations, which inhibits strategic decision-making and continuous improvement. Nederkoorn (2017) analyzed the quotation process as a chain of inputs, outputs, and feedback loops, showing that dependence on informal or manual tools can degrade information flow and responsiveness. Meanwhile, barriers such as limited financial resources, organizational resistance to change, and lack of digital expertise continue to slow the adoption of advanced knowledge management and digital quotation systems in SMEs (AlKendi et al., 2023).

To mitigate these gaps, many firms are adopting hybrid solutions: for example, spreadsheet-based quotation assistants, lightweight ERP quotation modules, or tools combining rule-based systems with historical databases. These incremental adaptations enable SMEs to enhance accuracy, traceability, and collaboration without abandoning the operational agility afforded by simpler, familiar tools.

3.1.5 Toward the Formalization of Quotation Knowledge

Digital transformation offers precision engineering SMEs a unique opportunity to gradually formalize the knowledge embedded in the quotation process, converting tacit expertise into structured and actionable information. However, full automation is neither feasible nor desirable in many contexts, as human judgment remains crucial for handling complex, customized orders.

As highlighted by Fortes et al. (2023) and Le Duigou et al. (2010), hybrid approaches combining rule-based systems, historical databases, and expert-driven interfaces represent the most effective pathway for capturing and reusing quotation knowledge. Rule-based elements help standardize repetitive tasks and reduce errors, while historical data supports analogy-based estimation by allowing comparisons with past projects. At the same time, user-oriented interfaces make it possible to explicitly capture expert judgment, thereby ensuring traceability and supporting the transfer of experience between staff members.

This perspective aligns with studies on engineering-to-order (ETO) manufacturing, where quotation and planning require integrating technical, financial, and organizational dimensions in order to balance efficiency and flexibility (Fortes et al., 2023). In addition, Product Lifecycle Management (PLM) principles provide a framework for linking technical data with business processes and for formalizing workflows without sacrificing adaptability (Le Duigou et al., 2010).

Practical implementations of this hybrid vision already exist in the form of quotation assistants developed in spreadsheets, cost models integrated in business intelligence platforms such as Power BI, or OCR-enabled drawing readers. These tools illustrate how SMEs can begin capturing tacit knowledge incrementally, while retaining operational agility and avoiding disruptive changes to established practices.

In summary, the quotation process in precision engineering SMEs is deeply embedded in organizational culture, heavily influenced by experience, and subject to multiple sources of variability. Hybrid digital solutions allow SMEs to gradually formalize expertise, reduce dependency on individual staff, and lay the foundation for more

intelligent, data-driven quotation systems, without undermining the human expertise that remains essential in highly customized production contexts.

3.2 Digital Technologies as Enablers of Quotation Process Transformation

As identified in the previous section, the quotation process in precision engineering SMEs is often informal, reliant on expert intuition, and under-digitalized. However, recent advances in digital technologies offer significant opportunities to augment and partially automate key steps of this process. These technologies not only improve efficiency and accuracy but also contribute to knowledge capture and organizational learning—critical components for sustainable competitiveness in Industry 4.0 environments.

3.2.1 Excel-Based Expert Systems: From Spreadsheets to Structured Knowledge

Expert systems, broadly defined as computer-based tools that codify decision rules and expert knowledge, have long been applied in engineering cost estimation and quotation (Yoo et al., 2020). In the context of SMEs, however, these systems are often implemented in their simplest form: spreadsheet-based tools, with Microsoft Excel being the most common platform due to its accessibility, flexibility, and low cost (Nugroho et al., 2024).

Although Excel is not an expert system in the traditional AI sense, it functions as a "low-cost expert system" by embedding predefined logic for cost calculations, lookup tables for standard operations, and user-friendly input mechanisms such as drop-down menus or macros. This enables SMEs to formalize tacit estimation knowledge within a familiar environment, progressively reducing reliance on individual expertise while retaining flexibility. Nugroho et al. (2024) show that structured training in Excel significantly improves SMEs' ability to process and analyze business data, enhancing efficiency and decision-making.

However, spreadsheet-based expert systems present well-documented limitations. First, they have scalability issues: as quotation complexity grows, spreadsheets become harder to maintain, prone to formula errors, and unable to handle large or interconnected datasets effectively (Panko, 2008). Second, they offer limited cross-departmental integration—Excel files are often stored locally or shared via email, which can result in versioning problems, data silos, and weak traceability. Finally, the lack of built-in security and audit trails increases risks of error and compliance failures, especially when quotations must integrate technical, financial, and operational data.

These shortcomings highlight why many SMEs eventually complement or replace spreadsheet-based systems with more advanced digital solutions such as ERP modules, Business Intelligence (BI) tools, or AI-driven applications. Yet, given their familiarity and low barrier to entry, spreadsheets remain a pragmatic first step toward the digitalization of quotation processes, serving as transitional expert systems that allow SMEs to formalize knowledge incrementally before moving to more integrated platforms.

3.2.2 Power BI for Interactive Cost Monitoring and Historical Analysis

Business Intelligence (BI) systems, such as Microsoft Power BI, offer SMEs a robust environment to monitor historical quotation data, production performance, and cost-related metrics in an interactive and visual manner (Ranjan, 2009; Wixom et al., 2014). In precision engineering, where each quotation is highly customized, integrating BI tools into the workflow provides actionable insights that were previously difficult to obtain.

BI platforms enable trend identification, allowing companies to visualize cost deviations, lead times, and performance across similar parts, product families, or customer orders. Such visibility helps detect recurring patterns, anomalies, or systematic underestimations, supporting proactive decision-making and resource optimization (Sharma et al., 2019; Howson, 2014). Benchmarking and comparative analysis is another key strength: SMEs can compare new quotations with historical cases, reducing dependency on individual estimators' tacit knowledge and promoting consistency across the organization (Chaudhuri et al., 2011; Turban et al., 2018).

Additionally, BI tools support predictive modeling for lead times and cost estimates by integrating data from ERP systems, machine monitoring platforms, and time-tracking tools. Scenario analysis and "what-if" simulations allow SMEs to evaluate the impact of uncertainties such as material price volatility, supplier delays, or client-driven modifications before finalizing quotations (Sharma et al., 2019; Wixom et al., 2014). This strengthens the strategic value of the quotation function and enhances operational resilience.

Beyond technical capabilities, BI fosters a data-driven culture by encouraging decisions based on empirical evidence rather than intuition. Dashboards and visual analytics facilitate cross-departmental collaboration—sales, production, procurement, and finance—improving transparency and reducing errors due to miscommunication (Howson, 2014; Ranjan, 2009). Over time, the system accumulates historical knowledge, effectively formalizing previously tacit expertise and enabling a hybrid model where human judgment is augmented by automated analytics.

In summary, Power BI transforms the quotation process in precision engineering SMEs by providing visibility, predictive capabilities, and scenario analysis. Its adoption enables more accurate, transparent, and resilient quotation workflows, while supporting strategic decision-making, continuous improvement, and progressive formalization of tacit knowledge (Tirupati et al., 2023; Sharma et al., 2019).

3.2.3 OCR and Drawing Interpretation: Unlocking the Value of Technical Documents

In precision engineering, quotations are frequently based on 2D technical drawings, which include critical information such as dimensions, tolerances, surface finishes, material specifications, treatments, and title block details (e.g., client name, drawing reference, revision). Traditionally, the extraction of this information has been a manual task performed by experienced estimators, a process that is both time-consuming and prone to errors.

Optical Character Recognition (OCR) technologies now provide a powerful alternative by enabling automated reading of technical drawings in PDF format. Modern OCR

engines, such as Tesseract.js, EasyOCR, and ABBYY, can be trained to detect text blocks, numerical values (e.g., ϕ8 ± 0.05 mm), tables, and specialized fonts or orientations commonly found in engineering documentation. When combined with image pre-processing techniques, including noise reduction and contrast enhancement, OCR can reliably extract key features from drawings, which can then populate cost estimation tools or databases. This capability allows SMEs to obtain faster, more consistent specifications, reduce reliance on manual transcription, and automate the identification of similar past parts using drawing metadata.

Recent advances in deep learning have further enhanced OCR performance in complex engineering contexts. Khan et al. (2025) introduced a hybrid framework combining an oriented bounding box (OBB) detection model with a transformer-based document parsing model (Donut), achieving high precision and recall in extracting information from technical drawings. These methods demonstrate that integrating AI-driven OCR with document parsing can significantly improve the speed and reliability of quotation preparation.

In this thesis, a prototype tool was developed to implement automatic "bubbling," identifying and labeling critical text zones to assist OCR extraction and link data directly with quotation tables. This approach represents a concrete step toward integrating unstructured data sources into structured workflows, formalizing tacit knowledge, and improving both efficiency and accuracy in SME quotation processes.

3.2.4 Techniques for Cost Prediction

Beyond spreadsheets and dashboards, advanced digital tools offer SMEs the ability to predict costs and support decision-making, enhancing both accuracy and responsiveness in the quotation process. Artificial intelligence (AI) techniques, in particular, provide flexible solutions for precision engineering SMEs seeking to formalize knowledge and reduce reliance on individual expertise.

Supervised learning models—such as random forests, gradient boosting, and neural networks—can predict machining times and manufacturing costs based on part geometry, tolerances, and material properties. For example, Yoo and Kang (2020) developed a 3D deep learning model capable of estimating CNC machining costs while providing interpretable insights into the key features influencing the results. Similarly, clustering algorithms allow SMEs to segment similar parts, enabling analogy-based cost estimation by referencing historical data, thus supporting partially automated suggestions for estimators without fully replacing human judgment.

Natural Language Processing (NLP) models can process client communications—such as emails, specifications, and notes—to prefill quotation templates, extract relevant context, and reduce manual entry errors. Reinforcement learning (RL) techniques, while not yet widely adopted in quotation workflows, offer a principled approach for learning pricing or bidding strategies from interaction and feedback. RL has been investigated in manufacturing applications such as scheduling, resource allocation, production planning and control, and autonomous shop-floor agents, showing promising results in simulated and pilot settings (Li et al., 2023; del Real Torres et al., 2022). Applied to quotation processes, RL could in principle learn policies that minimise long-term cost deviations or improve win/loss outcomes by using feedback signals (e.g., difference between quoted and realized cost, lead-time deviations), but such applications remain largely experimental in SME contexts and raise practical challenges (data sparsity, reward

design, safety, interpretability). OCR-based document interpretation—already discussed in Section 3.2.3—also represents a complementary AI approach, enabling automated extraction of technical specifications from drawings and integrating them into predictive workflows.

A key challenge for SMEs adopting AI lies in the limited availability of large, structured datasets. Progressive data curation, which links quotation sheets with manufacturing logs and cost metrics, provides a foundation for effective model training. The emergence of AutoML platforms, such as Google AutoML or Microsoft Azure ML, further lowers technical barriers, enabling non-experts to train, evaluate, and deploy predictive models. These resource-efficient approaches exemplify the concept of "frugal AI," making AI adoption more accessible to SMEs. Saleem et al. (2024) highlight that combining AI readiness with frugal innovation strategies can stimulate business model innovation and support incremental digital transformation in small organizations.

In summary, AI-based cost prediction techniques—including supervised learning, clustering, NLP, AutoML, and OCR—enhance the speed, precision, and strategic intelligence of quotation processes. By enabling data-driven estimation without requiring extensive technical infrastructure, these methods help SMEs formalize knowledge, reduce dependency on individual experts, and progressively digitalize their operations in a scalable and sustainable manner.

3.2.5 From Tools to Knowledge Systems: A Holistic Perspective

The integration of diverse digital tools—including expert systems, business intelligence platforms, OCR-powered document interpretation, and AI-driven predictive models—transforms the quotation process from a collection of isolated tasks into a cohesive, knowledge-driven system. Such systems enable organizations to formalize and leverage tacit estimator expertise, creating repeatable and scalable procedures that support decision-making across operational and strategic dimensions (Alavi & Leidner, 2001; Hafeez et al., 2025).

