An exploratory study on process parameters impacting on quality of crankshaft grinding: A real world manufacturing use case

Master's Thesis in Production Engineering

Patra Vinay Manasseh
Wanninayaka Mudiyanselage Dilan Chandrajith

Department of Industrial and Materials Science
CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2026
www.chalmers.se

Master Thesis 2026

An exploratory study on process parameters impacting on quality of crankshaft grinding: A real world manufacturing use case

Vinay Manasseh Patra & Wanninayaka Mudiyanselage Dilan Chandrajith

Department of Industrial and Materials Science
Chalmers University of Technology
Gothenburg, Sweden 2026

An exploratory study on process parameters impacting on quality of crankshaft grinding: A real world manufacturing use case

Supervisors: Mohan Rajashekarappa & Elisa Margarita Gonzalez Santacruz
Examiner: Ebru Turanoglu Bekar, PhD

Master Thesis 2026
Department of Industrial and Materials Science
Chalmers University of Technology
SE-412 96 Gothenburg
Sweden
Telephone +46 31 772 1000

Typeset in LaTex
Gothenburg, Sweden 2026

Declaration of AI-assisted technologies

During the preparation of this work, the authors used Chat GPT, Copilot and Claude AI to improve the language and readability of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published thesis report.

An exploratory study on process parameters impacting on quality of crankshaft grinding: A real world manufacturing use case
Vinay Manasseh Patra
Dilan Chandrajith
Department of Industrial and Materials Science
Chalmers University of Technology

Abstract

Grinding is a critical finishing stage of most of the machined products. It directly influence the surface integrity, dimensional accuracy and product performance. But the studying about interaction between process parameters and quality outcomes are complex, since measuring of parameters are complicated. In the thesis, findings from systematic literature review (SLR), an exploratory data analysis (EDA) of quality data and evaluation of qualitative data via interviewing industry experts and academic researchers are presented. A mixed methodology is used, combining findings of systematic literature review, thematic analysis of interview inputs and exploratory data analysis of quality data.

The most critical process parameters such as depth of cut, wheel speed, workpiece speed, feed rate were affecting surface integrity, dimensional accuracy and production efficiency were identified via systematic literature review. Thematic analysis provided additional details such as dressing intervals, coolant behavior, machine conditions and material properties. The study further combined with a dashboard integrated with defect analysis. Overall, this study provides a structured understanding of grinding parameters towards crankshaft quality and discuss about future developments connected with data-driven decision making.

Keywords: Grinding, Crankshaft, Process Parameters, Quality Defects, Exploratory Data Analysis, Thematic Analysis,

Acknowledgements

This master thesis has been written at Production Engineering program at Chalmers University of Technology, in collaboration with Project AIMOps which is an on going research project in the department of Industrial and Material Science at the Chalmers University of Technology. We would like to express our deep gratitude to academic examiner Dr.Ebru Turanoglu Bekar who is a senior lecturer in the Department of Industrial and Materials Science, at Chalmers University of Technology for her patience and guidance, enthusiastic encouragement and useful critiques of this thesis work.

We would also like to thank our supervisors Mohan Rajashekarappa and Elisa Margarita Gonzalez Santacruz who are doctoral students at Department of Industrial and Materials Science for their valuable and constructive suggestions and feedback.

Lastly but not least, we would also like to express great appreciation to our industrial supervisor Kanika Gandhi who is manager at operational sustainability department at Heavy automotive manufacturing company, Magnus who is the Grinding specialist, Tobias who is Quality engineer, for their professional guidance and valuable support enabling us to visit the company and observe the plant operations.

Vinay Manasseh Patra , Gothenburg, June 2026
Dilan Chandrajith, Gothenburg, June 2026

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

AI	Artificial Intelligence
ANN	Artificial Neural Network
BN	Barkhausen noise
cBN	Cubic Boron Nitride
DT	Digital Twin
EDA	Exploratory Data Analysis
FTQ	First Time Quality
GDPC	Generalized Dynamic Principal Components
GDPC+	Enhanced Generalized Dynamic Principal Components
HEDG	High-Efficiency Deep Grinding
ICE	Internal Combustion Engine
IoT	Internet of Things
ML	Machine Learning
MOO	Multi-Objective Optimization
MQL	Minimum Quantity Lubrication
MRR	Material Removal Rate
NDA	Non-Disclosure Agreement
NSGA-II	Non-dominated Sorting Genetic Algorithm II
RUL	Remaining Useful Life
SGE	Specific Grinding Energy
SLR	Systematic Literature Review
TA	Thematic Analysis
TnT	Track and Trace

Nomenclature

Below is the nomenclature of symbols and parameters, that have been used throughout this thesis.

Symbol

V_s	Wheel speed
V_w	Workpiece speed
V_x	Feed rate
a_e	Depth of cut
R_a	Surface roughness
cBN	Cubic Boron Nitride
AE	Acoustic Emission

Contents

List of figures (add to table of contents)

List of Figures

List of tables (add to table of contents)

List of Tables

1
Introduction

This chapter provides a concise overview of the background, research aim and gap, the study's contribution, and the case description.

1.1 Background

Modern manufacturing systems are undergoing transformation, moving away from traditional production systems to systems that integrate digital technologies. These technologies enable organizations to enhance their data driven decision making . However, alongside the focus on digital transformation comes the challenge of dealing with the massive amounts of heterogeneous data generated by process sensors, quality systems, maintenance records, and material certificates, in highly demanding environments such as automotive manufacturing, these systems are essential identifying and examining how process parameters affect product quality. Within a manufacturing setting, production is carried out through a sequence of operations. This study focuses primarily on the grinding stage of that sequence.

Grinding is a manufacturing process in which material is removed by abrasive grains on a grinding wheel, and it is mainly used for finishing operations. In the automotive sector in particular, grinding is one of the most critical finishing operation, strongly linked to requirements such as dimensional accuracy, surface integrity, and material behavior of the part [1]. Therefore, it represents a key stage in the overall manufacturing chain. Traditionally, grinding has been employed to achieve tight tolerances and superior surface finishes. As a result, even small variations in process parameters such as feed rate, wheel speed, coolant behavior, or dressing interval can exert a substantial influence on the final product quality.

Recent technological advances, however, have extended the use of grinding to bulk components such as crankshafts, enabling both roughing and finishing to be performed using grinding processes [2]. Although prior grinding research has explored process parameters, thermal phenomena through physics based models, tool wear, and quality characteristics typically as separate topics a significant gap remains. In particular, few studies bring together process data, quality outcomes, and expert knowledge within a real industrial environment. Most existing work focuses on simulation based modeling and controlled laboratory experiments, and only a small number of publications deal specifically with crankshaft grinding. Beyond the crankshaft domain, there is also limited research on systematically integrating and analyzing multi-modal production data to reveal relationships between process parameters and crankshaft quality under real manufacturing conditions.

This study seeks to close that gap by combining a systematic literature review (SLR) and interviews with industrial experts from various departments along the grinding line, as well as with academic researchers specializing in grinding, together with an exploratory data analysis (EDA) based on an actual crankshaft grinding dataset. In addition, a data-driven approach is applied to determine and analyze which types of process data are necessary to explain quality variations in grinding operations.

1.2 Research problem & gap

As discussed in the previous section, grinding is a high-precision manufacturing process in which even small deviations can lead to crankshaft instability, ultimately affecting engine performance and overall cost. Modern grinding machines, equipped with advanced technologies, can address these issues while simultaneously producing large amounts of data. Nevertheless, even with access to this manufacturing data, companies often lack a systematic way to integrate and utilize it. A structured approach could enable organizations to pinpoint and investigate potential opportunities for process optimization, thereby improving the product quality.

Although prior studies do not focus exclusively on crankshaft grinding, they do address grinding related topics such as grinding performance, process understanding, thermal behavior, surface integrity and condition based tool monitoring. Nevertheless, there is limited insight into how these individual aspects can be integrated and jointly analyzed to reveal and support the relationships between process parameters and quality outcomes in crankshaft grinding.

This situation underscores a distinct gap in both research and practice, highlighting the need for a comprehensive and integrated understanding of process, quality, and maintenance data, which combines a review of existing literature, input from industry professionals and academic experts, and in addition a standardized method of data collection. Together, these elements would systematically capture and examine key grinding parameters, including process and maintenance related factors and finally quality defects.

1.3 Aim

The aim of this Master's thesis is to identify and investigate quality-related problems, analyze how process, quality, and maintenance functions interact, and determine which process data are required to enable future correlation analysis between process parameters and quality outcomes.

1.4 Research question

RQ1: What grinding process parameters affect the quality and production of crankshaft manufacturing?

RQ2: What are the interactions between process, quality and maintenance teams working within the grinding process?

RQ3: What multi-modal data need to be collected and explored to correlate between process parameters and quality defects in crank shaft manufacturing?

1.5 Research contribution

This thesis contributes to Crankshaft grinding process through :

- Systematic literature review addressing process parameters, quality problems, and data-driven methods in grinding,
- Empirical findings from industry specialists, academic researchers and their views on process parameters, quality aspects, and challenges encountered in crankshaft grinding,
- An exploratory data analysis providing insights on data quality and defect patterns,
- Finally, a three-pillar, mixed-method approach is employed, integrating a literature review with both qualitative and quantitative analysis.

1.6 Case description

Crankshaft manufacturing is a highly accurate and complicated process where proper forging, accurate machining, controlled heat treatment and fine finishing operations such as grinding. Each stage has its own variations in manufacturing and they directly influence the product quality at the end. In below section, it gives a structured case description of grinding lines focusing on power train system at an automotive manufacturing company.

Currently the grinding team is experiencing quality issues such as roundness, straightness, surface roughness grinding burns with their product. They expect to formulate a relationship between process parameters affecting for the afore mentioned quality issues using data driven approaches using the data from quality, process, production and maintenance departments from the same line.

1.6.1 Overview

The component passes through several operations before reaching the grinding line, where it is machined to its final, tight tolerances. Grinding represents the most critical machining operation in crankshaft production, as this is the stage at which the part attains its precise surface finish before moving on to subsequent processes. At this point, key quality attributes such as diameter, tolerance, roundness, straightness, and surface integrity are closely monitored. To maintain consistent product quality, the grinding wheel is periodically dressed at predefined intervals, guided by Barkhausen noise (BN) measurements, which verify that the wheel is cutting the material properly rather than simply plowing it.

As briefly mentioned in earlier sections, the grinding line is currently experiencing quality-related problems with its process. The company aims to investigate, assess, and analyze these issues using a data-driven approach. The foundation of this investigation is to first understand the relevant process parameters through academic literature, identifying which specific parameters influence the observed quality issues. Building on this, they seek to determine exactly which data must be collected for subsequent data analysis, enabling them to correlate process parameters with quality outcomes and ultimately identify the root cause of the defects.
The company currently faces the following challenges:

- Grinding-related quality problems,
- Data acquisition and multi-modal data integration.

This case describes a real-world manufacturing challenge in a highly optimized production environment, where significant difficulties are linked to data-related aspects. As modern manufacturing organizations increasingly pursue Industry 4.0, automation, AI/ML, and smart manufacturing initiatives, this situation provides an excellent opportunity for research. The company is actively pursuing innovation and embedding data-driven manufacturing into its operations. We believe that conducting research on this topic enables the integration of academic insights with practical industrial applications, thus contributing meaningfully to both research and industry.

1.7 Thesis outline

The following chapters in this thesis is organized as :

Chapter 2: Theoretical Background
Provide a theoretical framework that is pertinent to grinding operations, associated quality defects, and Exploratory Data Analysis (EDA).

Chapter 3: Methodology
Presents the structured research design used in this study, based on a mixed-methods framework.

Chapter 4: Results
This chapter presents the results obtained from the reviewed literature, the qualitative analyses, and the examination of industrial data related to EDA.

Chapter 5: Discussion
Insights from the literature review, qualitative study, and exploratory data analysis are triangulated to discuss the implications, research contributions, and industrial relevance.

Chapter 6: Conclusion
This chapter presents a summary of the research findings and offers recommendations that outline directions for future studies.

2

Theoretical Background

This chapter gives a brief understanding of the literature review, previous work conducted on the issue, and provides some insights on challenges and gaps within the related area.

2.1 Grinding process

One of the most important components of an internal combustion engine (ICE) is the crankshaft, which converts the reciprocating motion of the pistons into rotational motion. Crankshafts are structurally complex components [3]. According to Krajnik et al. (2021) and Quingyu Meng et al. (2023), grinding is a precision machining operation generally performed as the final step when working with high-strength steels or materials that are difficult to machine[2, 4]. It is used when high dimensional accuracy, low surface roughness, good surface integrity, and the capability to machine difficult-to-cut materials are required, especially in the automotive, aerospace, and bearing sectors [2, 1]. In grinding, material is removed by an abrasive wheel whose periphery consists of grits that function as cutting edges. Because a large number of these cutting edges simultaneously engage the workpiece with very small undeformed chip thickness, the process generates high temperatures, making thermal damage a critical concern. Comley et al. (2006) investigated a high-efficiency deep grinding process using cylindrical plunge grinding and optimized the process for automotive steels through thermal modeling. Their work showed, through both simulations and experimental measurements, that it is possible to maintain low workpiece temperatures [5]. Another review, "*Advances in modeling of fixed-abrasive process*," examines grinding behavior governed by process parameters such as wheel speed, depth of cut, and feed rate, which in turn influence the final workpiece quality. Although research specifically focused on crankshaft grinding is still relatively limited, recent advances suggest continued progress and promising prospects for data-driven methodologies[6].