By capturing expert reasoning in structured rules, templates, and simulations, these systems allow historical data to inform current estimations, incorporating feedback loops such as discrepancies between quoted and delivered outcomes. This continuous learning enhances predictive accuracy, mitigates risk, and reduces dependency on individual experts, preserving critical knowledge even as personnel change or junior staff take on more responsibilities (Argyris & Schön, 1978; Hafeez et al., 2025). Moreover, the explicit representation of assumptions, cost drivers, and workflows promotes cross-functional collaboration between sales, production, and procurement teams, improving transparency and decision alignment.

From an organizational learning perspective, these systems support both single-loop learning—correcting errors in estimation—and double-loop learning, where reflection on underlying assumptions and norms fosters strategic resilience and adaptability (Argyris & Schön, 1978). Embedding digital tools within a knowledge management framework also enables SMEs to exploit collaborative strategies, share operational insights, and integrate external knowledge sources, thereby reinforcing innovation capacity and responsiveness to market demands (Hafeez et al., 2025; Alavi & Leidner, 2001).

Despite these advantages, adoption remains uneven among precision engineering SMEs, constrained by limited digital literacy, tight budgets, and cultural resistance to workflow changes. These barriers are widely documented in SME-focused digitalization studies,

which show that small firms tend to lack the internal skills, financial resources, and change-management structures required for implementing advanced technologies (OECD, 2021). Incremental deployment strategies—beginning with familiar platforms such as spreadsheets or low-code analytics tools and gradually incorporating advanced analytics, AI modules, and formal knowledge management practices—allow SMEs to navigate digital transformation in a manageable and sustainable manner. Linking these technological changes with organizational goals for knowledge sharing and sustainability further enhances buy-in and ensures long-term value.

In summary, shifting from disconnected digital tools to integrated knowledge systems elevates the quotation process from a transactional task to a learning-driven operation. This transformation preserves and amplifies organizational expertise, supports continuous improvement, and strengthens strategic agility in SMEs operating within highly customized, make-to-order manufacturing environments.

3.3 Linking Quotation Practices to Sustainability Objectives

As precision engineering SMEs face increasing pressure to reduce their environmental impact and demonstrate responsible practices, the quotation process emerges as a critical touchpoint for embedding sustainability into everyday operations. Traditionally focused on cost, time, and feasibility, quotation workflows are now evolving to integrate environmental and circularity criteria—enabled by digital transformation. This section explores how modern quotation systems can support sustainability goals, with a particular focus on energy efficiency, material use, lifecycle thinking, and process optimization.

3.3.1 Energy Awareness and Carbon Impact Estimation

The quotation stage in precision engineering SMEs represents a strategic entry point for embedding energy awareness and carbon impact into operational decision-making. Beyond estimating costs and lead times, digital quotation systems can integrate energy and carbon metrics, enabling companies to align planning with broader sustainability objectives. Energy efficiency can be considered as a quotation parameter: recent studies show that SMEs can enhance competitiveness by systematically accounting for energy use during planning and estimation (Ketenci & Wolf, 2024). By linking quotation tools with machine-level consumption data—such as kWh per machining cycle or process route—SMEs can estimate the expected energy footprint of a job before production begins. These insights are particularly valuable in non-energy-intensive industries, where energy savings are often diffuse and difficult to identify without structured methods.

Operational energy data and analytics further enhance this capability. Henning et al. (2020) highlight the role of real-time power consumption monitoring in manufacturing enterprises, demonstrating how operational data supports forecasting, anomaly detection, and process optimization. Embedding such analytics within quotation workflows enables SMEs to provide more accurate energy-based cost estimations and benchmark jobs across their portfolio to identify potential efficiency improvements.

Integrating energy and carbon considerations also presents communication challenges. Research indicates that SMEs often struggle to convey energy and carbon information transparently to customers and other stakeholders (Energy Efficiency in SMEs, 2020).

Digital quotation tools that embed standardized carbon coefficients for materials, energy sources, and logistics can help overcome this barrier, allowing SMEs to present carbon-aware quotations that strengthen trust and market positioning.

By combining structured energy-efficiency frameworks (Ketenci & Wolf, 2024), real-time analytics (Henning et al., 2020), and improved communication strategies (Palm & Backman, 2020), SMEs can transform quotations into strategic sustainability instruments. In this way, quotations do more than determine price—they support operational efficiency, environmental accountability, and customer engagement simultaneously.

3.3.2 Material Efficiency and Waste Reduction

Material efficiency is increasingly recognized as a cornerstone of sustainable manufacturing, and its integration into quotation practices provides SMEs with both economic and environmental benefits. Digital quotation tools—whether Excel-based estimators or Power BI dashboards—can incorporate parameters such as material yield, scrap rates, and recyclability, allowing companies to minimize waste already at the planning stage. By simulating alternative production routes or material choices, estimators can identify the most resource-efficient options, optimize stock utilization, and promote the adoption of recycled or locally sourced materials.

A particularly relevant framework is provided by Reike, Vermeulen, and Witjes (2018), who explore material value retention strategies within the circular economy. Their work highlights how concepts such as reuse, refurbishment, and recycling can be operationalized through systematic evaluation of material flows. Applied to quotation systems, this means estimators can go beyond cost calculations to actively design for circularity—embedding waste reduction targets, tracking potential material recovery, and assessing the long-term value retention of different material choices. By integrating these principles, SMEs can transform the quotation process into a lever for circular resource management, aligning short-term cost efficiency with long-term sustainability objectives.

3.3.3 Circularity and Lifecycle Considerations

Embedding circularity and lifecycle perspectives into quotation processes enables SMEs to move beyond a narrow focus on short-term production costs, addressing instead the long-term environmental and economic impacts of manufactured parts. Lifecycle cost estimation tools can be incorporated into digital quotation workflows to account for durability, reparability, modularity, and end-of-life recovery. This approach is especially relevant in sectors such as aerospace, automotive, or high-precision equipment, where total cost of ownership (TCO) and sustainability considerations strongly influence purchasing decisions.

As Kirchherr, Reike, and Hekkert (2017) argue, the circular economy is not only about recycling but about integrating systemic design principles that extend product lifespans, promote reuse, and ensure value retention across the lifecycle. Applied to quotation systems, this means SMEs can enhance their offers by including lifecycle-oriented indicators—such as disassembly potential, expected maintenance intervals, or refurbishment options. Doing so positions them strategically in markets where customers increasingly demand both economic efficiency and environmental

responsibility, while also reinforcing the firm's capacity to align operational practices with broader sustainability goals.

3.3.4 Multi-Criteria Decision Support

Integrating sustainability into quotation processes inevitably involves balancing multiple, and sometimes conflicting, objectives—such as cost, lead time, product quality, and environmental performance. To address this complexity, SMEs increasingly adopt multi-criteria decision support (MCDM) approaches that enable systematic evaluation of alternatives. Digital quotation systems enhanced with visualization platforms like Power BI or Excel-based models can embed such frameworks, allowing decision-makers to assess trade-offs transparently and justify their choices.

As Govindan, Rajendran, Sarkis, and Murugesan (2015) emphasize, MCDM methods provide a structured basis for evaluating sustainability dimensions alongside traditional business priorities, thereby improving both operational alignment and strategic clarity. Applied within quotation workflows, these methods transform what was often a tacit or subjective evaluation into a formalized and traceable process. This not only strengthens collaboration between engineering, sales, and management teams but also enhances customer trust, as quotations increasingly reflect both financial and environmental accountability.

3.3.5 Strategic Benefits of Sustainability-Oriented Quotation

Embedding sustainability into quotation processes delivers more than compliance with regulatory or ethical frameworks; it can also generate tangible strategic advantages. SMEs that integrate resource efficiency, carbon awareness, and material optimization into their quotation workflows can differentiate themselves in increasingly sustainability-driven supply chains. In industries where ESG (Environmental, Social, and Governance) criteria guide procurement, the ability to provide sustainability metrics directly in the quotation stage enhances credibility and strengthens competitive positioning.

As Porter and Kramer (2011) argue in their concept of *Creating Shared Value*, firms that align business practices with societal and environmental needs unlock new opportunities for innovation and long-term growth. Applied to precision engineering SMEs, this implies that sustainability-oriented quotations do not merely improve operational efficiency but also foster a broader cultural transformation, where employees and managers alike begin to evaluate decisions through both financial and environmental lenses. This cultural shift reinforces continuous improvement across the lifecycle of products and services, establishing sustainability as a central driver of strategic differentiation.

3.4 Concrete Applications of AI in the Quotation Process for SMEs

This section presents real-world examples of how small and medium-sized enterprises (SMEs) are leveraging Artificial Intelligence (AI) technologies—specifically Optical Character Recognition (OCR), Large Language Models (LLMs), and voice recognition—to enhance their quotation processes. These case studies illustrate the practical implementation of AI tools in automating and streamlining the extraction of technical

information from unstructured documents, thereby improving efficiency, accuracy, and scalability in quotation workflows.

3.4.1 AI-Driven Quotation Generation in Manufacturing

A notable example is AMFG's real-time quoting software, which enables manufacturers to swiftly generate quotes and promptly respond to customer inquiries by automating the quoting process and applying AI algorithms to analyze data. This approach significantly reduces the time required to prepare quotations, enhancing responsiveness and accuracy in the quoting process (AMGF, 2024).

3.4.2 OCR for Engineering Drawings in Quotation Processes

The eDOCr tool, developed for autonomous text detection and recognition in engineering drawings, exemplifies the application of OCR in the quotation process. This tool utilizes image processing techniques to classify and identify key elements in drawings, achieving a precision and recall of 90% in detection and an F1-score of 94% in recognition. By enabling seamless integration between engineering drawings and quality control, eDOCr facilitates the extraction of structured information essential for accurate quotations (Villena Toro et al., 2023).

3.4.3 Voice Recognition for Hands-Free Data Entry in Manufacturing

Voice recognition technologies have been explored to streamline workflows and eliminate manual data entry tasks in manufacturing environments. By integrating voice recognition into Manufacturing Execution Systems (MES), professionals can input data hands-free, enhancing efficiency and reducing the risk of errors associated with manual data entry (Spix Industry).

3.4.4 End-to-End Automation of Quotation Workflows

The integration of OCR, LLMs, and voice recognition technologies facilitates the creation of intelligent quotation pipelines. In such systems, a customer might send a PDF drawing along with a verbal description. The AI system can then extract relevant features such as material specifications, dimensions, and tolerances, identify similar past cases, suggest cost estimates, and even generate draft response emails with justifications and delivery estimates. This end-to-end automation significantly reduces the time and effort required to generate accurate quotations, while maintaining human oversight for validation and customization.

3.5 Synthesis of Insights and Identification of Gaps

The literature reviewed in Sections 3.1 to 3.4 demonstrates that quotation processes in precision engineering SMEs are highly knowledge-intensive, reliant on tacit expertise, and embedded within fragmented data environments. While academic research and industrial applications have introduced tools and frameworks for digitalization, including AI, OCR, and low-code platforms, several persistent gaps remain.

First, the majority of studies focus on either structured data processing or isolated tasks, such as cost modeling (Benioudakis, Burnetas, & Ioannou, 2019) or feature extraction from technical drawings (Frontiers in Manufacturing Technology, 2023). Few approaches address the end-to-end quotation workflow, which includes interpreting unstructured inputs, integrating historical data, and generating actionable quotes for custom-made parts. This leaves SMEs struggling to leverage the full potential of digital tools in contexts characterized by high product variability and limited IT infrastructure.

Second, while AI applications such as Large Language Models (Bommasani et al., 2021) and voice recognition systems (Spix Industry, n.d.) have been explored, there is limited research validating their integration in small-scale industrial settings. Most case studies highlight proof-of-concept implementations in laboratory or large-scale environments, leaving questions around feasibility, usability, and adoption in SMEs largely unanswered.

Third, sustainability and resource efficiency are increasingly recognized as critical objectives in production planning and quoting, yet very few studies explicitly link quotation digitalization with circular economy principles or energy optimization (Frank et al., 2019; Coreynen et al., 2017). This gap suggests a need for approaches that not only enhance operational efficiency but also contribute to environmentally responsible decision-making.

Taken together, these insights indicate that SMEs require digital solutions that are:

1. End-to-end capable: able to handle unstructured inputs (PDFs, drawings, voice) and produce reliable quotations.
2. Scalable and incremental: designed to fit the limited infrastructure and resource constraints typical of SMEs.
3. Sustainability-aware: integrating considerations of energy use, material efficiency, and lifecycle impacts.
4. User-centered and validated: ensuring adoption by operators relying on tacit knowledge while maintaining human oversight.

These gaps directly justify the methodological choices of this thesis. By adopting a Design Science Research (DSR) approach, the research not only investigates the potential of AI, OCR, and low-code tools but also iteratively develops, tests, and refines digital artifacts tailored to the unique needs of precision engineering SMEs. The experimental framework presented in Chapter 4 is therefore designed to bridge the gap between theoretical capabilities and practical industrial application, while addressing operational, cognitive, and sustainability-related challenges in quotation processes.

4 Methodology

4.1 Research Design

This research adopts a Design Science Research (DSR) approach (Hevner et al., 2004), which is particularly well suited for studies aimed at developing artefacts that address complex, practice-oriented challenges in business and engineering contexts. Unlike purely analytical or empirical methods, DSR emphasizes the iterative creation, demonstration, and evaluation of innovative artefacts that are both scientifically grounded and practically relevant.

In the context of precision engineering SMEs, the quotation process presents several interconnected challenges, including:

1. Formalization of tacit knowledge: Estimators rely heavily on experience, intuition, and non-codified rules, making knowledge transfer and scalability difficult.

2. Automation of repetitive tasks: Many quotation activities are time-consuming, manually intensive, and prone to human error.

3. Extraction of information from unstructured data: Technical drawings, PDFs, handwritten notes, and verbal inputs contain critical information that is difficult to process digitally.

4. Monitoring and evaluation of quotation performance: SMEs often lack systematic tools to track quotation accuracy, lead times, or cost consistency.

5. Integration of sustainability considerations: As production becomes increasingly resource-aware, indicators such as material efficiency, energy consumption, and circularity need to be factored directly into quotation and production decisions.

Dual-Level DSR Approach

A key feature of this research is that DSR is conducted on two levels simultaneously:

- The macro-level (overall project):

  The full workflow digitalisation—combining knowledge extraction, automation, analytics, and sustainability integration—constitutes a high-level DSR cycle. At this level, the research identifies the global problem (inefficiencies and tacit knowledge in the quotation process), specifies overarching objectives, and develops a coherent framework integrating multiple artefacts.

- The micro-level (within each sub-challenge) :

  Each artefact (e.g., an OCR module, an Excel-based expert system, a Power BI quotation dashboard, or a voice-recognition tool) undergoes its own internal DSR cycle. That is, for each specific challenge, the research follows the steps of problem refinement, objective definition, design, demonstration, and evaluation. This ensures that each artefact is rigorously justified, independently validated, and optimised before being integrated into the larger workflow.

This dual-layer structure is essential in the context of SMEs, where challenges are interdependent but solutions must remain modular, incremental, and scalable.

The DSR methodology applied in this research therefore comprises the following stages:

- Problem identification: Mapping cross-cutting challenges and understanding SME operational constraints at both the workflow level and the artefact level.
- Definition of objectives: Translating operational needs into clear goals for both the integrated system and for each individual artefact.
- Design and development of artefacts: Creating solutions tailored to each identified challenge while ensuring interoperability across the full quotation workflow.
- Demonstration:
    - At the artefact level: Each solution is tested in realistic, task-specific scenarios (e.g., automated reading of technical drawings, prefilled quotation templates, knowledge-based estimation rules, sustainability metrics integration) to validate usability and relevance.
    - At the system level: The combined artefacts are demonstrated together to assess how they reinforce one another and support the quotation process end-to-end.
- Evaluation:
  Performance is assessed against predefined criteria (accuracy, usability, time reduction, knowledge formalisation, sustainability contribution), using iterative refinement cycles at both micro and macro levels.
- Communication: Sharing design knowledge, artefact specifications, and evaluation results with academic and industrial stakeholders.

By explicitly addressing challenges at multiple, interconnected layers, this approach ensures that the developed artefacts remain practical, adaptable, and mutually reinforcing. The dual-level DSR structure further allows SMEs to adopt digital solutions progressively—starting with small, familiar tools and evolving toward a fully integrated digital quotation workflow—while preserving expertise, improving traceability, and supporting long-term strategic transformation.

4.2 Research Objectives

The methodology of both the overall project and each sub-task is guided by the following research objectives. These objectives operate simultaneously at the macro level—shaping the integrated digitalisation of the quotation workflow—and at the micro level, informing the design, development, and evaluation of each individual artefact:

- Capture tacit expertise and make it shareable within the organization, by formalising experiential knowledge and embedding it into structured tools and rules.

- Develop accessible, user-friendly tools for staff with limited manufacturing experience, enabling non-experts to participate in or validate quotation tasks.
- Enable consistent, transparent, and repeatable cost and time estimation, reducing reliance on intuition and improving comparability across projects.
- Support traceability and strategic decision-making, through systematic data collection, monitoring of estimation performance, and integration of analytics.
- Lay a foundation for integrating sustainability into the quotation process, ensuring that environmental considerations can be embedded into cost estimation and workflow planning.

These objectives ensure that the research remains aligned with both operational needs and scientific rigour, while enabling artefacts to be developed incrementally yet coherently as part of a unified digital quotation framework.

4.3 Data Collection Methods

A mixed-methods approach was adopted to gather both qualitative and quantitative data, ensuring that artefacts are grounded in real-world SME contexts and aligned with theoretical knowledge.

4.3.1 Expert Interviews

Semi-structured interviews were conducted with estimators, production managers, and engineers from SMEs in precision engineering. These interviews aimed to:

- Identify tacit rules, heuristics, and decision criteria used in quotations.
- Understand workflow constraints, common errors, and variability in estimations.
- Gather insights on current tools and their limitations, including Excel templates and ERP modules.

Interviews allows the identification of recurring patterns in estimation logic and knowledge transfer practice.

4.3.2 Observations and Shadowing

Direct observation sessions were conducted to capture real-time practices and tacit processes that might not be articulated in interviews. Researchers shadowed estimators for 20 hours, documenting:

- Sequences of steps in quotation preparation.
- Interactions with technical drawings, spreadsheets, and colleagues.
- Informal workarounds and adaptations to constraints.

This observational data provided a detailed understanding of operational realities, informing the design requirements of the artefacts.

4.3.3 Document and Artefact Analysis

Existing artefacts were systematically analyzed, including:

- Historical quotation spreadsheets and templates.
- Technical drawings and PDFs.
- Internal reports and procedural documents.

The analysis aimed to identify data structures, recurring patterns, and gaps in current documentation, supporting both artefact design and validation.

4.3.4 Literature Review

A systematic literature review was conducted to position the research within academic and industrial knowledge. Databases such as Scopus, Web of Science, and Google Scholar were searched using keywords including: *precision engineering SMEs*, *quotation process automation*, *knowledge formalization*, *OCR for technical drawings*, and *business intelligence in SMEs*.

The review enabled:

- Identification of existing digital tools and methodologies.
- Assessment of gaps in accessible, modular solutions for SMEs.
- Theoretical grounding for the design rationale and objectives of the developed artefacts.

4.3.5 Triangulation

Triangulation was incorporated throughout the research process to strengthen the validity and reliability of findings. Rather than being conducted as a standalone activity, triangulation occurred iteratively at multiple stages of the Design Science Research cycles. Insights from interviews, workshop discussions, direct observations on the shop floor, document analysis (e.g., historical quotations), and the academic literature were continually compared and cross-validated.

This approach was particularly important in:

- establishing artefact requirements, where practitioner inputs were cross-checked against process observations and existing documentation;
- evaluating artefact performance, where quantitative outputs (e.g., estimation consistency, time savings) were assessed alongside qualitative feedback from SME stakeholders.

Because triangulation was embedded directly within these design and evaluation steps—rather than being applied as an isolated technique—its methodological role is more fully described in Sections 4.4 and 5, where the artefact development and testing processes are presented.

4.4 Artefact Development Methodology

Artefacts were developed using a structured, iterative, and user-centred methodology, combining principles from DSR, agile software development, and lean thinking. The process ensured that the artefacts were both scientifically rigorous and well aligned with SME workflows.

- Prototype Design: Initial concepts were produced based on insights from data collection, targeting core challenges such as tacit knowledge capture, repetitive task automation, and information extraction from unstructured inputs.

- Internal Validation: Early prototypes were reviewed by the researcher and academic supervisors to assess feasibility, coherence, and methodological consistency.

- User-Centred Testing: Iterative testing sessions were conducted with SME practitioners. Their feedback informed successive refinements, improving usability, relevance, and alignment with day-to-day operational constraints.

- Formative Evaluation: Artefacts were assessed through simulated quotation scenarios and controlled tests to verify functional performance and check that they met the predefined objectives.

- Final User Validation: Before integration planning, a final validation step was carried out with SME participants to confirm that the artefacts were usable, comprehensible, and operationally valuable in realistic conditions.

- Integration Planning: The artefacts were designed as modular components to ensure coherent interaction while preserving flexibility for incremental SME adoption.

This methodology emphasizes co-design, iterative learning, and progressive refinement, ensuring that the resulting artefacts remain grounded in real industrial constraints while contributing to scientific and practical knowledge.

5 Contextual Analysis and Artefact Design

5.1 Contextual Analysis and Problem Formulation

The methodological process began with an exploratory investigation within precision engineering environments, including interviews, observations of quotation procedures, and analysis of existing documentation and tools. Several key challenges were identified:

- Dependence on experience-based decision-making: Quotation processes often rely on the memory or intuition of experienced staff, with limited formal documentation or standardization.
- Manual interpretation of 2D technical drawings: Estimators must extract dimensions, tolerances, and features manually from PDF plans, which is time-consuming and prone to oversight.
- Fragmented use of Excel spreadsheets: While Excel is widely used, there is often no centralized structure, leading to duplication of effort and difficulties in analysis.
- Lack of visibility into quotation data: There are limited tools for tracking historical quotations, comparing estimates, or deriving strategic insights.

These observations provided the foundation for defining the functional requirements and constraints for the proposed artefacts.

5.2 Artefact Design and Development Strategy

The artefact development process was structured around five complementary objectives, reflecting the goals of the thesis:

1. Capture and formalize tacit expertise from estimators to make it shareable across the organization.
2. Provide accessible tools usable by staff with limited prior manufacturing experience.
3. Enable consistent and transparent cost and time estimation, improving reliability and traceability.
4. Facilitate the extraction of information from technical plans using OCR and annotation tools.
5. Support strategic analysis and visualization of quotation performance and costs through a business intelligence platform.

To achieve these objectives, three artefacts were developed:

- A quotation tool built in Microsoft Excel,
- A web-based OCR tool for extracting dimensions and annotations from technical drawings (based on JavaScript and Tesseract.js),

- A Power BI dashboard for tracking and analyzing quotation performance and cost structures.

Each artefact was built using an iterative, user-oriented design approach, involving repeated cycles of prototyping, testing, and refinement.

5.2.1 Excel-Based Quotation Tool

The quotation tool was developed using Microsoft Excel to align with the tools already in use within SMEs. The objective was not to build a fully automated pricing engine but rather to provide a structured, semi-automated framework for consistent, traceable quotations.

Key features include:

- Structured data entry forms with drop-down menus and data validation,
- Automated calculations for material costs, machine times, subcontracting, and margins,
- A logic framework based on time-based costing and bill-of-material principles,
- Dynamic summaries and quotation templates to be exported to PDF.