2.1.1 Factors influencing grinding

Grinding involves material removal, wheel wear, thermal phenomena, and coolant behavior. Material removal itself can be classified into three primary mechanisms: plowing, grinding, and shearing[1]. In an experimental study by Comley et al. (2006), titled "*A high material removal rate grinding process for the production of*

automotive crankshafts", specific grinding energy is identified as a key fundamental parameter, defined as the energy required to remove a unit volume of material. Their results indicate that, in high efficiency deep grinding (HEDG), the specific grinding energy (SGE) decreases as the material removal rate increases[5].
In addition to MRR, wheel wear is another essential factor in grinding.As the wheel continues to operate, its abrasive grains gradually wear down, causing the grit to lose its sharp edges and become less sharp over time, altering the grinding wheel topography, which affects dimensional precision and can contribute to excessive heat generation[6]. Wheel wear typically occurs through three main mechanisms mentioned below and shown in Fig 2.1:

1. Attritious wear
2. Fracture wear
3. Bond fracture

Attritious Wear: This refers to the slow dulling and smoothing of abrasive grains due to continuous sliding contact. As discussed in *"Advances in modeling of fixed-abrasive processes"*, attritious wear generally dominates during the early phase of machining[6].

Fracture Wear: In this phase, abrasive grits fracture under high mechanical stresses this phenomena helps the grinding wheel. As the author points out in his article, this type of fracture can actually be advantageous, because it produces a self sharpening effect by continually sharping the cutting edges. However, macro-fracture may rapidly degrade the wheel profile and introduce form errors[6].

Bond Fracture: In this case, failure occurs at the interface between the bonding material and the abrasive grit when the shear stress surpasses a critical limit, causing the loss of active cutting edges[6]. Figure 2.1 illustrates these different wear mechanisms in a grinding wheel.

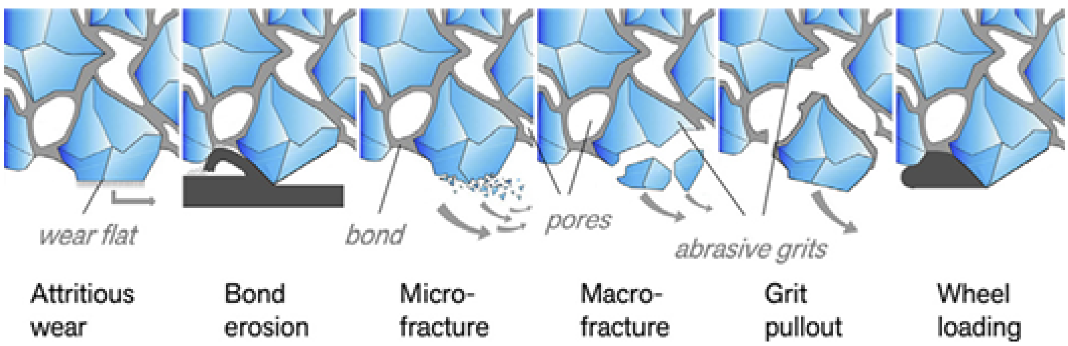

Figure 2.1: Fracture mechanism of grinding wheel by "Peter Krajnik et al." [6]

Another key aspect of crankshaft grinding is its thermal behavior, which has a direct impact on surface integrity, dimensional accuracy, and tool life. Because a crankshaft has a complex, non-uniform, and asymmetrical rotary geometry, the grinding forces vary along its profile, leading to a non-uniform, time-dependent temperature field [7]. The cited author emphasizes that the heat generated during machining mainly arises from sliding, plowing, and chip formation at the tool–workpiece interface. The mechanical energy introduced during the grinding process is transformed into heat and is then distributed among the workpiece, grinding wheel, chips, and coolant [5]. Of these, the workpiece absorbs a substantial portion of the heat, which in turn influences its surface quality.

Building on classical moving heat source models, later studies have proposed more realistic heat flux distributions that better capture actual grinding conditions. Whereas earlier models often relied on oversimplified geometries, subsequent work has demonstrated non-uniform heat sources that reflect the stochastic nature of abrasive interactions. Recent developments further incorporate coupled thermomechanical effects, linking kinematics, material behavior, and heat generation within predictive models [6]. These integrated approaches have markedly enhanced the capability to simulate and predict temperature evolution during grinding.

A similar pattern is reported widely in the literature, showing that the thermal loads generated during grinding are directly proportional to the process parameters, particularly depth of cut, wheel speed, and feed rate. Among these, depth of cut is identified as the most influential factor governing the thermal load [7]. While higher MRR typically leads to greater heat generation, the partitioning of heat is nonlinear. In particular, when chips remove a significant portion of the thermal energy, the heat impact on the workpiece can be reduced even as the overall heat flux increases [7].

2.1.2 Critical grinding parameters

Primary focus while machining crankshaft is selecting appropriate parameters, as this will directly affect the thermomechanical state of the crankshaft[1].

2.1.2.1 Process parameters

The main process parameters governing grinding performance are wheel speed (v_s), workpiece speed (v_w), depth of cut (a_e), and feed rate (v_x). These variables influence both the surface integrity and the grinding forces at the interface between the grinding wheel and the workpiece. Among these parameters, wheel speed and depth of cut are the most critical.[1] As discussed in the article "*A comprehensive review on the grinding process: Advancements, applications and challenges*", an increased depth of cut results in higher material removal rate (MRR), which in turn raises grinding forces and temperature. Likewise, increasing the wheel speed can enhance surface finish, but at the expense of higher thermal loads if the operating conditions are not optimized. The interplay among these parameters ultimately dictates the overall efficiency and stability of the grinding process[1].

2.1.2.2 Grinding wheel

Another parameter influencing machining performance is the grinding wheel. Its key properties include the type of abrasive, grit size, bonding material, and surface topography. Abrasives such as cubic Boron Nitride (cBN) and diamond are commonly employed in crankshaft grinding due to their high hardness, thermal conductivity, and wear resistance[8, 9].

2.1.2.3 Coolant

Lastly, regarding coolant parameters since grinding generates heat, a significant amount of this heat is transferred to the workpiece. This can cause thermal damage [1], so a well-designed cooling strategy is essential in crankshaft production. Common approaches include flood cooling, minimum quantity lubrication (MQL), and cryogenic cooling. These methods are used to control thermal effects by lowering the grinding temperature and thereby reducing the risk of grinding burns.

2.1.3 Quality outcomes

Quality outcomes for a crankshaft span a wide range of factors, including dimensional accuracy, surface integrity, and production performance. These aspects are essential because the crankshaft operates under continuous cyclic loading while converting energy from the engine, and therefore must meet tight tolerances to maintain durability and reliability.

2.1.3.1 Surface integrity

One important dimension of quality is surface integrity, which encompasses surface roughness, microstructure, residual stresses, and surface burns. In grinding, the wheel–workpiece interaction directly governs the resulting surface quality. Previous studies indicate that surface roughness (R_a) is strongly affected by the tool material and cutting parameters [10]. Additionally, data-driven investigations have shown that high-frequency vibrations in the range of 700–2000 Hz have a pronounced impact on surface roughness (Ra); using this vibration range enables machine learning models achieve above 90% accuracy in predicting surface finish [11].

2.1.3.2 Dimensional accuracy

Since the crankshaft has a highly complex, non-uniform geometry and must meet extremely tight tolerances in terms of roundness, straightness, and alignment, its manufacture is especially demanding. Because grinding is usually performed at the finishing stage, any deviation in this process directly affects the final quality. Process parameters that influence dimensional accuracy include wheel speed, depth of cut, and workpiece speed. Numerous grinding studies indicate that these parameters have a major impact on both dimensional accuracy and surface integrity [1]. If they are not properly controlled, they can cause form errors and degrade the overall quality of the crankshaft.

2.1.3.3 Production level metrics

From a system-level perspective, quality is commonly assessed using First Time Quality (FTQ)—that is, the proportion of parts that meet the required specifications without any rework. In a crankshaft production line, FTQ is influenced by numerous interacting processes, making it a system-level performance measure. Data-driven studies have shown that:

- FTQ is impacted by complex interactions across multiple processing stages.
- ML models can be applied to identify the key process variables that affect quality [12].

An illustration of the grinding quality dimensions is shown below:

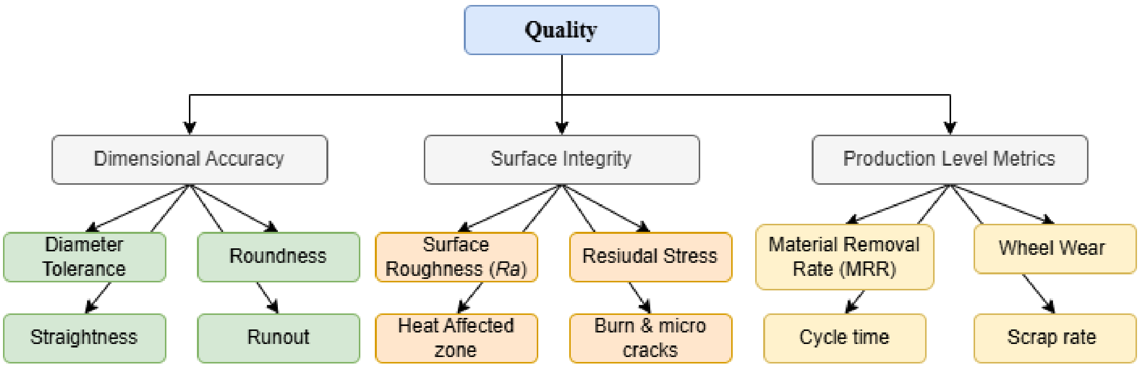

Figure 2.2: Quality dimension of Grinding

2.1.4 Maintenance

Modern grinding machines typically employ abrasive grinding wheels such as CBN, which have become industry standards because of their high hardness and long service life [2]. These wheels require regular sharpening to prevent rubbing rather than cutting; to maintain an effective dressing interval, some machines use sensors and process signals to determine when the wheel should be dressed and how long the dressing interval should last. If the dressing interval is too short, it can introduce inconsistencies, whereas excessively long intervals cause the wheel to become dull.

The latest generation of machines is equipped with multiple sensors that collect valuable data about the process. Notable research has focused on grinding wheel condition monitoring [5], multi-sensor monitoring [13], and sensor-based prognostic maintenance frameworks that use degradation signals to update time-to-failure estimates and schedule maintenance, with the goal of reducing costs and preventing unexpected breakdowns [14]. The concept of intelligent grinding envisions machines that can autonomously plan process parameters, monitor wheel condition, and update the process state; such systems can also learn from historical data and operator expertise to achieve "first pass right" and zero-defect grinding [15].

2.2 Data-driven approaches in grinding

To improve the reliability, precision, and responsiveness of grinding processes, Industry 4.0 technologies including the Internet of Things (IoT), cloud computing, data analytics, machine learning (ML), and artificial intelligence (AI) are employed to build an intelligent manufacturing system[16]. Lishu et al. discuss about intelligent technologies in grinding process driven by data, where data can be utilized for tool condition monitoring[17].

2.2.1 Use of sensor data (force, temperature, acoustic emission)

Recent studies on grinding highlight the increasing role of data-driven methods and workflows in intelligent manufacturing. The grinding process produces large amounts of heterogeneous data such as machine states, forces, temperatures, and acoustic emissions which are regarded as key assets for understanding and controlling grinding operations [17, 18]. Both studies agree that an organized "data-driven model" is necessary for effective data utilization, incorporating layers for data acquisition, preprocessing/fusion, mining/analysis, data representation, and service/decision making [17, 18]. In this context, multi-sensor data are processed using neural networks and transformers to predict remaining tool life, underscoring the importance of multimodal time-series machining data [19]

2.2.2 Characteristics of grinding data

Grinding data is characterized by volume (large quantities of data), value (low value density), velocity (high processing speed), and veracity (stringent data accuracy requirements) [17].

2.2.3 Digitalization and smart manufacturing approaches

The deep integration of Industrial AI, cyber-physical systems, and the industrial internet aims to "green" enterprises and raise efficiency to a higher level. Key functions of these smart methods include real-time condition awareness, optimal decision-making, visual monitoring of dynamic performance, and global optimization of the entire production process [20]. The study by Amouzgar et al. can be regarded as an innovative method for intelligent process planning in crankshaft machining, employing multi-objective optimization and an automated code pipeline to reduce time and cost while enhancing surface quality through data-driven strategies consistent with Industry 4.0 [21]. Kaufmann discusses AI-based grinding frameworks that integrate virtual sensors, resilient analytics, and streaming architectures to lower rejection rates in production by ensuring strong quality influence and system stability [18]. Digital Twins (DT) facilitate the representation of the connection between digital models and real-world systems through physics-based and data-based twins. In particular, data-based twins employ machine learning models to identify

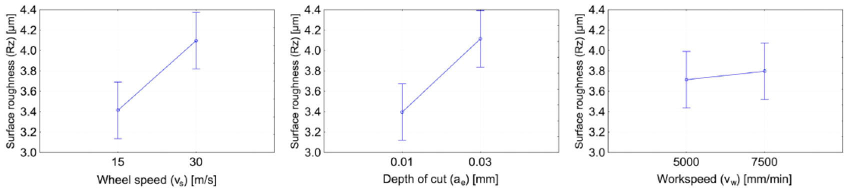

Figure 2.3: Surface Roughness against wheel speed, depth of cut and workspeed[22]

relationships between inputs and outputs[16].

2.3 Related work

This section mentions about the similar studies most related to the use case in the thesis study. The studies presented here are directly focused on process parameters affecting grinding quality and gives a future vision in the development areas.

Several studies have been investigated about finding the process parameters affecting grinding quality[22, 10, 11, 18, 7]. In the study of [22], the impact of grinding parameters on a Nickel-based super-alloy(Inconel 625) like wheel speed, depth of cut, work speed (feed speed), grinding direction and abrasiveness of grinding wheel has been tested. It is a material which is widely used in aerospace and high temperature applications due its resistivity for corrosion and mechanical strength. This material is classified as a difficult to machine material with its poor thermal conductivity, high shear strength, presence of hard carbides and work hardening tendency. In our case also, the same difficulties related to machining are observed. In this paper, it is found that 60%-90% of the high heat generating at the grinding is transferred into the material. These challenges leads to a thermal damages, residual stresses and micro-cracks. Since surface integrity is crucial in grinding, the above mentioned issues are impacted directly to quality. Surface roughness, micro-hardness and micro-structural changes are affecting surface quality while high temperature is causing work hardening, plastic deformation and surface deterioration.