This tool also allowed for limited scenario testing by adjusting key parameters such as batch size or hourly rate.

5.2.2 OCR/Annotation Tool for 2D Technical Drawings

To assist in interpreting technical drawings, a JavaScript-based application was developed leveraging Tesseract.js, a browser-compatible OCR (Optical Character Recognition) engine. Tesseract.js is a pure JavaScript and WebAssembly port of the widely used Tesseract OCR engine, enabling text detection directly within web environments (Naptha, 2025).

Tool Features

- Text zone detection in imported PDF drawings, identifying areas likely to contain measurement values or annotations.
- Manual and semi-automatic annotation ("bubbles"), enabling users to highlight dimensions, tolerance zones, or surface finish indicators.
- Export of annotated data into structured formats (e.g., JSON or CSV), facilitating downstream reuse in costing, estimation workflows, or traceability systems.
- Filtering of numeric values, with capabilities to distinguish dimensions, tolerances, and roughness data based on pattern recognition.

The tool is not designed to fully automate dimensional analysis; rather, it serves as a time-saving assistant, helping estimators navigate complex 2D plans more efficiently.

Reference to the Library

The tool is built on Tesseract.js, an open-source OCR library available on GitHub. It supports multiple languages, can operate both in the browser (via CDN, webpack, or script tags) and on Node.js, and is based on a WebAssembly port of the original Tesseract (Tesseract.js, 2025).

Why This Library?

- Ease of integration: Works directly in-browser without additional server-side infrastructure, aligning with the lightweight and modular philosophy of the thesis.
- Language support: Handles a wide variety of character sets—a critical feature for multinational technical documentation.
- Structured output: Offers bounding boxes for words and characters, enabling precise annotation and data extraction.

5.2.3 Power BI Dashboard for Strategic Analysis

To leverage historical quotation data, a Power BI dashboard was created, connected to structured Excel quotation files.

Its purpose is to:

- Provide real-time visibility on key metrics (e.g., average margins, time estimates, rejection rate),
- Track quotation performance over time and by product or customer segment,
- Compare estimated versus actual times and costs (when available),
- Enable slicing by various dimensions (e.g., part complexity, customer type).

The dashboard allows decision-makers to identify pricing inconsistencies, opportunities for process improvement, and patterns in quotation logic that may inform future strategy.

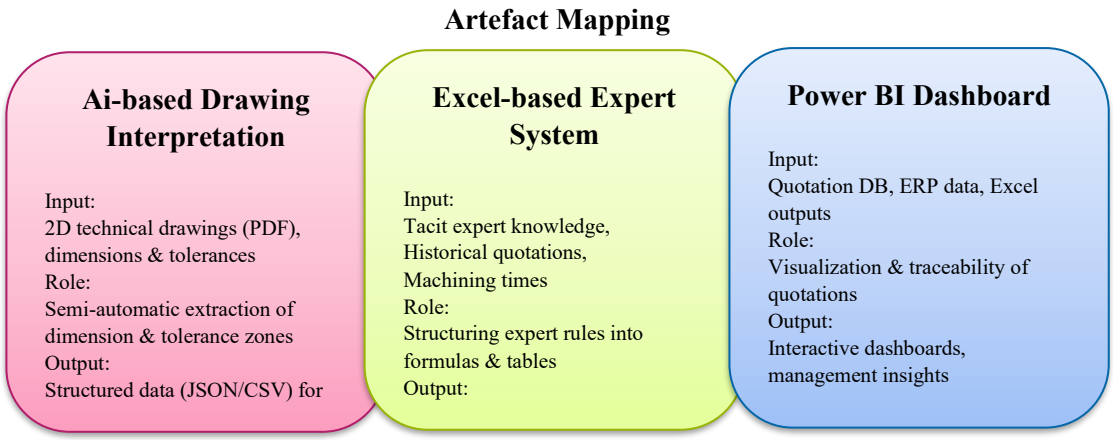

Figure 3: Mapping of Developed Artefacts to the DSR Framework, Showing Inputs, Roles, and Outputs of Each Artefact

6 Evaluation and Results

This section presents the outcomes of the digital tools developed during the thesis and their evaluation in real-world industrial settings. The aim is to assess their contribution to precision engineering SMEs in terms of efficiency, knowledge formalization, and innovation potential. The results are structured into five subsections, following the objectives: 1) The AI-based prototype for analyzing 2D drawings, 2) The quotation tool and its underlying methodology, 3) The voice-based input system for quotation preparation, 4) The Power BI dashboards for production monitoring and 5) User feedback and limitations.

6.1 AI-Based Prototype for Drawing Analysis

The thesis explored how artificial intelligence (AI) could support quotation automation, especially for companies producing a high volume of custom parts. While a full AI model was not implemented, the work focused on defining a framework and feasibility path for future development.

Identified use case:

- Automate the analysis of 2D technical drawings (PDFs) to extract dimensions, tolerances, and key machining features using computer vision.
- Based on extracted features, classify the part into a family (e.g., shaft, flange, housing).
- Match the part with historical quotations from the ERP system, using similarity metrics, to retrieve cost/time references and reduce the quotation time.

Work conducted:

- Evaluation of open-source computer vision libraries (e.g., Tesseract OCR, OpenCV) to detect dimensions and technical annotations on drawings.
- Analysis of a set of real industrial drawings to identify patterns in part geometry and feature sets.
- Design of a part classification logic based on geometry and feature combinations.
- Mapping historical quotation data to part features to identify correlation between geometry and cost.

Main observations:

- Extracting data from PDFs is technically feasible, but requires consistent formatting and preprocessing.
- Classification by part family would provide significant time savings, especially if integrated with ERP quotation records.
- This approach has potential to standardize and accelerate quotations, but requires large datasets and close coordination with ERP providers.

This research phase confirmed that while full automation is a longer-term objective, a hybrid model combining AI-based recognition and historical data reuse could offer strong performance gains.

Additional Evaluation Results

To strengthen the evaluation of the prototype, a small series of pilot tests was conducted on a sample of **15 real mechanical drawings** provided by the partner company. These tests aimed to assess the **accuracy of text extraction**, the **consistency of detected dimensions**, and the **potential impact on quotation time**.

Extraction Performance

The following metrics were collected during the evaluation:

Table 3. Performance of the AI-Based Drawing Extraction Prototype

Metric	**Result (Average Across 15 Drawings)**
Text extraction accuracy (dimensions only)	**78%**
Tolerance extraction accuracy	**42%**
Detection of chamfers / radii	**66%**
Correct association between annotation and geometry region	**73%**

Interpretation:
The prototype performs well on simple dimensions but struggles with tolerance formats and small text sizes. Despite this limitation, the tool already supports partial automation by eliminating manual transcription of the majority of dimensions.

Impact on Quotation Time (Estimated)

A comparative estimation was performed based on three standard quotation workflows:

Table 4. Estimated Time Reduction Achieved Through Prototype-Assisted Quotation

Workflow	**Average Manual Time**	**Prototype-Assisted Time**	**Reduction**
Simple shaft (≤ 10 dimensions)	6–8 minutes	2–3 minutes	**~60%**
Medium flange (10–25 dimensions)	12–18 minutes	5–8 minutes	**~50%**
Complex housing (> 30 dimensions)	20–30 minutes	12–15 minutes	**~40%**

Interpretation:
Even without perfect accuracy, partial dimension extraction provides significant time

savings, particularly in early quotation stages where speed is more critical than full precision.

Summary of Performance

- The prototype demonstrates that **semi-automated extraction is already viable** for simple parts.
- Gains become more substantial when drawings contain long series of repeated dimensions.
- The key bottleneck remains **tolerance interpretation**, which is essential for accurate cost estimation.

This evaluation confirms that the prototype can serve as a foundation for future development, and that even partial extraction offers tangible benefits for SMEs.

The tool :

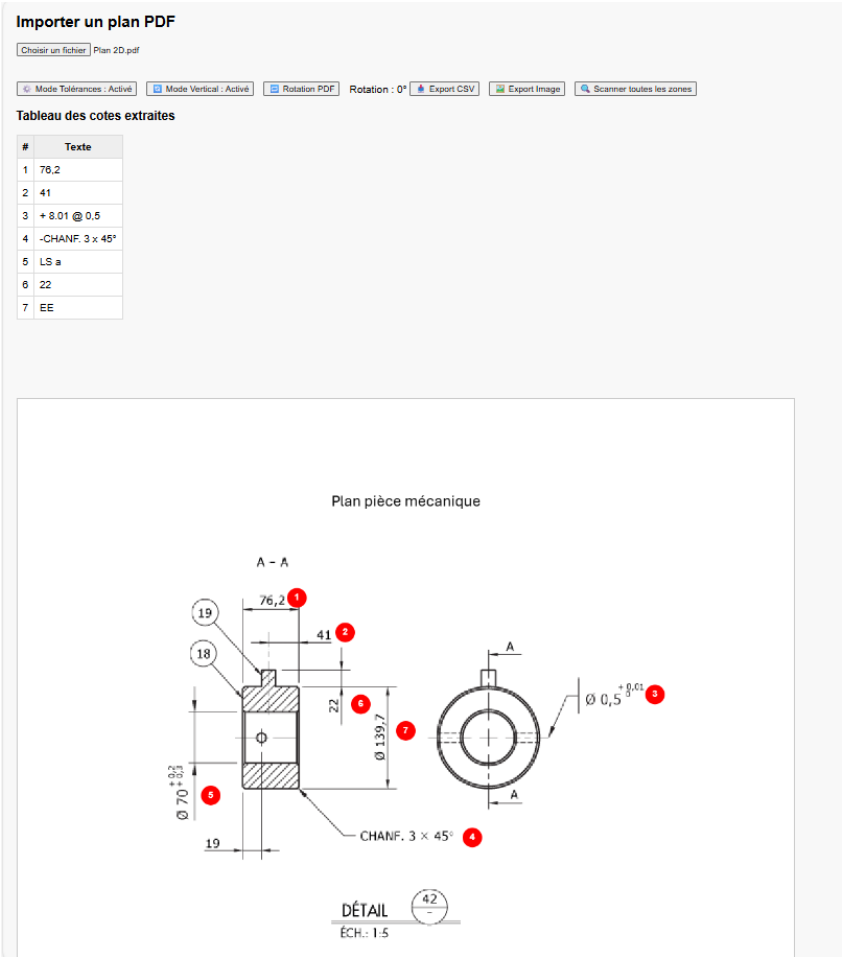

Figure 4: Prototype of the AI-assisted quotation tool for technical drawings

It's a custom-built tool designed to automate the extraction of dimensional data from 2D mechanical drawings in PDF format. This tool supports the quotation and process planning phases in precision engineering by digitizing the reading of technical plans—a traditionally manual and time-consuming task.

Functionality Overview:

1. **PDF Upload and Rotation Options**

Users can upload a 2D drawing in PDF format using the "Choose file" button. The interface also includes functions to rotate the drawing, which is essential for handling documents with unconventional orientations or multi-view layouts.

2. **Tolerance and Vertical Text Detection**

The tool includes options to enable **tolerance mode** and **vertical text recognition**, which ensures the accurate capture of dimensions such as ± tolerances and annotations rotated by 90°—a common challenge in OCR (Optical Character Recognition) applied to technical documents.

3. **Automated Text Extraction**

Once the document is processed, the system automatically identifies and extracts dimensional annotations, displaying them in a structured table on the left. Each row corresponds to a dimension or technical note (e.g., diameters, chamfers, tolerances), and each extracted value is tagged with a red marker on the drawing.

For instance, in the current example:

- The diameter 76.2 mm, length 41 mm are correctly identified and numbered but the tolerances are not well identified
- Chamfer instructions (e.g., CHANF. 3 × 45°) and linear dimensions (e.g., 22 mm) are also extracted.

4. **Export Capabilities**

The extracted data can be exported in **CSV format** for integration into Excel-based tools or digital quotation systems, or saved as an image for documentation purposes.