Wheel speed, depth of cut, work speed has shown positive linear relationships with surface roughness as shown in Fig 2.3. Changing abrasiveness from coarse(60) to fine(80) and changing from up grinding to down grinding has reduced the surface roughness. Wheel speed has found to be the most influential parameter while depth of cut increases forces and roughness. When increasing depth of cut, it increases cutting forces and lower the specific energy while adversely affecting the surface roughness level. Abrasiveness affects surface finish leading finer grits give a better surface finish and work speed has found to be less significant. Inconel 625 shows strong work hardening behavior in grinding, where higher wheel speeds gives more work hardening[22]. One of main gap in this research is limiting only to Inconel 625, where limited research are available on grinding behavior.

According to [10](thesis about marine diesel engine crankshaft grinding), the influence of grinding parameters on surface texture are evaluated. Further it emphasizes cutting regimes which impacts directly on surface texture and crankshaft repairability. In this paper, a new technology is developed to grind crankshaft of marine engine without removing it from engine. This study provides optimal and most appropriate grinding parameters using a proposed 3D surface texture model based on parameters such as mean arithmetical deviation of surface roughness (RaT) and spacing parameters (Sm1 and Sm2), which were measured using a Taylor Hobson 3-D stylus profiler. The results in this study shows surface roughness is increased with grain size, radial feed, and grinding depth while axial feed shows less influence. Further, it shows grinding depth and radial feed influence primarily on spacing parameter (Sm1) while grain size and axial feed are influencing on Sm2. However, despite of the 3D surface measuring parameters, the study shows relationship between material properties and grinding parameters. This is related to our work, due to the analysis of influence of grinding parameters on surface quality.

Apart from the studies focused on impacting parameters, there were studies regarding predicting surface roughness. [11] proposes an experimental model where vibrations signals are collected via an accelerometer connected to tailstock and power data are collected via a powercell connected to grinding wheel motor VFD. High-frequency vibration signals was found to be a significant factor which determine surface roughness. The surface roughness of test samples are manually measured using a perthometer (precision instrument used to measure the surface roughness and texture of materials using a contact probe) and data is stored. Then a feature extraction is done where acceleration and power can be selected as significant features. A physics-based process-machine interaction (PMI) model and a data driven random forest model were combined in order to predict surface roughness. Then in the validation of predicted values and observed values, it has shown accuracy exceeding 90% of test data. Further, it was shown that energy content in 700-2000 Hz range was another important predictor of surface finish[11]. Findings shows that grinding is influenced by cutting forces and machine vibrations. Further, this study demonstrate the potential of a sensor-based monitoring system that be used for improving prediction of surface quality.

In the study of Kaufmann et al, an AI-based framework for Deep Learning Applications in Grinding is proposed in order to process control the cylindrical grinding[18]. The study emphasize that wheel wear is critical for surface quality and process stability. Further it highlights the fact that, feed rate, wheel speed, lubrication condition and wheel topography influence towards wheel wear. Different machine learning methods such as Support Vector Machines, Artificial Neural Networks and Hidden Markov Models are used for predictive analysis to understand the complex interactions between wheel wear and grinding parameters. Industrial practitioners are facing a challenge of faulty signals/sensor faults when acquiring data for AI models. To avoid the interruption of the prediction due to breakdown/fault of physical sensors a level of resilience is introduced in this study. An approach of virtual sensors in the process of data acquisition and analysis of AI-based framework provides a predictive analytic layer. When a physical sensor get faulty, the training protocol is shut down and input channel is switched to virtual sensor layer without interrupting the prediction process due to the fault in physical sensor[18]. It demonstrates an error free, intelligent, data-driven approach for enhance reliability in grinding process.

In the study about "Research and process optimization of crankshaft grinding parameters based on Gaussian heat source model", the interactions among grinding process parameters (wheel speed, grinding depth and feed rate) were analyzed using Box-Behnken design and a linear regression equation which was established to get a response on surface optimization[7]. The cause for grinding burns are found to be the high temperature in grinding zones further disturbed by the non-uniform crankshaft geometry. When temperature exceeds material transformation level, occurrence of phase transformation, martensite formation, crack formation and thermal damage occurs. Here the Gaussian heat source model is used to predict grinding temperature and analyze thermal behavior compared with rectangular heat source and triangular heat source. Grinding depth, wheel speed and feed rate are found to be the most significant parameters affecting temperature. Grinding depth is found to be the most influential factor while wheel speed influence second. A Response Surface Method (RSM) is used to find the optimal combination of affecting factors of grinding avoiding burns. The findings of the study shows the importance of analyzing thermal behavior for grinding parameter optimization and maintaining surface integrity in crankshaft grinding.

Through the related work discussed above; [10] gives a surface quality analysis, [22] gives a grinding parameter analysis, [11] gives process dynamics analysis, [18] gives an analysis about AI & monitoring while [7] gives an analysis on thermal effect & optimization. In this research about deciding grinding parameters affecting quality of crankshafts, the parameters that should be collected and analyzed are decided based on previous studies, via qualitative analysis of semi-structured interviews of industry and academic experts and via a descriptive data analysis visualized in a dash board.

2.4 Exploratory Data Analysis

2.4.1 Role of EDA in preprocessing industrial grinding data

During EDA, data originating from multiple sources are cleaned, examined, and visualized prior to pattern detection. EDA is carried out to uncover patterns, test hypotheses, verify assumptions, and investigate relationships within the data[12]. Kaufmann et al. describe AI-based grinding frameworks that incorporate synchronization, filtering, aggregation, and feature extraction steps, which in turn generate predictive models that also encompass descriptive EDA[18]. Systematic preprocessing of time-series data, geometric data, and operational data facilitates effective fusion and model correlation, as demonstrated using a multimodal tool-condition dataset[19].

2.4.2 Methods used to identify correlations (correlation matrices, distributions, trends)

Industrial studies commonly use correlation analysis, trend analysis, and feature-importance evaluation to link process parameters with product quality. Insights gained from data preparation, exploratory analysis, and machine learning guide the enhancement of part quality[12]. Correlation analysis between multimodal features and wear indicators has also been applied in framework development for tool-wear estimation and RUL (Remaining Useful Life) prediction[19].

2.5 Analytical methods for exploring relationships

Quasi-linear regression which is combined with ANN(Artificial Neural Network) is used by Pavlenko and the team to parameterize cutting-force models in crankshaft grinding [23].

2.5.1 Statistical method

The process parameters against forces, temperature, wear and quality related to crankshaft grinding has been modeled using a quasi-linear regression combined with ANN(Artificial Neural Network)[23]. Cao and team use a physical wear prediction model using regression-calibration relationships between speed, force, temperature, hardness and wear coefficients in order to predict the temperature and surface roughness[24].

2.5.2 Data analysis frameworks

A framework consisted of five main stages are proposed by Xinyan Ou and the team to analyze data for diagnosing and improving FTQ(First Time Quality)[12]. Further Li and the team also has presented a similar framework which the final layer is named as data service layer where the different users can take customized services.

1. Data Fetching :First the data is collected from the sources and useful data is categorized into classes.
2. Data preparation :For an effective data analysis, data need to be preprocessed to avoid noise. It includes data integration, data cleaning, by removing outliers, completing data, correcting inaccurate, dealing with duplicates and enriching data.
3. Exploratory analysis and modeling :In data analysis, EDA is a method use to analyze data sets to summarize main characteristics with visual methods. It enhances the data set to discover patterns, testing hypothesis and checking assumptions.
4. Visualization and analysis report :After analysis is done, choosing of ML models and features can be done. The analyzed data can predict a result inline to a given feature.

5. Output tools and decisions :After analysis report is done, diagnosing of root cause or required improvement solution can be proposed based on results.

2.6 Machine learning models

2.6.1 Architectures used for process controlling

Architectures enables the adjusting of parameters in considering the part quality. Sensor-based modules get data from physical bodies and digital models enables a reference value so as to generate new process parameters[16].

An intelligent approach to optimize robot grinding quality(surface roughness, Ra) and grinding time has been taken by Ruizhi Li and team by using a non-dominated sorting generic algorithm II (NSGA-II).

2.6.2 Implementation of process control systems

Autonomous process control system can be created by integrating a monitoring module, control module, DT module and data collection module as developed by Park and the team in a real manufacturing system.

2.6.3 Applications in using predicting models

For the purpose of predicting surface roughness, grinding forces, wear defects, AI and data driven models are used in practical manufacturing applications[25]. Roughness degradation has been modeled using the wear-prediction modeled connected to operating parameters like temperature, wear volume and surface topology[24]. In the test conducted by Pavlenko, cutting forces in crankshafts are predicted by ANN-regression hybrids[23]. For the prediction of FTQ of crankshafts, Ou and team has used machine learning model on online data classifying first time quality defects and tracing root causes[12].

2.6.4 Strengths and limitations in using prediction architectures

Data-driven and AI approaches handle non-linear and multivariate data in an efficient way with accurate and fast calculations[23]. AI based frameworks help for adaptive process controlling focused on cost reduction by process monitoring, online process signal analysis[18]. Further, the studies of Hinz and team regarding monitoring grind surfaces enable real time or online quality estimations[26].

Dependence on labeled data and limited physical interpret-ability where NN-Neural networks are acting like black boxes and fragility of sensor failures encourages virtual sensors and resilience concepts[27].

2.7 Analytical tools

2.7.1 Common tools and implementation

For data pre-processing, EDA and creating machine learning models, Python is the most commonly used language model [12]. Most of the times Python is used for AI based frameworks, edge computing, streaming/batch processing architectures which are consisted with big-data eco systems[18]. MATLAB is also used in similar platforms in optimization and simulation environments for process planning and MOO (Multi Objective Optimization) though the specific tools are not specifically named[25, 21]. There are some other commercial statistical packages like Minitab and SPSS, which we could not find details within the searched literature.

2.7.2 Signal processing and monitoring

Commonly in the area of grinding, force, temperature, vibration and control states are acquired and processed relying both on real-time data and historical data[17, 24, 18]. Virtual sensor architectures are used in processing raw signals, detecting faulty signals, reconstructing missing signals for the sake of robust online monitoring[18].

2.7.3 Missing integration between process, quality and maintenance

Across the literature we conducted, we can find studies which address the three areas process, quality and maintenance rarely. In the studies of Cao, the linking of process parameters to surface quality can be found while no connection with maintenance decisions are mentioned[24]. The relationships between cutting force identification and FTQ prediction on process and quality can be observed without a direct connection to maintenance[12, 23]. GNN-Transformer RUL prediction is showing relationships between maintenance, but does not connect with geometric quality or defect patterns[19].But broader intelligent manufacturing frameworks highlight the connections between decision making, controlling and operations, execution and process controlling in a fully integrated intelligent manufacturing solution[20, 17].

2.7.4 Limitations in current models

In most of the studies carried out about the models, limitations have been imposed due to small size of samples, high dimensionality and concept drift. Hu and the team has used fuzzy broad learning with prior knowledge for a small sample machining prediction model to compensate for limited data[28]. Studies by Diaz shows that GDPC/GDPC+ demonstrating unsupervised clustering on dynamic streams can be unstable under many reasons requiring for further robustness enhancements[27]. Controlled surface monitoring systems and extensive parameter studies are required for image setups to achieve reproducibility [26]. It is observed limited physical insights in many black-box neural networks used in grinding and crankshaft force predictions, where transparency and interpretability is missing[23].

2.8 Challenges in crankshaft grinding

Grinding is considered to be a key process in machining where the product has a direct impact on its accuracy, performance and service life[17]. The process of manual process planning for grinding is a "demanding and time consuming" process due to the balancing of machine, surface roughness and tool cost[21]. Achieving an optimal combination of grinding process parameters only based on manual experience is difficult[25]. Developing of scientific methodologies to determine required parametric values are discussed in many literature[23].

Root cause analysis in grinding becomes more complex due to too many inline factors which affect the quality directly and indirectly[12]. Challenges related to lack of reliable data acquisition solution, limited non-representative data, non-shared grinding data bases obstructs the usage of intelligent systems[17]. Further the human errors and sensor failures also contribute towards challenges related to resilient control systems[18].

There are limitation related to small samples, high dimensionality and concept drift where small machining predictions motivates to use fuzzy broad learning to compensate with the limited data[28]. According to Diaz and team it shows that unsupervised clustering on dynamic streams become unstable due to transients, demanding more robustness[27]. Further the tests by Hinz and team shows that, neural models for monitoring the surface quality requires carefully controlled imaging facilities and studies to achieve reproducibility[26].

3

Methodology

This chapter outlines the research methodology adopted for this study. Its primary purpose is to familiarize the reader with the nature of the research objectives, which are addressed using a mixed-methods approach.

3.1 Research design

This section briefly describes and showcase the mixed methodology employed for this project.

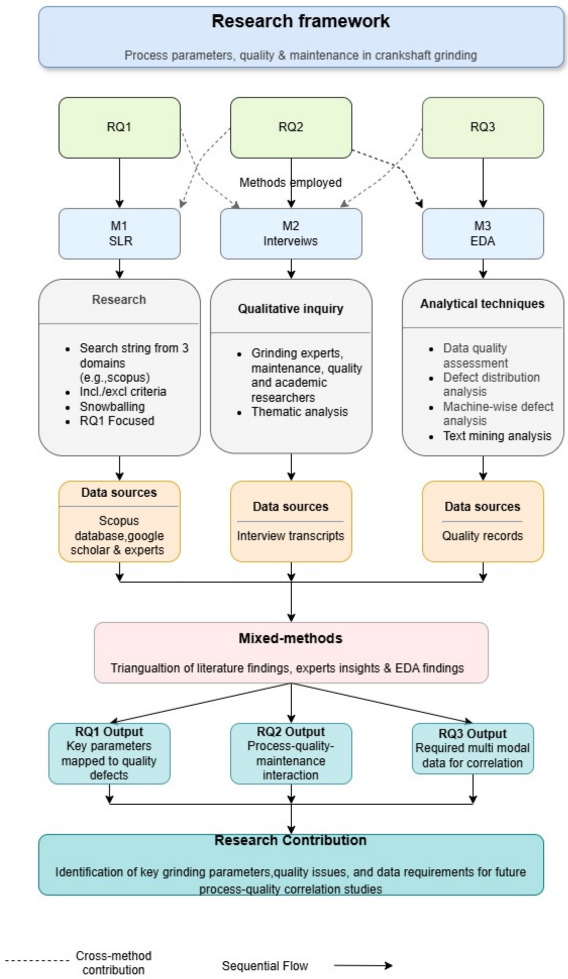

Figure 3.1: Research framework

Fig 3.1 shows how this project combines three research pillars integrating with triangulation approach combining SLR, interviews and EDA.

- Pillar 1 : Systematic Literature Review (SLR)
- Pillar 2 : Thematic Analysis (TA) for interview inputs from experts
- Pillar 3 : Case Study by conducting EDA

To tackle each pillar in a structured manner, a sequential and integrated workflow was developed , in which every pillar was investigated through interconnected research questions. The structure which is based on the three research questions, has a sequential as well as interconnected flow. The systematic literature review (SLR) identifies the key grinding parameters related to grinding quality defects. Research question 1 (RQ1) is mainly answered through a systematic literature review, complemented by expert and academic researcher interviews, which together provide proof and validation. These activities are explained in detail in result section. The interview insights from the experts answers both RQ1 and RQ2 determining key parameters affecting grinding quality and determining interactions between quality, maintenance and production. The interviewees came from diverse backgrounds, and academic researchers were also involved to broaden and deepen the conceptual understanding. Result section presents the outcomes of qualitative study that constitutes pillar 2 of this project. The quantitative component of this research was guided by Exploratory Data Analysis (EDA) to investigate patterns and explore the relationships between process parameters and grinding defects answering the RQ3. The objective here was to identify and visualize what type multi-modal data was needed to establish correlations with quality. This is addressed using EDA, which guided the analysis of the company's available datasets. The interviews additionally clarified which data types were relevant and accessible. Result section provides the complete methodology, analysis, and data sources used to address pillar 3. A key strength of this methodology is the triangulation and integration across different data sources such as literature findings, expert interviews and quality data. This mixed methodology enables an exploratory and holistic investigation, contributing for the understanding of process parameters impacting crankshaft grinding quality.

3.1.1 Ethical considerations

Ethical consideration in this research were aimed at protecting participants rights, dignity and welfare while allowing valuable insights.
Key principles included in this study are:

- Informed consent: Participants in the qualitative study were briefed on the study's purpose, scope, potential risks, and anticipated scientific benefits before agreeing to take part.
- Voluntary participation: Team meetings were scheduled in advance, and consent was obtained from all involved members. Participants were free to join or withdraw from the meetings at any time.
- Confidentiality and anonymity: The researchers signed an NDA with the case company before gaining access to any transcripts, recordings and data. All details and data are anonymized and masked in this report, protecting and

preserving the confidentiality of the information provided by the company.
- Scientific validity: The research was grounded in a systematic literature review, the qualitative component was analyzed using thematic analysis, and the research questions were formulated, documented, and reported in a transparent and honest manner.

3.2 Qualitative analysis

3.2.1 Systematic literature review

This study was conducted using a Systematic Literature Review (SLR) combined with forward and backward snowballing. This integrated strategy was chosen to ensure coverage of the established body of work and to obtain highly relevant sources, particularly in the field of crankshaft grinding, where the number of available publications were limited. The SLR procedure followed the sequential steps described in [29] to systematically identify and retrieve the relevant articles.

1. First, the scope of the project was defined and the relevant search terms were determined.
2. An appropriate database was then selected.
3. Inclusion and exclusion criteria were established.
4. Titles and abstracts were screened.
5. Full texts were reviewed.
6. Data were extracted from the selected articles.

This stepwise method offered a clear, thorough, and precise account of the review procedure. Scopus was chosen as the primary database for this project, as it provides an extensive collection of peer-reviewed literature and research articles, containing more than 100 million records.

3.2.1.1 Search strategy

Initial search string was aimed at getting the results for Research question 1 (RQ.1). "(("grind*") AND ("manufacturing" AND "PROCESS PARAMETERS") AND ("quality" OR "defect" OR "inspection" OR "tool life") AND ("data-driven" OR "machine learning" OR "ML" OR "artificial intelligence" OR "AI" OR "industry 4.0" OR "condition monitoring")) " For this keywords further filtration was applied for example: **year** was limited to 2011 till present and **study area** was limited to engineering and computer science. While peer reviewed journal articles, conference papers with full text were filtered in the Scopus database, a complete prisma diagram of the search can be found in Figure 3.2.
The literature search was conducted using three primary sources.
- Scopus,
- Google scholar,
- From experts recommended publications,

The above mentioned keyword string was aimed at retrieving articles from three different focus areas. one from Grinding aspect, one from process and quality and finally from Data driven aspect. Using this string in Scopus database a total of 32 articles were extracted.

3.2.1.2 Inclusion & exclusion criteria

To verify and do a systematic analysis articles selected for our study ensured that they were reliable.

Studies were included if they:
- Focused on grinding crankshaft,
- Discussed Process parameters and quality relationships,
- Addressed application close our area of interest,
- Were in full text peer reviewed articles or conference papers,
- Selected papers were published in english.

Studies were excluded if they:
- Lacked process & quality related analysis,
- Unrelated to precision grinding (cylindrical)

3.2.1.3 Snowballing

To strengthen the SLR and obtain more domain specific papers on crankshaft grinding which were not fully indexed in general databases, snowballing was applied in both directions. Backward snowballing involved reviewing the reference lists of selected papers to discover additional relevant publications [30], while forward snowballing focused on identifying new papers that cited the studies under examination [30].

This approach was particularly effective for this specific case study, as the number of available articles were relatively small compared to the broader grinding research field. A set of highly relevant articles served as the initial seed for the snowballing process an example of seed paper is shown *"Intelligent Grinding"* by Wegener et al. (2026) served as seed for backward snowballing here total of 63 articles were retrieved further after applying filtration, and screening total of 4 papers were included. This can be seen in the below figure

3.2.1.4 Selected literature summary

The combined application of SLR and the snowballing technique resulted in a total of 27 papers, which were systematically collected using databases, snowballing and expert inputs. These studies focused on grinding processes, quality aspects, maintenance, and data-driven methods. The initial search in Scopus identified 32 articles from the period 2011 to the present. After removing papers limiting to subject area, document type and language, the remaining papers underwent title and abstract screening, reducing the number to 10. Subsequent full-text screening led to the exclusion of 5 more articles. As this number was insufficient for our

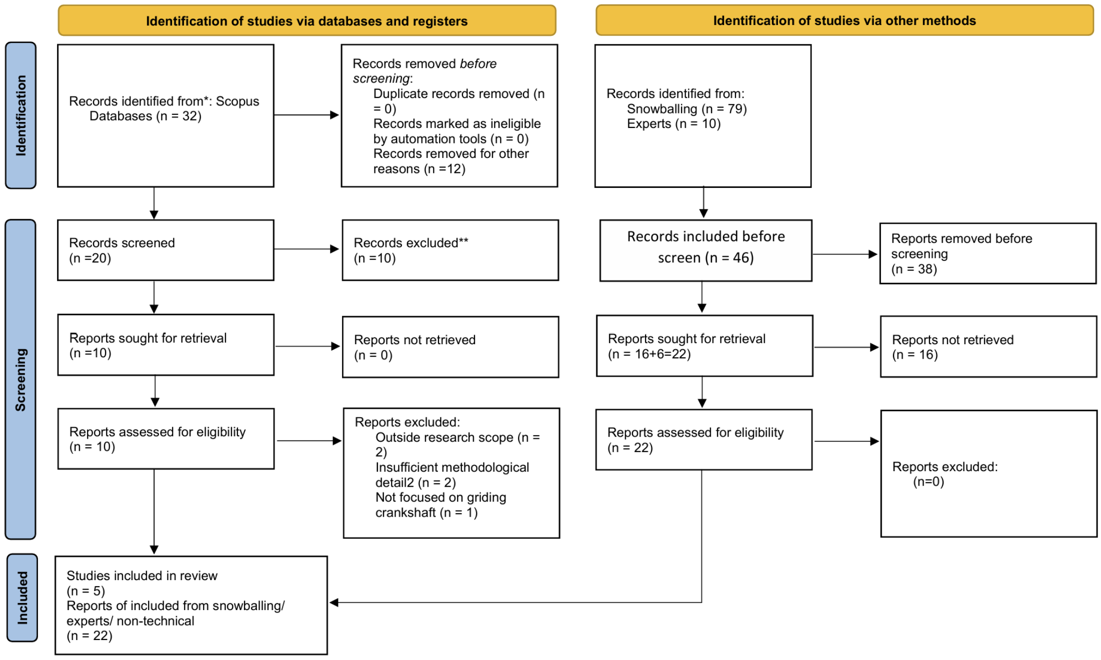

Figure 3.2: Prisma flow for Literature study [31]

study, snowballing was employed to further enhance the literature base. Through snowballing and expert recommendations, additional domain-specific studies were identified and included were 22. This overall process gathered 27 papers aligning with the PRISMA framework, a structured methodology commonly used in systematic reviews to enhance transparency.

3.2.2 Semi-structured interviews

Supporting the literature study additional qualitative analysis of this research is equipped with "Thematic Analysis", where the raw data can be moved to meaningful insights in a systematic way[32]. The insights from industry practitioners as well as researchers from academia who are involved in grinding researches were gathered to analyze data . As highlighted in the qualitative research guide, general qualitative inquiry is suited to studies that pursue “rich, contextual insights into perspectives and the dynamics of particular phenomena within their real-world setting” [33]. This is closely aligned with our aim of understanding how automotive practitioners perceive process parameters, interations between production, maintenance and quality.
Thematic Analysis was chosen for this study for the following reasons:

- The master’s thesis does not aim to develop a new theory (thus, grounded theory is not applicable).
- The thesis does not focus on exploring lived experiences (making phenomenology unsuitable).
- The thesis does not involve cultural immersion (therefore, ethnography is not relevant).
- The thesis does not employ iterative cycles of intervention (hence, action re-

search is not appropriate).

Instead, this qualitative approach further complements the data-driven EDA by drawing on practitioners' knowledge and experience to contextualize the quantitative findings further in the research.

3.2.2.1 Data collection: semi-structured interviews

Data were collected through semi-structured interviews with both industry and academic specialists who possess expertise in grinding processes. Practitioners were selected from a range of engineering functions, including process, quality, production, and maintenance. This approach is consistent with qualitative research guidelines that advocate the use of open-ended questions to elicit in-depth, nuanced accounts of participants' perspectives.

3.2.2.2 Selection strategy and participant profiles

Participants were recruited through purposive sampling, focusing on individuals with some key criteria:

- Specialization in grinding and direct hands-on operational experience.
- Strong domain knowledge, such as familiarity with process parameters.
- Experience with quality issues as well as an understanding of quality-related data.
- Background in maintenance activities.
- In addition to industry professionals, two academic researchers with expertise in grinding and machinability of material were included to provide a research-oriented perspective.

This selection strategy ensured that the insights obtained from the interviews were firmly rooted in practical experience and domain-specific expertise. The experience of the industrial practitioners ranges from 5 years to over a two-decade period reflecting a wide range of process experience, problem solving and developments. The researchers were actively engaged in the area of grinding and machinability of materials with a deep knowledge about particular areas with a background in research.

Interviewee No:1 (Process specialist)

First interviewee was working with crankshafts for continuous 28 years and and 12 years focused on crankshaft grinding. He is a manufacturing technology specialist skilled in the area of grinding and super finishing. Further, he was responsible for process operations and future improvement in the process. He is working with the global network around the world by visiting exhibitions, different companies in order to evolve the process and finding better ways of grinding.

Interviewee No:2 (Quality specialist)

The second interviewee was an expert in quality aspects of crankshaft grinding. He was responsible for reviewing the quality defects occurred during production. Further he was responsible in educating grinding machine operators about maintaining proper grinding quality.

Interviewee No:3 (Maintenance specialist)
Third interviewee was a maintenance responsible person in the crankshaft grinding section. She was initially an operator in same department from 2021 and now she is proceeding with the new role since 2025. Her main responsibilities are planning and scheduling maintenance activities in the grinding section. She was responsible for the maintenance KPI's, and leading technicians and electricians in the field.

Interviewee No:4 (Production operator)
Forth interviewee was an operator in grinding section for five years counting total experience of ten years working in grinding section of another premise with same organization. He was mainly responsible in grinding, focusing on measurements, taking crankshafts to measuring room and checking for defects. He was a person who is working directly with the grinding machines, changing process parameters to operate the machines with better quality.

Interviewee No:5 (Professor and researcher in grinding)
The fifth interviewee was a researcher in modeling and optimization of manufacturing processes, specializing in grinding technology. He was working with leading automotive manufaturing organizations developing powertrain production and serving as director at Metal Cutting Research(MCR) group. He has authored over 130 publications and hold 5 patents/patent applications.

Interviewee No:6 (PhD student researching on materials and manufacturing)
The sixth interviewee was a doctoral student at Chalmers University focusing on turning, the machinability of materials, understanding how the material influences the process. He was working with sensor monitoring in both turning and grinding processes.

3.2.2.3 Interview structure

The interview questions were designed to investigate:

- Which parameters experts consider to have an impact on grinding quality.
- What data is currently available, along with its limitations and associated challenges.
- How experts collaborate with process, quality, and maintenance teams, and how they interpret recurring defects.
- Potential opportunities for data-driven improvements.

Online interviews were recorded and transcribed with the participants' consent. For in-person interviews, audio was recorded and subsequently transcribed for analysis.

3.2.2.4 Selection of thematic analysis

This study uses thematic analysis (TA) as the primary method of analysing qualitative data inputs recieved via six interviews conducted among four industrial practitioners and two academic researchers. Braun and Clarke systemized thematic analysis as a method for identifying, analyzing and reporting patterns/themes within qualitative data[32]. Compared to other methods TA is a flexible method suitable for researches where both industrial and technical knowledge are captured alongside each other in identifying patterns across experts' perspectives[32].