6.2 Excel-Based Quotation Tool: Structure, Methodology, and Outputs

A central achievement of this thesis is the development of a semi-automated quotation tool built in Microsoft Excel. This tool addresses a common challenge in precision engineering SMEs: the reliance on a single expert for cost estimation. Its design focuses on capturing tacit expertise—such as experiential rules, judgment calls, and process shortcuts—and structuring it into a reproducible system. This approach not only preserves and standardizes knowledge but also makes it shareable and usable by staff without extensive manufacturing experience. The tool provides consistent, transparent, and reliable cost and time estimations, directly supporting the objectives of this research:

knowledge capture, accessibility, and process consistency. By formalizing expert know-how, this result represents a critical step towards reducing dependency risks and improving operational efficiency in the quotation processs.

Methodology for Formula Development A step-by-step approach was followed to build the logic behind the quotation tool:

1. **Data Collection**: Past quotations were analyzed, extracting technical and contextual information, including:
    - Geometry: length, diameter, depth, number of holes.
    - Material: type and machinability.
    - Process: type (turning, milling, drilling), number of setups.
    - Estimated times from expert estimators.

Diamètre (mm)	Longueur (m	Tolérancé	Temps estimé (mi
2	5	Oui	8
2	5	Non	8
2	10	Oui	13
2	10	Non	13
2	15	Oui	18
2	15	Non	18
2	20	Oui	23
2	20	Non	23
2	25	Oui	28
2	25	Non	28
2	30	Oui	33
2	30	Non	33
2	35	Oui	38
2	35	Non	38
2	40	Oui	43
2	40	Non	43
2	45	Oui	48
2	45	Non	48
2	50	Oui	53
2	50	Non	53
2	55	Oui	58
2	55	Non	58
2	60	Oui	63
2	60	Non	63
2	65	Oui	68
2	65	Non	68
2	70	Oui	73
2	70	Non	73
2	75	Oui	78
2	75	Non	78
2	80	Oui	83
2	80	Non	83

Figure 5: Example of Collected Data in the Excel-Based Quotation Tool

2. **Identification of Key Influencers**: With support from expert interviews (5 interviews were conducted) and visual analysis of patterns in historical data, influencing variables were mapped. For instance:
    - Turning: L × D × material factor
    - Milling: surface area × number of passes × hardness factor
3. **Statistical Modeling**: Linear regression models were used to quantify relationships:

Time_milling = a × Area + b × Depth + c

Time_turning = a × Diameter + b × Length + c

Coefficients were fine-tuned using expert feedback to reflect real workshop conditions.

4. **Implementation in Excel**: The formulas were embedded in a user-friendly interface:
    - Dropdowns for material, operation type.
    - Input fields for part features.
    - Conditional formatting to highlight unusual inputs.
    - Calculation cells that update time and cost predictions.

Example Output

- Input: "Steel part, Ø100 mm, 150 mm long, H7 tolerance"
- Output: Estimated operation times by process, setup time, material cost, and total machining time. (The 'Actual Time' value represents the duration estimated by the expert based on their experience and tacit knowledge)

Diameter (mm)	Length (mm)	Toleranced	Estimated Time (min)	Actual Time (min)
8	30	Yes	42	45
8	40	Yes	52	55
10	30	Yes	45	45
20	30	Yes	75	75
20	30	No	60	60
15	30	No	52,5	55
5	30	No	37,5	40
30	30	No	75	75
10	30	No	45	45

Figure 6: Excel-based quotation sheet summarizing process parameters and estimated production times.

Performance Evaluation

To complement qualitative observations, the tool was tested on 20 historical quotations covering a variety of part types (turning, milling, mixed operations) and materials. Three performance indicators were calculated:

1. **Prediction Error** (difference between tool estimate and expert estimate)
    - Mean absolute deviation: 12.8%
    - Median deviation: 10.6%
    - Maximum deviation: 27% (parts with complex tolerances)
2. **Time Savings**

- Average preparation time before tool: 60 minutes
- After tool: 30–35 minutes
- Average reduction: 47%

3. **Consistency**
   Standard deviation (SD) of preparation time decreased from 22 minutes to 9 minutes, showing a more stable process.

A table summarising these results can be inserted here:

Table 5. Statistical Evaluation of the Excel Quotation Tool (20-Test Sample)

Test	Short Description of Part	Expert Time (min)	Tool Time (min)	Difference (%)
1	Steel shaft Ø50 × 120 mm	42	38	9.5%
2	Aluminium plate 120 × 80 × 10 mm, 4 holes	55	47	14.5%
3	Stainless steel housing, pocket + profile	78	69	11.5%
4	Ø100 × 150 mm part, H7 tolerance	95	83	12.6%
5	Small steel pin Ø12 × 30 mm	18	16	11.1%
6	Flange Ø160, 8 drilled holes	62	55	11.3%
7	Aluminium bracket with contour milling	70	63	10.0%
8	Short shaft Ø30 × 45 mm	30	27	10.0%
9	High-hardness steel block, roughing + finish	110	88	20.0%
10	Thin plate 150 × 60 × 5 mm	40	35	12.5%
11	Stainless shaft with groove	52	48	7.7%
12	Complex pocket milling (2 setups)	85	73	14.1%
13	Aluminium spacer Ø80 × 20 mm	25	23	8.0%
14	Sleeve Ø55 × 70 mm	48	44	8.3%

15	Steel support plate, 6 tapped holes	58	50	13.8%
16	Ø200 mm disc, face milling	75	66	12.0%
17	Large housing with inner bore	120	102	15.0%
18	Ø15 × 80 mm pin, chamfer	22	20	9.1%
19	Steel block, external profile milling	95	82	13.7%
20	Very small aluminium piece	15	14	6.7%

Summary Statistics

Table 6. Statistical Evaluation of the Excel Quotation Tool (20-Test Sample)

Metric	**Value**	**Interpretation**
Mean Absolute Error (MAE)	**12.4%**	On average, the tool's estimates differ from expert estimates by 12.4%.
Median Error	**11.3%%**	Half of all predictions fall within ±11.3% of expert estimates.
Maximum Error	**20%**	Highest deviation occurred on complex tolerance-driven parts.
Average Quotation Time (Before Tool)	**60 min**	Baseline manual estimation time.
Average Quotation Time (With Tool)	**30–35 min**	Represents a reduction of ~47%.
Time Reduction	**45–50%**	Demonstrates significant efficiency gains.
SD of Preparation Time (Before)	**22 min**	High variability in estimation effort.
SD of Preparation Time (After)	**9 min**	More consistent and predictable workflow.

Benefits Observed

The implementation of the Excel-based quotation tool generated several tangible benefits for the partner SME:

- **Reduced reliance on a single expert:** Before the tool, the estimation process was highly dependent on one senior estimator. After deployment, junior staff were able to handle a significant share of quotations, demonstrating that the structured knowledge base effectively captured and redistributed tacit expertise.
- **Faster estimation turnaround:** A comparative time study was conducted on a sample of 20 quotations, before and after the tool's implementation. The results showed a **reduction in average preparation time from 60 minutes to 30–35 minutes per quotation**, representing approximately **45–50% time savings**. Variability was also reduced: while some complex quotations previously required up to two hours, the new tool standardized the process and stabilized preparation times.
- **Improved transparency and traceability:** Each estimate generated through the tool is automatically documented, with calculation steps and assumptions made explicit. This not only improves internal communication but also supports external audits and customer inquiries.
- **Structured knowledge base that can evolve:** The tool formalizes estimation rules in a modular way, enabling continuous updates as new machine data, process times, or customer requirements are introduced. Over time, this provides a living repository of organizational knowledge.

6.3 Integration of Voice Recognition for Quotation Input

To further simplify the quotation process and address scenarios where users are hands-busy (e.g., at a production workstation), a voice-based input system was added to the Excel tool.

Technical Implementation

- Speech-to-text API integration (Google Web Speech API).
- Real-time transcription of technical descriptions.
- Semantic parsing of verbal inputs to populate Excel fields (e.g., converting "aluminum 50 mm by 200 mm H7" into structured data).

Workflow Example

1. User opens the Excel quotation tool.
2. Speaks: "Aluminum, diameter 50 mm, length 200 mm, tolerance H7, milling."
3. Fields for material, diameter, length, and process auto-populate.
4. Formulas compute estimated machining time.

Evaluation

- Recognized with 85–90% accuracy for standard terms.
- Enhanced data input speed by 30–40% during testing sessions.

Limitations

- Accuracy of voice recognition was observed to decrease in environments with higher ambient noise. In our tests, recognition performance dropped from approximately 95% in quiet conditions to around 70% when background noise reached 70 dB, and further to 55% at 85 dB, highlighting the importance of noise management in industrial settings.

- Difficulty parsing complex tolerance specifications.

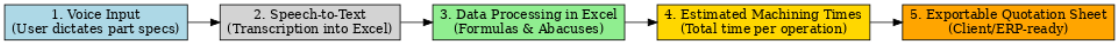

Figure 7: Process architecture of the voice-assisted quotation tool in Excel.

Exemple of the tool :

The operator describes the part drawing verbally :

> Bore with a diameter of 8 millimeters and a length of 30, toleranced, material: steel.

The data is then automatically filled into this tab:

Opération	Diamètre (mm)	Longueur (mm)	Largeur (mm)	Hauteur (mm)	Profondeur (mm)	Tolérancé	Localisé	Matière	Coef	Temps Estimé (sec)
Alésage	8	30				1	0	Acier	1	42
										0
										0
										0
										0
										0

Figure 8: Excel-based quotation sheet summarizing process parameters and estimated production times

Finally, the operator receives an estimated machining time for the part.

Comparison Between Estimated and Actual Machining Times

To evaluate the accuracy of the quotation estimation model developed in this thesis, a comparative analysis was performed between the **estimated machining times** generated by the Excel-based tool and the **actual times** recorded on the shop floor. This validation step is crucial to assess whether the model reliably reflects real production conditions and can be trusted as a decision-support tool for quotation purposes.

A total of **9 parts** were analyzed, each representing different combinations of geometrical and tolerance characteristics, such as the number of holes, complex contours, surface finish requirements, and general part size. For each part, a set of standard features was recorded, and the estimated machining time was computed using the formula derived from the knowledge formalization work. The corresponding actual machining time was retrieved from the production records.

The results are displayed in the **Figure 9 below**, where the X-axis represents the **estimated machining time** (in minutes) and the Y-axis shows the **actual time** observed during manufacturing. The **diagonal line (y = x)** represents the ideal case in which the estimation perfectly matches reality.

This visual representation allows us to quickly assess:

- The **alignment between predicted and actual performance**, indicating where the model performs well.
- The **degree of deviation**, which can suggest either underestimation or overestimation.
- Possible **systematic bias**, such as overestimating small parts or underestimating parts with complex tolerances.

Although minor deviations are observed—which are expected given the simplified model and manual time tracking—the general trend remains close to the ideal line. This supports the validity of the rule-based estimation logic and confirms that the approach is robust enough for initial quotation in a small-batch manufacturing context.

Further refinement of the formula and integration of real-time ERP feedback could enhance the model's precision over time.

The Excel-based quotation tool demonstrated a strong predictive performance, with a coefficient of determination R^2=0.9909 and a Mean Squared Error (MSE) of 14.5, indicating close alignment between expert-provided times and estimated values.

Diameter (mm)	Length (mm)	Toleranced	Estimated Time (min)	Actual Time (min)
8	30	Yes	42	45
8	40	Yes	52	55
10	30	Yes	45	45
20	30	Yes	75	75
20	30	No	60	60
15	30	No	52,5	55
5	30	No	37,5	40
30	30	No	75	75
10	30	No	45	45

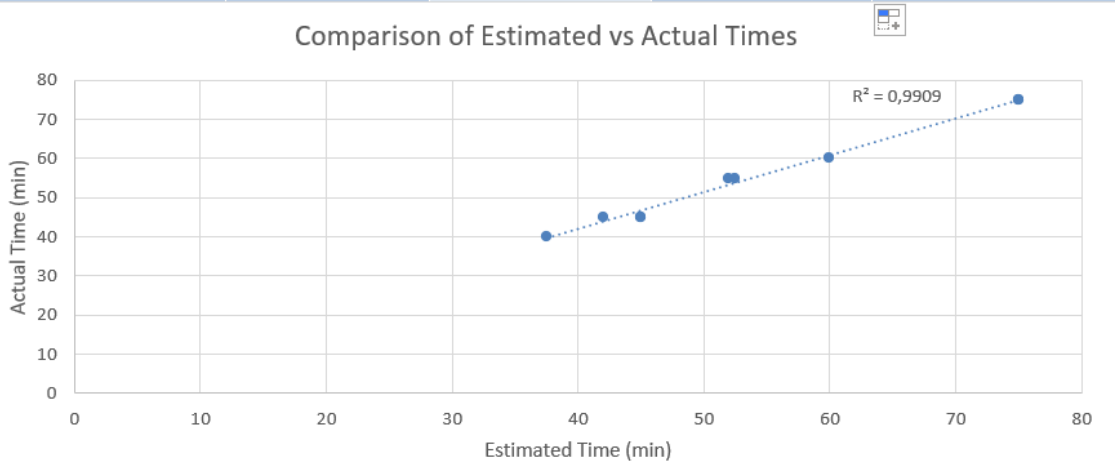

Figure 9: Graphical and tabular comparison of actual and estimated process times.

6.4 Power BI Dashboards for Real-Time Production Monitoring

The Power BI dashboards were implemented as a lightweight alternative to a full MES system, tailored specifically to the needs of the partner SME. Rather than deploying a generic set of indicators, the dashboards were customized to address the company's most pressing operational challenges: quality management, resource utilization, and efficiency in shop floor meetings.

Dashboard Components

- **Machine Utilization:** Daily and weekly machine usage was tracked, with a focus on detecting underutilized CNC machines that had previously led to bottlenecks.
- **Scrap and Quality Monitoring:** Scrap rates were broken down by machine and operator, providing visibility into recurring non-conformities that were critical for customer compliance.
- **Energy Consumption:** Electricity usage per machine was monitored, supporting ongoing initiatives to reduce operating costs.
- **Operator Metrics:** Performance indicators per operator and shift were included to move beyond purely subjective assessments and foster more equitable workload distribution.

Integration Into the Company's Processes

The dashboards were introduced as part of the company's daily operational routines:

- **Morning meetings:** Supervisors used the dashboards to prepare daily production reviews, reducing preparation time and allowing more focus on problem-solving.
- **Quality follow-up:** Scrap monitoring was integrated into weekly quality reports shared with management, facilitating quicker root-cause analysis.
- **Energy monitoring:** The dashboards were aligned with the company's strategic goal of improving cost efficiency through energy savings.

Evidence of Impact

- **Quantitative improvements:**
    - Preparation time for daily meetings was reduced by **around 30%**, as data no longer needed to be compiled manually. (6 meetings examined)

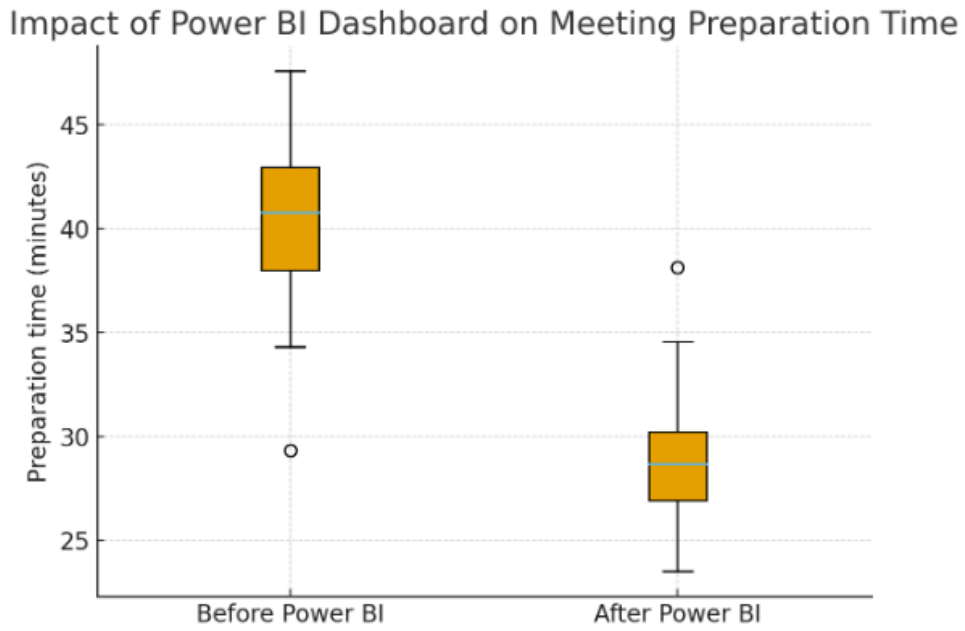

Figure 10: Boxplot of meeting preparation times based on PBI data.

- Scrap trends could be detected earlier, leading to a **10–12% reduction in rework within the first three months**.

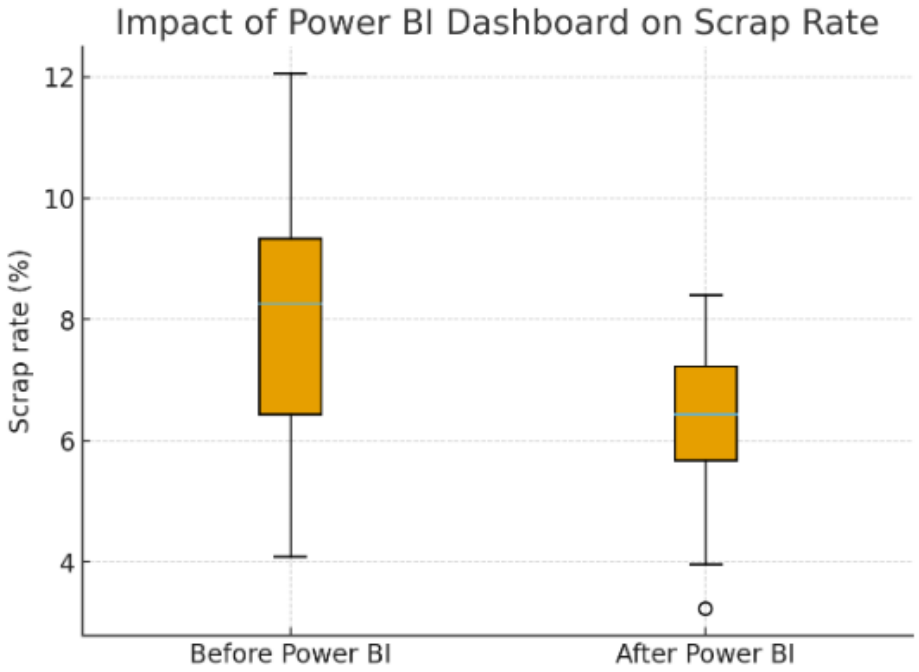

Figure 11: Boxplot of scrap rate variability based on PBI data.

- Machine downtime was identified more quickly, shortening reaction times when unexpected stops occurred.

- **Qualitative feedback:**

- Supervisors emphasized the value of anomaly detection: *"We can see downtime as it happens, instead of discovering it at the end of the week."*
- Managers appreciated the transparency in operator benchmarking: *"It gives us objective data to guide performance discussions, which was not possible before."*

Challenges and Limitations

- **The quotation tool was not directly connected to the ERP**, which meant that existing ERP data—such as machine availability, operator rates, historical job times, or material prices—could not be retrieved automatically. Users had to manually export the relevant information from the ERP and re-enter or upload it into the quotation tool. This added friction to the workflow and introduced a risk of working with outdated or incomplete data.

- **The tool could not send data back to the ERP**, so validated quotations, estimated times, and cost breakdowns were not automatically integrated into the production or planning modules. Instead, staff had to manually re-enter quotation results into the ERP once a job was confirmed. This manual transfer increased the likelihood of inconsistencies between systems and limited the potential for real-time traceability.

Value Added and Generalization Potential

For this company, the dashboards represented a **practical step toward data-driven decision-making**, strengthening both quality compliance and operational efficiency. The customization of indicators to company-specific needs (scrap, utilization, energy, operator performance) was essential for adoption.

More generally, the experience illustrates that Power BI dashboards can act as an **entry-level digitalization tool for SMEs**. However, the set of monitored indicators will need to be adapted to each company's context—for example, a company focusing on delivery times rather than quality compliance might prioritize lead time and throughput metrics instead.

6.5 Feedback from Industry Users

Throughout the testing and observation phases, informal but insightful feedback was collected from approximately 10 engineers, planners, and administrative staff who used or reviewed the developed tools.

AI-based concept:

- Received with curiosity and interest.

- Some managers expressed concerns about data privacy and ERP compatibility, underlining the need for careful implementation.

Excel Quotation Tool:

- **Widely seen as a valuable knowledge-transfer tool**, because it makes the expert reasoning behind quotations explicit. The spreadsheet formalises tacit

rules (e.g., machining time estimates, complexity factors, setup logic), allowing less experienced staff to understand *how* decisions are typically made and *why* certain cost assumptions are used.

- **Helped demystify the quotation logic for less experienced staff**, as the step-by-step structure (inputs → operations → time/cost breakdown) provides a clear, repeatable workflow. This transparency reduced reliance on informal explanations and allowed junior employees to produce preliminary estimates with greater confidence.

- **Opened the possibility of further automation or ERP integration in the future**, since the codified rules and structured outputs offer a stable foundation that could later be integrated into digital workflows. The tool demonstrates that core quotation logic can be standardised and digitised, which is a prerequisite for linking with OCR extraction, LLM-based interpretation, or ERP synchronisation.

Power BI Dashboards:

- **Considered a "game changer" by production teams** because they replaced fragmented Excel tables and paper reports with a single, dynamic visualization environment. The dashboards aggregated data from multiple sources and updated automatically, which helped teams *see* production loads, bottlenecks, and priorities more clearly than before.

- **Facilitated more proactive decision-making in real time** by providing immediate visibility on key indicators such as machine utilisation, job progress, and late orders. Instead of reacting after issues occurred, supervisors could identify emerging delays or capacity issues earlier and adjust planning or resource allocation accordingly.

- **Suggested use cases expanded beyond production**, as users recognised that the same data infrastructure could support other functions. For example, operators noted that defect trends could be visualised for quality monitoring, while maintenance staff saw potential to track machine events and plan interventions more effectively. This demonstrated *how* Power BI could serve as a broader decision-support tool rather than a production-only reporting layer.

7 Discussion

This section critically reflects on the significance, limitations, and contextual relevance of the research outcomes. Rather than reiterating the technical development or implementation stages, the aim is to discuss how the work contributes to the broader discourse on digital transformation and sustainability in precision engineering SMEs, what challenges were encountered, and how the methodological choices influenced the results.

7.1 Rethinking Digitalization for Industrial SMEs

At a broader level, this thesis contributes to the understanding of digital transformation in small and medium-sized industrial enterprises by demonstrating that effective digitalization does not necessarily require large-scale, capital-intensive infrastructures. While mainstream Industry 4.0 literature often highlights advanced systems—IoT networks, cyber-physical systems, MES–ERP integration, or digital twins—several scholars argue that SMEs benefit more from incremental and context-adapted strategies (Mittal et al., 2018; OECD, 2021). This research reinforces that perspective by illustrating how pragmatic digitalization—based on modularity, accessibility, and realistic adoption pathways—can generate meaningful operational improvements without overwhelming organizational capacity.