The interview sample in this study expands over multiple organizational roles including operators, process specialists, maintenance specialists, quality specialists and researchers. Each one has a distinct view on grinding process. Thematic analysis is well suited since it helps in identifying recurring patterns of meaning across the data set allowing knowledge to be emerged from multiple voices simultaneously.

Thematic framework involves a multi-stage process:

Familiarization

Familiarization of data is a vital step in the process of data analysis in the qualitative methodology[32]. This step helps in establishing an intimate relationship with the data, which help in emerging meaningful insights.

In the process of familiarization with the data, approval was received for all the six interviews to be recorded and transcribed. For the purpose of properly documenting an interview, a high quality audio and recording is required for word-to-word transcription [34]. Some of the interviews were conducted online via Microsoft teams and rest in person. But we managed to record and transcribe all the interviews for the purpose of good quality documentation.Transcriptions of each interviews were double checked with the audio recording, where it helped to familiarize data more solidly and clearly. Transcribing of verbal data to written form expands the insights about the questions beyond the surface meaning. It helps to understand the underlying operational procedure, the actual way things happen in practically and practical challenges in operation.

Process included active reading and re-reading of data. according to Braun and Clarke, this step includes immersive reading where the researcher should fully engage with the content noting initial impressions and recurring patterns[32]. Initial note taking helped a lot in later phases in analysis in identifying repeated ideas and underlying emotions under the phrases. The special quotations and points mentioned by the interviewees were highlighted in the initial stage of transcription. This process helped to conserve time later stage, where the main points were referred to several times in the later processes. Further it helped to build a reflection about the inputs given by interviewees regarding the topic. Quotations helped to animate data in a way they provided a solid validation about the fact they are mentioning.

Generating initial codes

This is the step of identifying meaningful data segments from the whole data. Labeling of significant features of data which are related to the research question is done here. This step is useful in the later steps of theme development, where the complex data is segmented into analyzable parts via this step[35]. Manual coding was used in this thesis work since there were only six data sets to be reviewed, and also in the intention of getting more familiarity of the data. Further it created a good foundation in identifying patterns and relationships across the dataset. Manual coding helped in getting a deeper understanding of contexts behind the image.

While conducting the process of initial codes, first the text related to particular codes were highlighted within the transcribed text of interviews. Then those quotes from the transcribed texts were tabulated to a separate table. In this way, all the quotes related to research questions were tabulated and shown in appendix. The coding is a reiterative process, since you picked an input and going on coding, it shows some relationships as well as some distracts between the quoted text which makes you revise the code. The process of coding is non-prescriptive regarding the amount of codes to be coded or type of interpretation as semantic or latent[36].

Generating themes
The resulting codes are then grouped into broader themes linked to the research questions. Mind-mapping tools are employed to help organize and structure these themes more effectively. Generating of themes is to be started after finishing initial coding. The coded data is reviewed and analyzed, to combine them into shared meaning to form themes or sub-themes[32]. Important aspect of theme formation is the codes or data items should communicate meaningful detail which helps answering a research question[32]. Themes should be contradictory and distinctive, while they should produce coherant picture of the dataset. The codes which are not fit within the particular theme should able to be ignored, in order to avoid the risk of creating unwieldy and incoherent themes. Otherwise these few themes can divert the depth and breadth of data causing failures for successful. [36].

Reviewing potential themes
In this stage a complete review of the candidate themes decided or selected should be reviewed related to coded data and the raw data set. This is also a reiterative process where you find the candidate themes are felt to be answering the research question or fit with a meaningful interpretation of data[32]. Further, Braun and Clarke is suggesting some key questions to be asked to review whether the potential themes are fitting;

- Is this a theme?
- If it is a theme, what is the quality of this theme, the data set and research question?
- What are the boundaries of the theme?.
- Are there enough data to support the theme?
- Are the data too diverse and wide ranging?

With the above analysis, the validity of the themes can be checked. The themes were changed few times based on above review and finalized candidate themes can be shown below demonstrating their relationships.

Naming themes

Following review and refinement, each theme is clearly labeled and described to enhance clarity and interpretability. In this stage each individual theme were expressed in related to data set and research question. Each theme should provide coherent and consistent data that are not defined by other themes. All themes were expressed in a way that, they create a rigid narrative which is connected with data set and research question. This is a deep analysis of underlying data since the researcher has to extract what is related to respective theme. The extracts can be presented either by providing a surface-level description of what is stated by interviewee, or analyzing what is interpreted by the interviewee[36]. Here the surface level meaning was taken into analyzing, since all the facts were technical based facts.

Writing the report
Finally, the themes are written up and interpreted, and then connected with existing literature, thereby ensuring transparency in the analytic process. Further, it is opposed to the practices of a typical quantitative analysis where the research is conducted and writing up the analysis. In a qualitative analysis, a parallel and interwoven process of analysis along with the writeup is followed. The changing of codes, themes and iterative steps are to be included throughout the course of the research. Themes should be connected in a logical manner while keeping the consistency and isolated narration for each theme[32].

Figure 3.3: Six stages in thematic analysis[35]

3.3 Quantitative analysis

The quantitative component of this work was carried out through Exploratory Data Analysis (EDA) of crankshaft quality data collected from the grinding line. The aim of the analysis was to examine the existing data, identify patterns, and determine the data requirements for future correlation studies.
EDA was chosen because the available dataset included defect related information, free text quality descriptions, and details about defect locations. Consequently, the analysis concentrated on interpreting this information primarily through visualizations.

3.3.1 Data collection & case context

The dataset used in this study was obtained from a crankshaft grinding line and contained quality related information, including defect type, defect location, machine operations, cost of the defect, timestamps, crankshaft type, and free text descriptions entered by the operators. This dataset reflected real industrial conditions and offered insights into quality issues in an actual manufacturing environment. In addition, it served as a basis for identifying which data need to be collected to support future analysis.

3.3.2 Data preparation

The initial step before combining the datasets was to translate the free text columns and rows from Swedish to English. Next, the datasets were examined to identify common columns that could be used to join them. While reviewing the .CSV file, it was discovered that only a single column matched between the two datasets, namely the Timestamp column, but the timestamp formats differed in each dataset. Therefore, after translation, this column was standardized to the format (DD.MM.YYYY hh:mm:ss). Once the timestamp was standardized further processes were carried out :

- Handling missing values,
- Checking for duplicates,
- Standardizing the data,

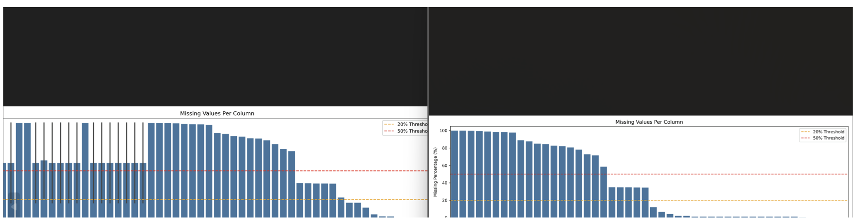

Figure 3.4: Before Vs After data cleaning

3.3.3 Analytical techniques

Following data preparation, descriptive statistics and visualization techniques were applied at this stage to explore patterns, and the analysis was organized into five main activities. It began with an examination of the data structure, where missing values and overall data completeness were evaluated to assess the reliability of the dataset. Visualizations were used to represent data quality and to highlight any gaps that could affect subsequent analyses of process quality.

To examine quality-related issues in the grinding process, defect distribution analyses, such as Pareto analysis, were conducted on the dataset to identify and prioritize the most influential defect categories contributing to quality losses. Additionally, a machine level analysis was carried out to investigate how defects were distributed across different machines, enabling the identification of recurring patterns and variations within the production system.

The dataset also included free text comments from operators, which documented information about the root causes of defects. These textual entries were analyzed using basic text mining methods, including phrase frequency analysis and the detection of recurring terms associated with quality deviations.Alongside these techniques, an interactive dashboard was developed to visualize quality related information. The dashboard included data on cost trend over a one year period, defect distribution across operations at which locations there was defect, defects by shift, and the relationship between defect type and location displayed as a heatmap. These visualizations supported decision making by improving visibility into quality-related patterns within the grinding line.

4

Results

This section describes the results we gained via the three pillar approach combining the results of systematic literature review(SLR), thematic analysis(TA) and exploratory data analysis(EDA).

4.1 Results from literature review

The literature review and qualitative investigation showed that grinding quality is affected by a range of parameters, including process, thermal, material, and maintenance-related factors. The results consistently indicate that process variables such as depth of cut (a_e), wheel speed (V_s), workpiece speed (V_w), feed rate (V_x), wheel wear mechanisms, and dressing intervals have a significant impact on grinding outcomes, including surface integrity (R_a; grinding burns), dimensional accuracy (roundness, straightness, diameter), as well as overall performance indicators (scrap rate, cycle time).

Furthermore, the reviewed studies underscore the growing role of data-driven manufacturing and the use of AI/ML to support decision making. Several works also stress the relevance of intelligent grinding, where machine learning algorithms are applied to predict tool life and enable condition monitoring. Nevertheless, there are still gaps regarding the integration of multi modal data from process, quality, and maintenance sources within real industrial grinding environments.

4.1.1 Critical process parameters

The review identified depth of cut, wheel speed, workpiece speed, feed rate, and specific grinding energy as the most influential process parameters governing grinding quality. Among these, (a_e) was found to have the strongest effect on surface roughness (R_a) and on the occurrence of grinding burns[22]. Although increasing the depth of cut enhances MRR, it simultaneously generates higher temperatures and increases grinding forces [1]. Likewise, wheel speed(V_s) strongly affects both R_a and dimensional accuracy. Several studies report that a higher (V_s) often leads to better surface quality due to reduced undeformed chip thickness; however, it also intensifies thermal loading, making it necessary to carefully control coolant delivery for effective heat removal[22]. In addition, the ratio of these two velocities is a major determinant of (R_a) the literature shows that a higher (V_s/V_w) ratio generally leads to a smooth surface, while a lower ratio tends to produce a rougher finish [23].

The literature further indicates that feed rate is another key factor influencing grinding quality. Radial feed tends to deteriorate (R_a), whereas an increase in axial feed can improve it [10]. Overall, these findings demonstrate that process parameters must be tuned in combination to achieve an appropriate balance between thermal and mechanical stability.

The process parameter metrics in Table 4.1 summarizes the parameters that simultaneously affect multiple quality dimensions—namely surface roughness, grinding burns, roundness, straightness, diameters, scrap, and cycle time. In particular, (V_s) and (a_e) emerge as having a pronounced influence on the overall grinding quality.

Table 4.1: Process parameter metrics

Parameter	**Surface Integrity**		**Dimension Accuracy**			**Production Metrics**	
	R_a	**Burns**	**Round.**	**Strgt.**	**Diam.**	**Scrap**	**Cycle**
Depth of cut (a_e)	✓	✓	✓	✓	✓	✓	✓
Wheel speed (V_s)	✓	✓	✓	✓		✓	
Workpiece speed (V_w)	✓	✓	✓	✓		✓	
Feed rate (V_x)	✓	✓					✓

Regarding the depth of cut (a_e), this parameter has a strong influence on surface integrity. Increasing (a_e) raises grinding forces and typically leads to higher (R_a) values. It can also affect the grinding zone temperature; a larger (a_e) can modify material properties, causing softening, accelerated wear, and crack formation [7].
Feed rate is another factor that can increase surface roughness. It can be divided into radial and axial components, which have different effects: raising the radial feed generally leads to excessive surface roughness, whereas increasing the axial feed tends to reduce it [25].

4.1.2 Grinding wheel metrics

Another emerging factor that influenced process performance was the grinding wheel. Findings from the literature indicate that both the physical properties of the wheel and its dressing parameters play an equally important role in determining grinding quality. For example, wear mechanism theory classifies wear into attritious wear, fracture wear, and bond fracture. These wear modes introduce instability in grinding operations and modify the wheel topography, which in turn directly leads to dimensional errors and contributes to excessive heat generation [6].

The reviewed studies further highlighted the critical role of the wheel state, which can be described in terms of wheel topography. In other words, the random distribution of abrasive grains and their protrusion height can govern the material removal rate (MRR), which ultimately affects the resulting surface quality. In the specific case of crankshaft grinding, where Cubic Boron Nitride (cBN) wheels are commonly used, the grit shape and concentration have a significant effect on power consumption and wheel wear [13].

Additional results from theoretical and qualitative analyses emphasize the concept of ‘wheel condition’, which affects both surface integrity and dimensional accuracy. Put simply, as the grinding wheel operates, the cBN grits gradually degrade, causing the wheel to lose its sharpness and produce more rubbing than cutting. This leads to grinding burns. To prevent this, wheels are periodically dressed. However, very short dressing intervals are associated with production losses, while excessively long intervals cause the wheel to become dull. Dressing at fixed intervals often produces a “sawtooth” pattern in quality, where surface quality is excellent immediately after dressing but then progressively deteriorates.

This relationship is illustrated more clearly in Table 4.2, where the findings show that wheel wear state and dressing interval directly influence surface quality, dimensional accuracy, and key production metrics.To overcome this reactive based dressing studies highlight condition based wheel monitoring where they use AE emission signals, vibration signals, AI/ML which can be used to detect and improve dressing strategies [6].

Table 4.2: Grinding wheel metrics

Parameter	**Surface Integrity**		**Dimensional Accuracy**			**Production Metrics**	
	R_a	**Burns**	**Round.**	**Straight.**	**Diam.**	**Scrap**	**Cycle**
Wheel wear state	✓	✓	✓	✓			
Dressing interval	✓	✓		✓	✓	✓	✓

4.1.3 Cooling & lubrication

As previously mentioned and discussed in the literature, grinding generates heat during machining, which directly affects quality and alters material behavior. Due to crankshaft’s complex geometry, the grinding forces and the resulting heat-affected zones vary continuously throughout the operation, making temperature regulation challenging. To control this heat, coolant either oil-based or water-based is used, which lowers wear volume and prevents severe changes in material behavior caused by excessive temperatures [1].

Table 4.3: Coolant & thermal parameters

Parameter	**Surface Integrity**		**Dimensional Accuracy**			**Production Metrics**	
	R_a	**Burns**	**Round.**	**Straight**	**Diam.**	**Scrap**	**Cycle**
Coolant flow	✓	✓					
Grinding Temperature	✓	✓					

The Overall findings from the literature indicates that crankshaft grinding quality is controlled by complex interactions among process parameters, grinding wheel condition, thermal behavior, and maintenance-related factors. Together, these elements directly influence surface integrity, dimensional precision, and production performance metrics [10]. Any fluctuation in these parameters, or an unsuitable selection of process settings, can lead to substandard part quality [7, 37, 13].

The findings further reveal that grinding quality cannot be understood by examining a single parameter in isolation. Instead, the literature shows that multiple factors interact simultaneously throughout the grinding process, collectively determining the final crankshaft quality.

4.2 Result from semi-structured interview

Few examples of coding from the "generating codes step" are shown in below table.

Table 4.4: Interview quotes and initial codes

Interview Quote (most representative)	**Initial Codes**
"if it's some adjustments that they are used to do it, they will do it without telling me"	Freedom of minor decision making
"The operator are in charge of knowing that all the measurements are okay"	Confidence and Experience of operators
"So, and also the operator, they are very skilled"	Believing the operators' skills

In this analysis, the initial codes (derived from most important representative codes) were assembled into second order codes. Then the initial codes were assembled into second order codes to form themes in next step. In the stage of reviewing of themes, aligning to the research question as well as the outputs given by the interviewees were reviewed. Few changes to the theme wording was done at this stage. In the stage of reviewing potential themes, the surface level meaning was taken into analyzing, since all the facts were technical based facts. Then the themes were defined and named as mentioned below;

- Experience of employees are valued and believed
- Digital tool usage
- Positive communications for problem solving
- Dressing interval playing a major cost factor
- Material quality affects grinding quality
- Coolant plays a major role
- Influence of machine condition on grinding quality
- Tradeoff between process parameters

4.2.1 Reporting

This phase is more interconnected with stage 5(Defining and naming themes). Themes which were defined at early stage are reported here. The themes are presented in below table where the readers can get insights on how the theme was created referring to initial quotes from interview, initial codes and second order codes.

Table 4.5: Theme:Experience of employees are valued and believed

Interview Quote (most representative)	**Initial Codes**	**Second Order codes**	**Theme**
“if it’s some adjustments that they are used to do it, they will do it without telling me”	Freedom of minor decision making	Employer autonomy	Experience of employees are valued and believed
“The operator are in charge of knowing that all the measurements are okay”	Confidence and Experience of operators	Experience of operators	
“So, and also the operator, they are very skilled”	Believing the operators’ skills	Experience of operators	

In related to the interaction between production, maintenance and quality inside the subjective organization, the above table summarize into the theme "Experience of employees are valued and believed". Initial coding converges the facts of freedom of decision making, confidence in process, expertise of employees and trust between teams into creating an environment where experience is valued and trusted. The interview quotes which were grabbed by representatives of each departments believe on the matter. On converging to this theme, the raw inputs wording shown here itself strengthen the theme. This belief and trust act as a strong backbone in maintaining a healthy relationship among different teams.

Table 4.6: Theme:Digital tool usage

Interview Quote (most representative)	**Initial Codes**	**Second Order codes**	**Theme**
"it's recording it to QDAS, and we already have we have all the data in QDAS"	Data stored in cloud systems	Data storage	Digital tool usage
"Power BI we have and also the RNC and the T&T, but That's the all tools I use"	Using of digital tools for scrap reporting	Scrap reporting	
"we use (X)MMS to report the problem"	Issue reporting via (X)MMS	Maintenance issue reporting	

The theme produced here in Table 4.6 regarding "Digital tool Usage" depicts the fact that the organization is equipped with different data recording platforms and data storage sources. These tools are utilized in the processes of reviewing for root causes, retrieving data for improvement and for escalation of data between internal stakeholders. This shows that digital tools play an important role regarding maintaining a clear and data-based interaction between the production, quality and maintenance.

Regarding the interaction between teams for problem solving in Table 4.7, the inputs from all the interviewees of the organization were positive. It was evident that the escalation of problems from basement level to upper level was smoothly happening. Production operators use the digital systems to raise maintenance issues and they are logged properly in the databases. Frequent face to face meetings has leveraged the relationship between each teams and it gives a practical workaround for problem solving. Issues are analyzed later via reports, which acts as a major part of root cause analysis.

As per the inputs given by interviewees shown in Table 4.8, they are considering dressing interval as a major cost factor based on their prior conducted analyses or due to the cost of tools used in dressing. Further, from the academic inputs, it was strengthened that the dressing affects productivity directly.

According to Table 4.9 where interviewees inputs show the impact of material on quality. Factory interviewees confirmed that, though the same material specified in the specifications are received, the internal content in the material are changed slightly. It has been affected as a critical parameter affecting the grinding quality of the crankshaft. Further, academic researchers' inputs also confirmed that machinability is adversly affected by microstructure as well as non-metalic inclusions.

Table 4.7: Theme:Positive communications for problem solving

Interview Quote (most representative)	**Initial Codes**	**Second Order codes**	**Theme**
"If there's something they can't solve by themselves, usually after half a day or a day later when they have tried what they know, they contact me or my colleague"	Informing of problems to higher levels	Problem solving	Positive communications for problem solving
"we needed all the guys to solve it: production, quality, maintenance, and so that's a problem we finally solved, yeah"	Incorporating multidisciplinary people for problem solving	Collaboration in problem solving	
"We also have a morning meeting every day with production and maintenance, and we handle it right away and take care of it"	Inter-departmental face-to-face meetings	Communicating via meetings	
"If we see that we have a bad quality, we can see it in the capability reports"	Referring to reports for information	Communication via reports	
"We simply talk with the maintenance team and we use (X)MMS to report the problem"	Communication via digital modes and telecommunication (Production vs Maintenance)	Hybrid communication modes	

Table 4.8: Theme:Dressing interval playing a major cost factor

Interview Quote (most representative)	Initial Codes	Second Order codes	Theme
“There also could be maybe they need to decrease the sharpening interval. Dress interval”	Requirement for reducing dressing frequency	Dressing cost	Dressing interval playing a major cost factor
“this is the process that makes 75% of the cost, actually. It’s not the grinding, it’s the dressing”	Dressing cost as a major percentage	Dressing cost	

Table 4.9: Theme: Material quality affects grinding quality

Interview Quote (most representative)	Initial Codes	Second Order codes	Theme
“Material has such a big influence on everything that could actually be the most critical parameter that affects the end quality of the crankshaft”	Material as a critical parameter affect grinding end quality	Material affects quality	Material quality affects grinding quality
“Harder workpiece probably means a worse machinability. And then we do an analysis on the microstructure. So we start with non-metallic inclusions”	Machinability depend on material quality	Material quality affects machinability	

Table 4.10: Theme: Coolant plays a major role

Interview Quote (most representative)	Initial Codes	Second Order codes	Theme
"We also try to improve the cutting fluid, the cooling fluid, both flows and pressures"	Flow and pressure of coolant affect grinding quality	Cutting fluid flow and pressure	Coolant plays a major role
"Nozzle coolant, you know, because of the... It affects both shape and the burning issues on the machine. So the coolant need to get in the right point"	Positioning of the coolant jet	Coolant position	
"I think all of them are very important and depends on what the issues are. But in general, I would say coolant flow"	Coolant flow as a main process parameter	Coolant flow	
"For example, if you have burns, we often look at coolant and the material variation. If we can see, for example, the aluminum is going down or up. But the first thing we should check is coolant. Everything that do have to do with coolant"	Coolant and material affecting burns	Coolant and material	
"But coolant is important, right? So, but I mean, it's like, and I mean, you cannot do much about it"	Less effect from coolant	Less weight in coolant	

According to the inputs from Table 4.10 about the inputs about effect of coolant, industrial experts believed there was a huge impact of coolant on grinding burns while researchers weight on impact of coolant on grinding burns was less.

Table 4.11: Influence of machine parameters

Interview Quote (most representative)	**Initial Codes**	**Second Order codes**	**Theme**
"I would say, is the state of the machine, different components breaking down, wearing out. And the second will be the material coming in"	State and condition of machine affects quality	Machine condition	Influence of machine condition on grinding quality
"Will say about 80% of our quality issues is because of the machines in one in many ways"	State of machine affects quality	Machine quality	
"The machines have to perform so very, very good. They almost have to perform at 110% to produce with the right quality"	Performance of machine affects quality	Machine performance	
"Every movement in the machine is important"	Operational condition of each part of machine	Machine operational condition	

According to many inputs from process and quality as per Table 4.11, the condition of machine was highly considered towards part quality. Process experts believe grinding quality depends more on machine condition rather than material quality. Quality representatives believe, the root cause for 80% of quality issues is machine problems. Quality representatives believe the machines to be performed at a very high percentage of performance without issues to achieve a good quality output. Maintenance who is mainly responsible for the machine condition believe, every movement of the machine is important for a product to achieve its defined quality.

Table 4.12: Theme:Tradeoff between process parameters

Interview Quote (most representative)	**Initial Codes**	**Second Order codes**	**Theme**
"If you notice you have a bad straightness, maybe you can improve it by changing a few parameters, but instead the roundness will get worse"	Tradeoff between changing parameters affecting quality	Parameter tradeoffs on quality	Tradeoff between process parameters
"And maybe burns, burns can affect speed, the wheel speed as well. It can also affect the straightness and roundness"	Wheel speed affecting quality	Wheel speed	
"You have to look at the heat flow, and this will depend on the specific material removal, right, and specific energy"	Heat flow and specific energy controlling	Heat flow	

As shown in Table 4.12, a practical tradeoff between changing process parameters is existing. Another input was, When trying to adjust straightness by adjusting process parameters roundness is affected. Similarly, when the burns are adjusted by affecting speed, straightness and roundness are affected. It was evident from the interview inputs that, a tradeoff between process parameters existing over the grinding quality.

4.3 Results from quantitative analysis

The EDA analysis was conducted to analyze and investigate the available data quality, structure and characteristics of the dataset. Since the data set was from quality reports, it was used to explore the defect patterns, operations wise trends, visualize and access the data readiness in order to locate what multi modal data should be recorded in order to support future correlation between process and quality and answer RQ3. Current analysis was focused on identifying:

- The existing quality data,
- Defect distribution,
- Missing data patterns,
- Determine which types of data the company should collect to enable correlations with grinding quality,
- Conduct descriptive analyses and summarize the data,
- Visualize key performance indicators (KPIs) and/or develop quality dashboard.

4.3.1 Overview of case data

Building on section (4.3), the dataset used for the EDA was mainly derived from quality reports and defect records collected from the grinding line. Data from other departments was unavailable because it was difficult to retrieve it. The available dataset contained:

- Identified causes of defects,
- Locations on the part affected by defects,
- Free text descriptions of defect causes,
- Machine wise defect trends,
- Cost incurred to resolve the defect.

During exploration, it was found that the dataset was heterogeneous, originating from two different data sources. Moreover, the available data was not fully aligned with other relevant process areas, which constrained the ability to conduct correlation analysis between process parameters and quality outcomes. Despite this constraint, the available dataset still provided meaningful insights, specifically regarding:

- Periodic quality issues,
- Trends in machine defects,
- The structure of the existing dataset.

The analysis further revealed that, although the volume of generated data was high, it contained relatively little information that was useful for analytical purposes.

4.3.2 Data quality analysis

One of the key steps in assessing data quality was conducting a descriptive analysis [38]. However, implementing this step in an industrial setting proved to be challenging. Data from the previous year was extracted from the system for analysis and investigation. Because the data originated from multiple sources, integrating this heterogeneous information was difficult. Before moving on to the subsequent phases described in [38], an investigation of the company's grinding line was carried out, and discussions were held with grinding personnel. Based on this, data was collected from:

- Quality logs,
- Track and Trace (TnT),

The systems listed above represented the only data sources that could be included in this analysis, as they were the ones accessible at the time of EDA, after merging the data from the two systems, an initial investigation of the dataset was carried out to understand its characteristics. In addition to these systems, data also existed in process logs, maintenance records, material certificates, and within the machines themselves. However, extracting this information was difficult. Most of these systems had limited infrastructure for centralized data collection and storage, and there was insufficient linkage across the production line. For the data obtained from the Quality system, the initial analysis focused on:

- The available quality data,
- Merging the data into a single dataset,
- Missing values,
- Traceability between the two datasets,
- Data limitations.

The initial review of the dataset revealed inconsistencies and missing information. The missing value analysis indicated that numerous columns contained incomplete entries, and several manually entered cells were both partially filled and poorly structured. This is shown in Fig. (4.1). To better visualize the distribution of missing values, the columns were ordered in ascending order, with the X-axis displaying the percentage of missing data and the Y-axis listing the columns (variable names are concealed due to NDA constraints). The chart focuses on the 25 variables most affected by missingness and includes two reference lines at 20% and 50% missing data. It became clear that many variables surpassed the 50% mark, confirming that the dataset was severely inadequate.

To investigate this further, a heatmap was produced using random samples from the most affected columns, revealing that the missingness in the merged dataset was not random, as illustrated in Fig. (4.2). On the left side of the heatmap, several columns appear entirely red across all sampled rows, indicating a complete absence of data for those variables. This pattern suggests that these fields were either not informative to begin with or were completely lost during the merging procedure. In the central region of the heatmap, a mix of colors can be observed, corresponding to partially missing entries and highlighting inconsistencies in how the data were recorded.

This evaluation highlighted a common practical challenge in industrial environments i.e., The available dataset recorded was inconsistent, Manually recorded entries from the quality professionals lacked standardization, Synchronization between the datasets was only partially achieved since it contained different data structure.

These observations indicate that the data quality from the two systems already presents a considerable obstacle for any subsequent development work.