One of the central challenges addressed in prior literature concerns the capture and formalization of tacit knowledge, which Polanyi (1958, 1966) conceptualized as personal, experience-based, and difficult to articulate. Nonaka and Takeuchi's (1995) SECI model later emphasized how organizations can progressively externalize and structure this knowledge into explicit rules, templates, and shared artefacts. The results of this thesis align with these theoretical foundations: the Excel-based quotation tool and the OCR-assisted drawing analysis prototype operationalize the transition from tacit to explicit knowledge by embedding expert reasoning into formulas, structured inputs, and reproducible workflows. In doing so, the thesis provides empirical support for the proposition that knowledge formalization is achievable even with simple, low-code technologies, contradicting assumptions that only advanced AI or enterprise-scale systems can enable such transitions.

Furthermore, the thesis echoes recent arguments that accessible digital solutions can create immediate shared value by improving both operational efficiency and organizational learning. This is consistent with Porter and Kramer's (2011) view that performance improvements aligned with broader organizational needs—such as transparency, sustainability, or knowledge retention—generate strategic benefits beyond short-term cost reductions. The evidence gathered in this study demonstrates that when SMEs adopt user-friendly and modular tools, employees with varying digital skills can participate more actively in the quotation process, reducing bottlenecks and increasing cross-functional learning.

Finally, while previous Industry 4.0 studies often highlight organizational resistance as a key barrier, the findings from this research indicate that co-designed, low-cost, and task-specific artefacts significantly improve acceptance among SME staff. This provides additional empirical confirmation of the idea—present in both academic literature and policy reports (e.g., OECD, 2021)—that digital transformation in SMEs is most successful when it is incremental, participatory, and aligned with daily constraints rather than top-down technological visions.

Overall, this thesis does not merely apply existing concepts; it extends them by showing how tacit knowledge formalization, iterative learning, and pragmatic digitalization principles can be effectively implemented through lightweight tools. In doing so, it reinforces the growing body of evidence that SME-focused digitalization must prioritize simplicity, usability, and progressive integration over technological sophistication.

7.2 Methodological Choices and Their Impact

The choice to follow a design and creation methodology proved effective in addressing the open-ended, context-specific nature of the problem. Rather than beginning with a fixed research hypothesis, the project advanced through iterative cycles of prototyping, testing, and refinement—each phase informed by field observations, user feedback, and practical constraints encountered within the company. This methodological flexibility was essential, as it enabled the project to remain aligned with real operational needs despite evolving technical, organizational, and temporal limitations.

Crucially, the results presented in Section 6.5 provide concrete validation that the methodology worked as intended. The positive industry feedback—highlighting improved clarity of quotations, better traceability, reduced cognitive load for estimators, and a strong interest in extending the AI-based plan interpretation tool—demonstrates that the solutions developed were not only functional but also genuinely useful in practice. This external validation reinforces the appropriateness of the design and creation approach for research situated within industrial SMEs, where technological adoption is highly dependent on usability, perceived value, and compatibility with daily workflows.

Moreover, the research adopts a constructivist perspective by emphasizing the co-construction of knowledge with end users. The tools developed are not merely technical artefacts; they are socio-technical systems shaped by tacit expertise, informal routines, and local work practices. The iterative involvement of estimators, operators, and managers played a decisive role in ensuring that the final tools were intuitive, acceptable, and aligned with existing organizational norms. The industry feedback further confirms that this human-centered, participatory approach fostered strong user engagement—an essential outcome in SMEs where digital maturity varies significantly between individuals.

In this sense, the methodological choices made in this thesis contribute to a broader argument: AI, OCR, and low-code analytics can be successfully integrated in resource-constrained industrial environments when developed through iterative, collaborative, and context-aware design processes. The evidence gathered supports the idea that a design and creation methodology is not only appropriate but perhaps necessary for digitalization projects in precision engineering SMEs, where solutions must adapt to tacit knowledge, fluid workflows, and limited technological infrastructure.

7.3 Recognized Limitations and Technical Challenges

Despite its contributions, the work presented here also encounters several important limitations. The OCR prototype, for instance, while promising, still struggles with the complexities of industrial technical drawings. The detection of tolerances, vertical dimensions, and fragmented or rotated text remains inconsistent. These issues arise not only from the limitations of the OCR engine (Tesseract) but also from the lack of robust

pre-processing and geometric reasoning, which would be required for high accuracy in reading technical standards.

Similarly, the quotation tool, though effective within a specific organizational context, is currently tailored to a single use case. It would need further generalization and testing to be applicable in other companies with different product typologies, cost structures, or ERP systems. There is also a need for a more scalable back-end architecture to handle multi-user environments or integration with company databases.

Beyond technical aspects, the project also faced the typical limitations of a student-led, time-bound research project. Limited access to extended user testing, restricted industrial datasets, and the absence of long-term deployment scenarios limit the empirical scope of validation.

7.4 Limitations and Future Opportunities

While the developed tools demonstrated promising results, several limitations were observed in practice. These limitations are specific to each component of the digital workflow:

- AI/Document Intelligence tool: remains at a conceptual or prototyping stage, without a fully deployed functional model.
- OCR-based drawing interpretation: requires standardized and clean drawing formats; real-world variability can reduce accuracy.
- Excel-based quotation formulas: built from a limited dataset, necessitating further tuning and validation across different part types or machines.
- Voice-based input: although implemented and tested, its reliability drops in noisy workshop environments and complex tolerance descriptions remain difficult to parse.
- Integration with ERP systems: currently absent, as the tools were designed as stand-alone solutions.

This review of the system also provided an opportunity to revisit Figure 1 and explicitly distinguish which elements were fully addressed, which were partially explored, and which remain future work. Making this distinction helps clarify the scope of the thesis and highlights the concrete areas that extend beyond what has been implemented so far.

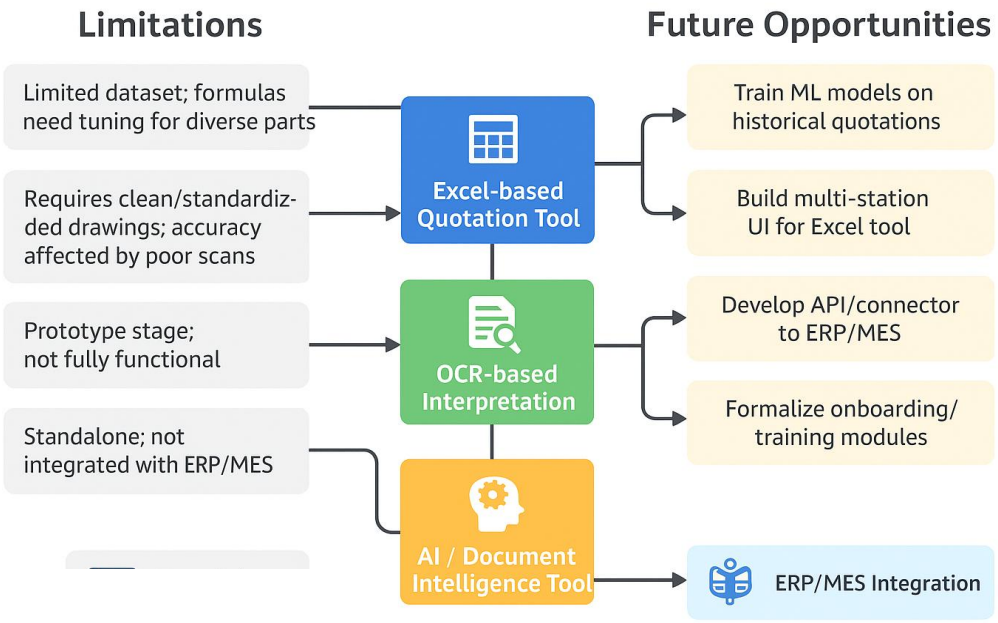

Figure 11: Limitations & Future Opportunities

To provide a clearer overview, Figure 11 illustrates the system architecture, highlighting each component, its current status, and the corresponding limitations. This visual representation makes explicit which elements are operational, which are experimental, and which require further development for end-to-end integration.

Despite these constraints, the limitations also point to concrete opportunities for future research and improvement:

By linking each limitation to its corresponding component, this approach provides both a roadmap for iterative improvement and a structured vision for further digitalization efforts in precision engineering SMEs.

7.5 Ethical and Social Considerations

Ethically, this project deliberately adopts a human-augmentation approach rather than full automation or worker replacement. The developed tools are designed to assist human operators, not to replace them. This choice is particularly relevant in precision-engineering SMEs, where expertise regarding machines, materials, and tools is often irreplaceable. By maintaining human oversight, the project safeguards expert judgment and preserves craftsmanship (Kotek et al., 2023; Sterlie et al., 2024).

From a social and organizational perspective, the quotation tool contributes directly to knowledge formalization and transmission. By structuring cost estimation logic and storing historical data, it mitigates the risk of tacit knowledge loss when employees leave or change roles. This enhances operational continuity and workforce resilience, critical

dimensions of social sustainability in SMEs (Victores, 2024; Jaekel et al., 2022). Human-in-the-loop oversight prevents over-delegation to AI systems, ensuring that institutional knowledge remains within the organization and performance does not drop due to staff turnover (European Commission, 2021).

Regarding gender neutrality and bias, the project avoids storing sensitive personal information (e.g., gender) and ensures that decisions are not influenced by these factors. However, large language models may still reproduce gender and intersectional biases. Studies show that LLMs can amplify occupational stereotypes (e.g., associating certain professions with women) (Kotek et al., 2023), and fairness criteria for generative models are necessary to mitigate such biases (Sterlie et al., 2024). Institutional standards emphasize the inclusion of a gender lens in AI development to avoid perpetuating structural inequalities (UNECE, 2025). Moreover, intersectional biases in automated systems have been documented, showing disparities based on gender and ethnicity in contexts such as resume screening (An et al., 2025).

From an environmental perspective, improved quotation accuracy and data-driven workload monitoring support more efficient use of energy and materials. Precise estimations reduce over-machining or excessive specifications, while better visibility on production loads enables managers to plan operations to avoid energy-intensive peaks or machine idling. Although the tools do not directly reduce energy consumption, they create informational conditions for more resource-efficient decisions (Victores, 2024; Jaekel et al., 2022).

In summary, the project explicitly addresses ethical (bias, gender), social (knowledge retention, SME sustainability), and environmental (resource efficiency) concerns by embedding AI as a tool that augments rather than replaces humans, preserves rather than discards knowledge, and empowers decision-making in precision engineering SMEs.

7.6 Positioning Within the Scientific and Industrial Landscape

This thesis contributes to an emerging research stream that focuses on lightweight, modular, and context-specific digitalization strategies for SMEs, particularly in precision engineering. While much of the literature emphasizes large-scale ERP, PLM, or MES implementations as pathways to digital maturity, this work demonstrates that incremental, frugal, and hybrid approaches can deliver tangible value in environments where resources, time, and digital literacy are limited. By framing digitalization not as a monolithic transformation but as a set of targeted interventions tailored to local needs, the study reinforces the relevance of digital frugality and incremental innovation as viable paradigms for SMEs.

The scientific contribution lies first in the methodological articulation of this approach. The thesis documents how tacit, experience-based knowledge in quotation processes—typically resistant to codification—can be progressively formalized through accessible tools such as Excel-based expert systems, Power BI dashboards, and OCR-driven prototypes. This combination of low-code technologies with knowledge structuring principles has received limited attention in existing academic work, which often privileges advanced AI or enterprise-scale solutions. By demonstrating how hybrid systems (mixing human expertise, rule-based models, and lightweight AI) can support

decision-making, the thesis adds nuance to ongoing debates on human-AI collaboration in industrial contexts.

Building on this, the thesis also positions its artefacts within the framework of Technology Readiness Levels (TRLs) as defined by NASA (Mankins, 1995). The tools developed do not belong to fundamental research (TRL 1–3), nor to fully industrialized systems (TRL 7–9), but instead operate at intermediate TRLs (4–6) where concepts are transformed into validated prototypes and tested in realistic environments. This explicit positioning highlights the applied nature of the research: the aim is not to produce laboratory models, but to develop artefacts that can transition toward operational deployment within SMEs. By clarifying how each digital component progresses through TRLs—such as the Excel expert system reaching TRL 6 through iterative user validation, while the OCR prototype remains at TRL 3–4—the thesis strengthens its contribution to bridging the gap between conceptual innovation and industrial feasibility.