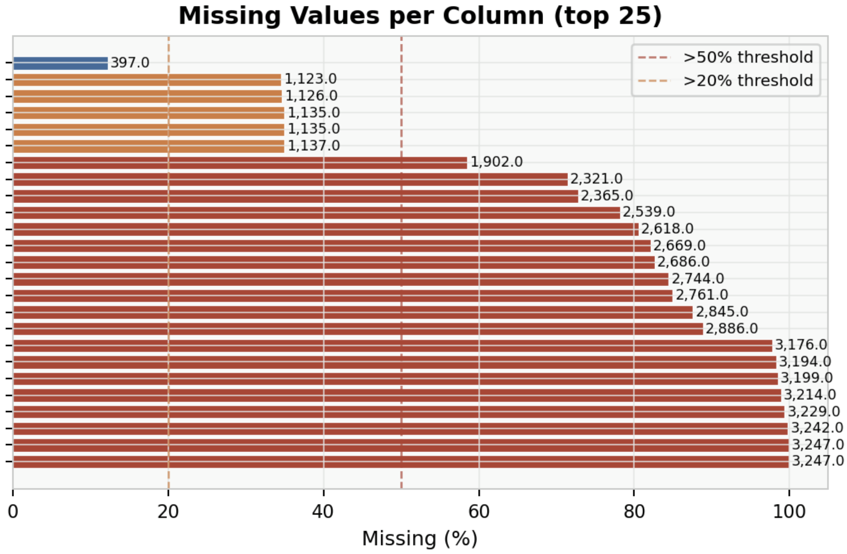

Figure 4.1: Missing values

4.3.3 Defect distribution

As shown in Fig. 4.1, the process began with an inspection of blank entries. A considerable share of the data had already been lost during pre-processing and integration. The remaining 62.2% of the records underwent a data quality evaluation, which uncovered inconsistencies across several columns. This is depicted in Fig. 3.4, where the left side presents the raw integrated dataset and the right side shows the cleaned version. During this stage, the dataset was refined by reducing missing values, removing irrelevant features, and consolidating columns with duplicate IDs into single columns. Columns containing 100% blank cells were eliminated, and most partially missing entries were converted to NaNs to simplify subsequent statistical analyses. Completely empty columns were dropped because they offered no useful information. Since the dataset also contained case log timestamps, these were standardized into a datetime format to support clearer visualization in later steps. Consequently, the resulting dataset was deemed sufficiently consistent and reliable for exploratory analysis.

During Visualization of the defect frequency, data revealed that a limited number of causes contributed to overall quality within the grinding line. during this exploration frequently occurring causes/defect were grouped and categorized into quality issues, such as: deviation in roundness, straightness and surface burns. To understand deeper Pareto analysis was performed on the data, where it shows certain type of defects appeared repeatedly this can understood from the Fig.(4.3) 80% of the defects were contributed from drilling, dimension error, burns, edge and straightness. This meant grinding quality was influenced by several interconnect operations rather than one single parameter.
In addition to finding out defects this also highlighted the cost which came around approximately Kr.4300/defect per annum.

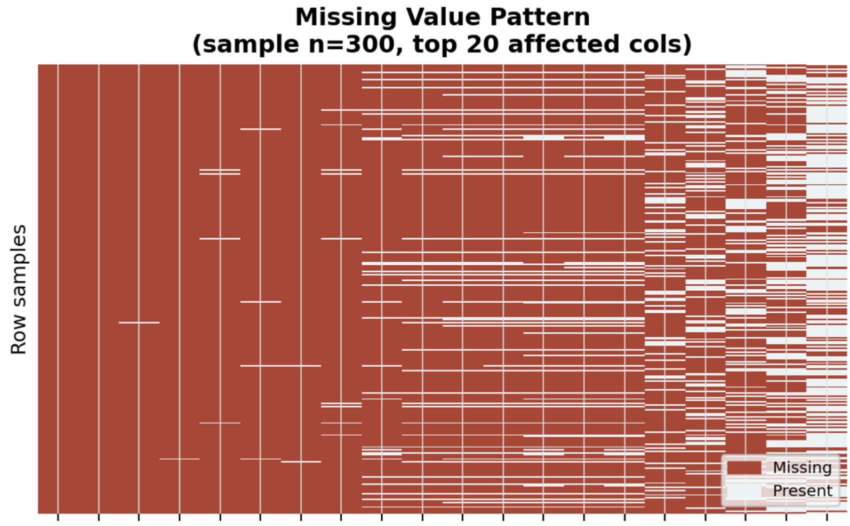

Figure 4.2: Heatmap_Missing value

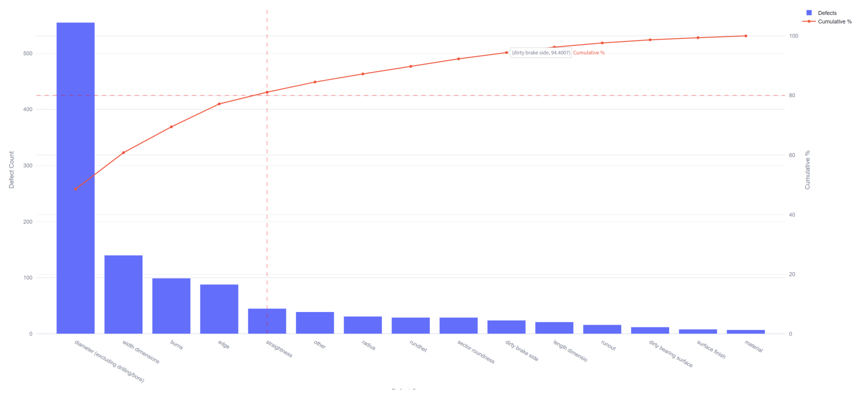

Figure 4.3: Pareto Chart: For Defects

4.3.4 Machine-wise defect

While examining machine-wise defects across different grinding machines, it became apparent that some machines showed higher counts for specific defect categories. This can be illustrated with two examples: one in which the defect frequency is highest at the selected location, Fig. (4.4), and another in which the same defect is least frequent at that location, Fig. (4.5).
As shown in these figures, it was possible to clearly identify hot spots within the grinding line and to highlight potential differences between machines, such as machine condition, wheel wear state, maintenance effectiveness, and process setup. These remain assumptions because, in the absence of detailed machine and process data, it was not possible to establish a direct relationship. Nonetheless, even with the available information, in-depth visualization of the quality data was achievable.

Heatmap analysis was also carried out for defects occurring at specific locations on the part. As shown in Fig. (4.6), "*Diameter*" emerged as the defect with the highest

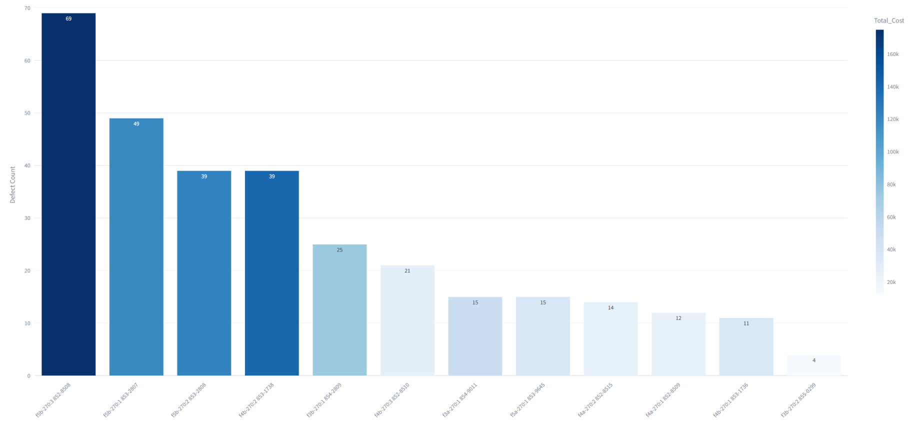

Figure 4.4: Defect A at location A

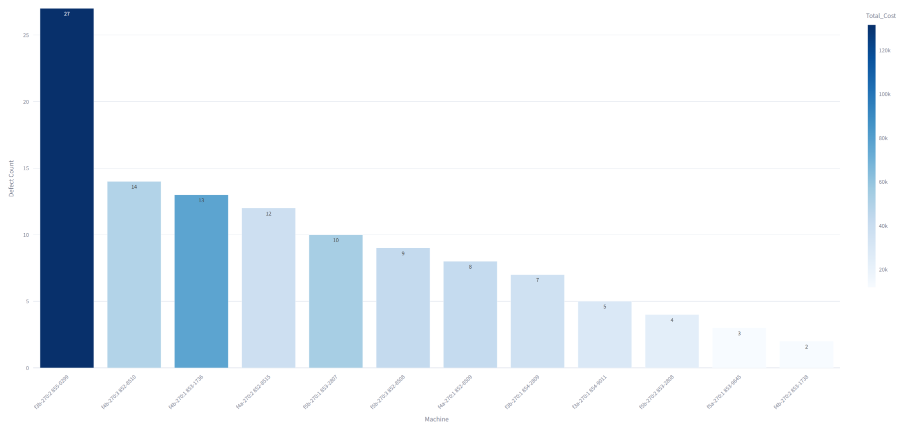

Figure 4.5: Defect B at location A

concentration within the grinding line. The heatmap was particularly useful for revealing operational patterns. Overall, the machine-wise analysis and the heatmap results underline the importance of systematically collecting machine and process data.

The analysis therefore indicates that the data collection should comprise:

- Dressing interval information,
- Process setup parameters,
- Machine related data(Start-stops, alarms),
- Wheel wear condition,
- Inspection results, for instance geometric measurements or images.

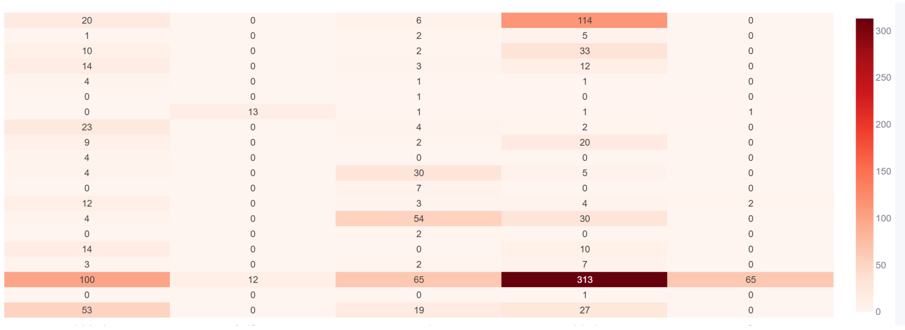

Figure 4.6: Defect Vs Location relationship

4.3.5 Text mining: Free text analysis

The free text column containing important quality-related information was text mined through several steps: removing special characters and symbols, converting all text to lowercase, tokenization, applying stop-word filters, performing phrase extraction, and finally conducting frequency analysis. Text mining revealed most frequently occurring phrases were identified to detect quality issues and dimensional deviations. Fig (4.7) illustrates the most common phrase extracted from this column.

The analysis showed that 'Diameter' and 'Dimension' were the most frequently occurring terms in the free text column. This reflects what operators were recording, but in an unstructured manner. Without linking these records to process or measurement data, it is hard to conclude based only on frequently occurring terms from text mining that these factors by themselves determine their relative impact on quality. This finding supported the evidence from the literature, enhanced data categorization, and supplied key inputs for the dashboard as well as subsequent evaluation phases.

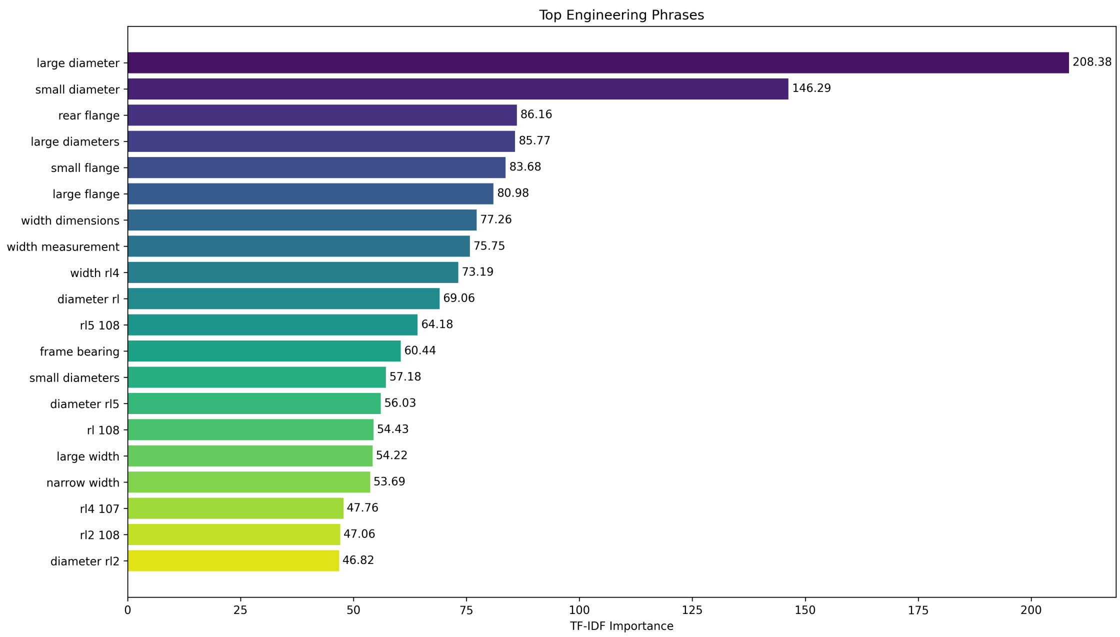

Figure 4.7: Recurring phrases from text mining

4.3.6 Dashboard development

The final results and analytical outputs were implemented as dashboard, which made the data much easier to interpret. The resulting dashboard functions as a central hub/platform for the grinding line, allowing visualization of patterns, identification of operations with higher defect rates, detection of trends over time, and monitoring of costs. It supports operators and engineers from various departments in identifying defects at the selected location, while improving traceability across the integrated dataset.

Even though the available data was limited to quality related information and was incomplete, this analysis establishes a foundation for implementing ML and for developing a data driven production architecture. The framework created in this study can facilitate the future integration of all relevant data into a single system for the grinding line.