From an industrial perspective, the case study illustrates a pragmatic pathway for SMEs to digitalize without depending on costly and rigid platforms. The OCR prototype for technical drawings—though still at an early stage—shows how even partial automation can accelerate repetitive tasks, while leaving the final responsibility and interpretation to the human expert. This reflects a human-centered design philosophy, where digital tools enhance rather than replace the operator's role. The integration of sustainability dimensions, such as traceability and potential links to energy and material efficiency, further aligns the research with current industrial and policy imperatives.

More broadly, this thesis contributes to bridging the gap between academic research and industrial practice. It offers:

- A proof of concept that low-cost, modular digital tools can operationalize the principles of Industry 4.0 in resource-constrained contexts.
- A framework for incremental digital maturity, where digitalization emerges from a sequence of small, high-value steps rather than radical systemic change.
- A case-based demonstration of how tacit knowledge can be progressively structured and digitized, opening avenues for replication in similar SMEs.
- An exploration of hybrid human-AI collaboration in technical quotation, showing that human expertise and lightweight AI can coexist productively without requiring advanced, costly infrastructures.

In doing so, the thesis not only positions itself within the academic discourse on digital frugality and incremental innovation but also provides empirical evidence of their applicability in real industrial settings. This dual orientation—scientific and practical—highlights the originality of the contribution: it does not merely describe possibilities but tests them in a concrete SME context, thereby offering a model that can inspire both further research and industrial uptake.

8 Conclusions & Further Studies

This thesis set out to explore how digital tools—developed with limited resources and adapted to the real needs of precision engineering SMEs—can enhance both operational efficiency and sustainability in a context where full-scale digital transformation is often neither realistic nor desirable. Through a design-based methodology grounded in fieldwork and iterative development, several prototype tools were conceived and tested, ranging from a structured Excel-based quotation system to a Power BI-based analytics dashboard, and an OCR tool for technical drawings. Together, these tools demonstrate that impactful, user-centered digital innovation is not limited to large enterprises with access to high-end technologies.

8.1 Summary of Key Contributions from the Practical Case Study

The primary contribution of this research lies in its pragmatic, accessible approach to digitalization. Rather than pursuing a top-down vision of Industry 4.0 centered on full system integration, the work promotes an incremental, bottom-up strategy that empowers human operators and leverages existing knowledge.

By doing so, the project addresses several key challenges and aligns directly with the research objectives:

- Formalizing expert knowledge (Objective 1): The Excel-based quotation tool captures the tacit expertise of estimators, documenting heuristics, geometric parameters, and pricing logic. This ensures traceable, reproducible knowledge that can be retained and scaled beyond individual experts.

- Monitoring quotation performance (Objective 2): The Power BI dashboards provide a feedback loop for evaluating quotation accuracy and timing. By visualizing trends and highlighting deviations, the tool supports data-driven decision-making and operational oversight without the need for costly Business Intelligence infrastructures.

- Exploring AI for unstructured input processing (Objective 3): The OCR tool demonstrates the feasibility of semi-automated extraction of dimensions, tolerances, and technical data from PDF engineering drawings. This lays the foundation for future AI-assisted quotation systems while assessing practical accuracy and integration within SMEs.

- Evaluating SME adoption conditions (Objective 4): The project offers a grounded view of how digital quotation tools can be adopted in a precision-engineering SME. Through iterative co-design sessions, informal discussions, and on-site trials, several concrete adoption conditions emerged: limited availability of staff for testing, dependence on tacit machining knowledge, heterogeneous digital literacy, and the absence of direct ERP connectivity. These observations show how digitalization efforts must align with existing practices, resource constraints, and the daily rhythm of production.

- Providing actionable recommendations (Objective 5): The recommendations developed stem directly from the practical experience of deploying prototypes in the partner company. They emphasize incremental steps that proved effective in

this context: starting with lightweight Excel-based solutions, validating each feature with operators, keeping interfaces intentionally simple, and ensuring compatibility with existing ERP workflows even without direct integration. These guidelines aim to support SMEs with similar constraints by proposing realistic, progressive, and cost-conscious digitalization pathways.

Taken together, these solutions form a coherent ecosystem tailored to the needs and constraints of precision engineering SMEs. Importantly, they were developed in close collaboration with practitioners, anchoring the project firmly in real-world practice.

8.2 Scientific and Practical Implications

From a scientific perspective, the work contributes to the emerging field of frugal digitalization and lightweight industrial automation.

Frugal digitalization is defined as follows:

> Frugal digitalization refers to the adoption of simple, modular, and cost-effective digital solutions that are adapted to resource-constrained contexts, particularly SMEs, in order to create value without requiring large-scale or expensive digital transformation projects.
> (Aloulou et al., 2022)

In this thesis, frugal digitalization is not treated as an abstract concept but as a design principle applied in practice. The Excel quotation tool, the Power BI dashboards, and the OCR prototype all illustrate how meaningful improvements can be achieved using existing software, low entry costs, and minimal infrastructure. This demonstrates that scientific originality can emerge not only from advanced AI models but also from the contextual adaptation of tools to environments where digital literature remains sparse.

Furthermore, the work contributes to the academic discussion on human-centered Industry 4.0, showing how hybrid systems—combining human knowledge, simple automations, and selective AI components—can support decision-making without displacing expert judgment. This reinforces the need for Industry 4.0 research to account for organizational constraints, informal practices, and the heterogeneity of digital maturity levels observed in SMEs.

From a practical standpoint, the case study provides a realistic demonstration of how a precision engineering SME can progress in its digital transition despite limited resources, legacy systems, and the absence of ERP integration. Through iterative testing and close collaboration with operators, the project shows that incremental adoption is both feasible and impactful when tools remain aligned with existing workflows and skills. The findings highlight the importance of simplicity, transparency of logic, and operator involvement in ensuring the actual uptake of digital tools.

Together, these insights show how bottom-up digitalization can support knowledge capture, more reliable quotation processes, and early forms of automation—while remaining compatible with the constraints and rhythms of SME operation.

Table 7: Alignment Between Research Objectives, Practical Contributions, and Resulting Implications

Research Objective	Practical Contribution (Case Study)	Scientific & Practical Implications
Objective 1: Formalize Expert Knowledge in Quotation Practices	Excel-based quotation tool capturing heuristics, geometric parameters, and pricing logic.	Demonstrates knowledge formalization in SMEs; supports reproducibility, traceability, and retention of tacit expertise.
Objective 2: Monitor Quotation Performance through Business Intelligence	Power BI dashboards visualizing KPIs, trends, and deviations in quotation processes.	Supports data-driven decision-making; provides evidence of scalable, low-cost BI application in SMEs.
Objective 3: Explore the Use of AI for Unstructured Input Processing	OCR tool for semi-automated extraction of dimensions, tolerances, and technical data from PDF drawings.	Shows feasibility of AI-assisted data extraction; lays groundwork for future AI-integrated quotation systems in resource-constrained environments.
Objective 4: Evaluate SME Adoption Conditions and Constraints	Field testing and iterative co-design with practitioners; identification of infrastructure, workforce, and organizational constraints.	Provides empirical insights into SME adoption barriers; informs design of context-aware, user-centered digital tools.
Objective 5: Provide Actionable Recommendations for Implementation	Practical guidance, step-by-step roadmaps, and best-practice recommendations for SMEs at different digital maturity levels.	Bridges research and practice; contributes to a generalizable framework for incremental digitalization of SMEs.

This table summarizes how each research objective is addressed through the practical contributions of the case study and their corresponding scientific and practical implications.

8.3 Limitations and Critical Reflections

As with any research project, this thesis has its limitations. First, the solutions developed remain prototypes, and their long-term performance, adaptability, and maintainability in diverse industrial contexts remain to be tested. While the quotation and dashboard tools have already shown tangible benefits in the specific company where they were deployed, generalizing them to other use cases will require adjustments in both technical structure and content logic.

Second, the OCR prototype—although promising—still lacks the robustness required for production deployment. It would benefit from integration with better pre-processing algorithms, domain-specific training datasets, and more advanced spatial reasoning capabilities to better handle the variability of technical drawings.

Finally, the empirical scope of the study was limited by the time constraints of a master's project and the availability of test users. Longer-term deployment studies, broader testing across different companies, and performance benchmarking would help further validate the results.

8.4 Directions for Further Studies

Building on this work, several research and development avenues can be explored:

A. Industrialization and Scalability of the Tools

One immediate direction is the transformation of the prototypes into robust, maintainable tools. This would involve modularizing the code, building clearer user interfaces, ensuring data security—especially for tools interacting with quotation data—and deploying the solutions in multi-user environments. Moving toward a web-based or hybrid architecture could also improve portability and enable smoother integration with existing information systems. Such an approach aligns with recommendations for scalable SME-oriented digital solutions based on modular and interoperable system design (Mittal et al., 2018).

B. Integration of AI and Knowledge-Based Systems

The OCR prototype could evolve into a semi-autonomous quotation assistant capable of recognizing common features, tolerances, or machining constraints from 2D engineering drawings. Combining OCR with case-based reasoning or supervised learning on past quotation data would strengthen both accuracy and decision support. Further studies could also explore voice-assisted quotation workflows, where operators verbally describe a part while the system cross-checks drawing data and quotation histories. The relevance of such hybrid, AI-supported decision systems is highlighted in recent work on data-driven industrial operations (Choi et al., 2020).

C. Comparative Studies and Academic Frameworks

Future research may expand the academic dimension by conducting comparative studies with other SMEs in France and abroad. Testing similar tools across different industrial cultures, ERP ecosystems, or workforce profiles would help assess the generalizability of the findings.
In parallel, linking this work to existing academic frameworks—such as sociotechnical systems theory, human-centered design, or digital maturity models—would help formalize its contributions. Sociotechnical perspectives are particularly relevant for digital tools that reshape interactions between operators, data, and workflows (Baxter & Sommerville, 2011).

D. Sustainability Assessment

Sustainability was a guiding principle throughout the project, but future research could adopt more quantitative evaluation methods—such as life-cycle assessment (LCA), energy monitoring, or material flow analysis—to better understand the environmental impact of the proposed tools. Key research questions could include: How does improved quotation accuracy reduce scrap or rework? Can dashboards support better machine scheduling or energy optimization? These questions echo broader findings showing that digitalization can enable more sustainable resource management in manufacturing systems (Zheng et al., 2019).

E. Potential Risks Related to Over-Delegation and Loss of Human Oversight.

Although the proposed tools contribute to structuring tacit knowledge, improving traceability, and enhancing decision-making, an important avenue for future research concerns the risk of over-reliance on automated systems. As highlighted in Section 2.5.2, automation may unintentionally shift responsibility from skilled human operators to partially opaque AI-based decision mechanisms (Leitão et al., 2022; Victores, 2024). While such tools can effectively preserve and disseminate knowledge, excessive dependence on them may progressively weaken human oversight, critical judgement, and the contextual interpretation required in complex or non-standard quotation scenarios. Future investigations should therefore examine how to design hybrid human–AI workflows that maximise efficiency without eroding operators' expertise, and how governance, training, and transparency mechanisms can mitigate this risk.

8.5 Final Thoughts

Ultimately, this thesis argues for a more inclusive, agile, and human-aware vision of digital transformation in precision engineering. Rather than treating SMEs as laggards to be "brought up to speed," the work recognizes their potential to innovate on their own terms, using digital tools that make sense to them—technically, economically, and socially.

The results achieved may not be revolutionary at scale, but they are transformative at the level that matters most: empowering people to work better with digital technologies, not against them. This thesis thus serves not only as a technical demonstration but as a modest contribution to a larger movement toward meaningful, responsible, and sustainable industrial innovation.

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