4.3.7 Data requirement for process-quality correlation

The exploratory analysis of the dataset indicates that quality is influenced by multiple factors. To address RQ3, and drawing on insights from the literature, expert interviews, and quality related data visualizations, the following multi modal data must be gathered to enable correlation analysis in the grinding line:

- Process parameter data, including feed rate, depth of cut, wheel speed, and workpiece speed,
- Coolant data (flow and pressure),
- Data on dressing intervals,
- Vibration and acoustic emission signals,
- Quality data which includes measurement records, images,
- Maintenance records,
- Operator's notes,
- Data related to the product material.

These findings provide a foundation for the industrial data requirements that are essential for future data-driven development within the grinding line.

5
Discussion

This chapter discusses the findings of the study based on research questions integrating systematic literature review, thematic analysis of the semi-structured interviews, and exploratory data analysis to explicitly address the research objective.

5.1 Integrated findings

The study focused on investigating crankshaft grinding process parameters which affects the quality and how multi modal data can be integrated within the manufacturing environment. The integrated findings from the the literature study, semi structured interviews and exploratory data analysis in order to interpret the findings related to research questions. Table (5.1) shows the summarized findings in the form of triangulation metrics.

It indicates that crankshaft grinding quality is shaped by a combination of interrelated technical and organizational factors. While the literature typically emphasizes process parameters independently, evidence via semi structured interviews from industry shows that quality is more commonly influenced by the interactions among the machine, process setup, wheel condition, operator choices, maintenance planning, and, finally, data.

To address RQ1, which examines process parameters influencing crankshaft manufacturing quality, findings from systematic literature review (SLR) indicate key grinding process parameters as depth of cut(a_e), wheel speed (V_s), workpiece speed (V_w), and feed rate (V_x). They play a significant role in determining surface integrity, dimensional accuracy, and productivity. The literature review identified depth of cut and wheel speed as the most critical parameters, directly influencing grinding forces, thermal loading, and surface integrity. Studies reported that, under optimized conditions, higher wheel speed improves surface quality. However the surface finish is enhanced, grinding burns and thermal stresses are tend to be increase. In contrast, increasing depth of cut raises the material removal rate (MRR) and reduces cycle time, but at the same time elevates surface temperature, which can cause surface burns. In contrast to these theoretical insights, feedback from industry practitioners highlight practical limitations. They indicate that continually adjusting these parameters for each individual part is not feasible in practice, especially in high volume automotive manufacturing. Although the theoretical research often

Table 5.1: Triangulation metrics

Parameter	**Literature Findings**	**Interview insights**	**EDA Findings**	**Suggestion**
Depth of cut (a_e)	Strong influence on R_a,Thermal load and grinding burns	Emphasized practical implications in continuous improvement	NO data available	Structured data acquisition is required
Wheel Speed (V_s)	Influence on surface and dimensional accuracy	Wheel speed is managed through dressing strategies	Machine wise defect shows instability	Real time monitoring required
Dressing interval	Strongly influences sharpness, surface quality, burns and cycle time	Considered one of the most critical factor	No data available	Condition tool monitoring can be adopted to improve efficiency
Coolant behavior	Critical for controlling temperature, and burn prevention	Practitioners prioritized coolant conditions	Burn related quality defects observed	Coolant monitoring or
Machine Condition	Limited emphasis on literature regarding machine	Experts insights shows machine condition contributes to major quality problems	Machines shows recurring defects	A unified system should be provided that includes both quality and maintenance records.
Material Quality	influences machinability and influences burns	Material variations linked to grinding burns	No material data available	Material certificates and material properties should be documented and incorporated into databases.
Data infrastructure	Literature highlights the use of AI/ML models for intelligent grinding	experts note challenges in accessing and retrieving the relevant data.	High amounts of incomplete, inconsistent, and poorly structured data	Data infrastructure is one of the biggest constraints facing in this case company

advocates dynamic optimization of parameters, one interviewee emphasized that such adjustments cannot realistically be implemented on a cycle basis in industrial setting.

These findings highlight a considerable gap between theoretical approaches and real world practice. In industry, priority is given to operational robustness rather than to theoretically optimal parameter settings. As a result, industry experts and operators tend to emphasize dressing strategies, paying particular attention to the grinding wheel and, especially, to dressing intervals, since this enables them to achieve the required surface quality within acceptable dimensional tolerances, instead of continuously adjusting the process parameters.

These observations indicate that future developments should emphasize adaptive process control rather than focusing exclusively on parameter optimization. One of the most robust findings emerging from the literature, interviews, and EDA concerned the grinding wheel.

The literature presents how wear mechanisms, dressing intervals, and wheel topography affect crankshaft grinding quality. Interviewees strongly reinforced this point, emphasizing that maintaining the wheel in good condition meaning desired sharpness ensured stable quality.

The results from interviews suggest that wheel condition can serve as a reliable indicator of overall process stability. As the wheel loses sharpness over time during machining, rubbing effect increase, temperatures rise, and dimensional errors occur. This behavior became clearer during EDA through defect distribution, machine-wise defect, text mining, where "*Diameter*" related defects repeatedly appeared in the quality data and remained dominant when analyzed on a machine wise defect basis. In addition, the findings propose that condition based wheel monitoring could benefit the company. Currently, dressing is carried out according to "*BN*" at fixed intervals. In the future, they may install acoustic emission sensors to monitor signals and apply ML models to predict the optimal dressing point, which could significantly enhance surface quality and increase production efficiency.

Findings from RQ1 & RQ2 indicates that the temperature at the grinding surface plays a critical role in the occurance of grinding burns. However, accurately measuring this temperature is inherently difficult due to factors such as coolant flooding and chip removal at the grinding interface. As a result, thermal models are often employed to predict grinding surface temperature in the analysis [5, 7]. Notably, the interview findings revealed different perspectives on this factor, largely by the backgrounds of interviewees from academia and the others from industry. When asked about the importance of coolant, one practitioner strongly asserted that coolant is the primary factor affecting grinding burns, whereas the researcher regarded it as one of the least influential factors, arguing that since grinding is always performed under cooling fluids, it is difficult to isolate and predict the contribution of thermal variables.

This divergence in views highlights the gap between theoretical understanding and practical industrial experience. While operators and industry experts readily detect coolant related issues in day to day operations, the literature indicates that thermal damage arises from a broader interaction among wheel characteristics, grinding forces, workpiece material, and process kinematics. These findings suggest that coolant should not be assessed in isolation, but rather as one element within an integrated thermal management strategy.

The second research question (RQ2), which examines the interactions between process, quality and maintenance within the grinding line, reveals that multiple departments collaborate collectively to identify root cause of quality issues. Several specialists pointed out that machine related problems can have more impact on quality, particularly when as the equipment was not maintained in an optimal condition to achieve the desired quality level to meet required standards.

The literature review further supported these findings offering valuable insights beyond traditional focus on process parameters. Earlier research had largely emphasized on process related parameters while paying relatively less attention to maintenance-related aspects. In contrast, the present findings underline the importance of incorporating maintenance consideration into analysis.

The interviews further reinforced the critical role of maintenance activities in ensuring process stability and consistent quality. Experts drew attention to the trade-off associated with dressing intervals: they noted that shorter intervals tend to raise production costs, whereas excessively long intervals can alter the grinding wheel's topography. These insights highlight the significant influence on maintenance decisions on production performance and quality outcomes.

Regarding RQ3, which focuses on identifying the types of multi-modal data required to investigate and correlate process parameters with quality defects in crankshaft manufacturing. The findings indicate that process parameters alone are not sufficient to account for these defects. Instead, effective data acquisition requires the integration of heterogeneous data sources, including process data, quality logs, maintenance records, machine condition information, and operator-recorded observations.

The literature also identifies several additional categories of industrial grinding data, such as vibration signals, acoustic emissions, temperature measurements, forces, power consumption, and wheel condition data. Previous studies have shown that sensor-based monitoring enhances the understanding of surface quality, enables the prediction of tool wear, and that ML models strongly depend on multi-modal datasets to optimize processes and predict defects.

The findings from interview provided insights on importance of data collection from machine parameters, dressing interval, coolant, maintenance records, quality reports, operators observations. In particular operator notes on solving quality related issues were consider highly valuable since it contains the knowledge that is unavailable in structure dataset. This shows how important is it to collect and combine structured and unstructured data.

Although the original aim of the thesis was to investigate how process parameters are correlated and how they influence part quality, the main industrial difficulty turned out to be extracting data from multiple, disconnected systems. Consequently, instead of focusing solely on correlation analysis, an exploratory data analysis (EDA) was carried out to identify and examine the key issues, such as:

- missing values,
- unstructured manual inputs,
- fragmented data,
- poor traceability,

The EDA clearly indicated that diameter related problems were the most frequently occurring defects documented in the quality reports. With the help of the developed dashboard for data visualization and analysis, the machines that contributed most to these defects were pinpointed. The dashboard also presents a breakdown of defect-related costs as well as machine-wise defect distribution. In addition, a heat map displaying the severity of quality defects along the crankshaft helps support root cause investigations. Overall, the dashboard can be implemented as a tool for the company to analyze and visualize quality related data.

These results highlight a genuine industrial challenge: while many academic works suggest advanced AI/ML-based data integration in manufacturing, real-world industrial environments often lack the necessary resources and infrastructure to reliably support such analytics.

In the absence of standardized data entry procedures across departments, appropriate infrastructure for acquiring useful machine data, centralized cloud based storage, and robust traceability systems, it is not feasible to extend the current visualization system into a predictive model capable of forecasting product quality from real-time process.

Through the exploratory data analysis conducted, it was evident that diameter issues were the major defect recorded in quality reports. Using the dashboard developed to visualize and analyze data, the machines responsible for the majority of defects were identified. A dashboard was developed to provide the cost breakdown of the defects and machine-wise defect distribution. A heat map describing the intensity of quality defect with respect to the location of the crankshaft can support root cause analysis. The dashboard can be deployed to use in the process of analyzing and visualizing quality data for the organization. As a future development, the visualization system could be extended into a predictive model capable of estimating product quality based on current process parameters.

5.1.1 Summary

Table (5.1) presents the triangulation process used in this study, combining evidence from the SLR, interviews, and EDA. This triangulated approach enhanced the study's validity by integrating multiple sources of evidence. While each individual pillar offered distinct insights, their combination provided a more holistic understanding of the process parameters influencing crankshaft quality.

The integrated findings of this research indicate that achieving stable crankshaft grinding quality requires more than simply optimizing process parameters; it also demands the systematic integration of multiple interacting factors, such as maintenance practices, operational expertise, and multi-modal grinding data. This underscores the value of a data-driven approach for optimizing production, enhancing quality, and enabling future intelligent grinding systems.

5.2 Contributions:Academic and industrial

The identification of process parameters affecting the grinding quality via the systematic literature review and thematic analysis conducted incorporating industry experts and academic researchers provides a solid base of parameters affecting grinding quality. It adds value as an input for industrial practitioners to decide which sensors to be accommodated for data acquisition in process of data analyzing to improve grinding quality. The developed dashboard acts as a useful root cause analysis tool, which can further be utilized for problem visualization and analysis. Academically, a solid basis of selecting process parameters affecting grinding quality is established with the systematic literature review and the outcomes of thematic analysis based on inputs of industry experts sand researchers.

5.3 Limitations

- This thesis focuses on developing a co-relation that supports the subjected automotive company to monitor and prevent quality issues in finishing stage.
- This study is limited to the crankshaft grinding process of two variants of crankshafts.
- The qualitative component of this research is based on semi-structured interviews from process experts from the subjected automotive company and academic experts in grinding area .
- Furthermore, this study is confined to the manufacturing sector of the product(crankshaft) and does not extend to other focused areas.
- The duration of the project is 20 weeks.

5.4 Recommendations

Based on the results obtained for the research questions, several recommendations can be suggested as directions for future work with both industrial relevance and academic value.

To better understand how process parameters influence grinding quality, future research should focus on measuring the temperature at the tool workpiece interface, wheel wear, and machine induced vibrations by using dedicated sensors for real time data acquisition and monitoring. In addition, carefully designed and controlled experimental trials in industrial settings could further clarify the impact of different process parameters.

Future work on the interaction between process, quality, and maintenance should emphasize the development of an integrated decision support system that can assist and adaptively support decision making aimed at improving the process and reducing defect occurrence.

Regarding data integration, priority should be given to implementing a cloud based, in house centralized system that aggregates real time data from processes, machines, maintenance records, production logs, quality reports, and material certificates into a single platform. Such an infrastructure would enhance the feasibility and performance of future applications involving machine learning, digital twins, and sensor-based intelligent manufacturing systems.

Future research should also investigate smart maintenance strategies. Integrating ERP platforms with the grinding line would significantly enhance traceability and enable advanced machine learning methods for defect prediction. Large, standardized datasets combined with sensor based monitoring will increase process transparency and predictive accuracy. Moreover, future work could examine the use of transformer based AI models for intelligent process monitoring, anomaly detection, and adaptive process optimization.

In summary, the future of crankshaft grinding will increasingly rely on smart, data driven manufacturing, in which process, quality, and maintenance are tightly interconnected within a unified environment.

6
Conclusion

The objective of this study was to explore how process parameters influence quality in crankshaft grinding, to analyze the interactions among process, quality, and maintenance functions, and to identify which multi modal data are collected to enable correlation between process parameters and quality. These three objectives were addressed through a mixed methodology approach, employing SLR, TA, and EDA on quality data.

Literature review revealed that grinding parameters such as depth of cut, wheel speed, workpiece speed, feed rate are the most influencing grinding parameters towards surface integrity, dimensional accuracy and production perspective. Wheel wear state and dressing interval were found to be impacted towards surface integrity and dimensional accuracy. Additionally, dressing intervals impacts highly on the production efficiency while coolant flow and grinding temperatures were impacting surface integrity.The conducted thematic analysis for the interviews with industry practitioners and academic researchers, gave insights about the interactions between process, quality and maintenance. All the teams were working collaboratively interconnected with each department for providing quality outcomes, without functioning in independent domains. Even in the problem solving processes, they were maintaining a positive communication trusting each others skills and expertise. EDA revealed that the available quality data contained a large number of missing values and inconsistent manual entries. Despite this limitation, diameter emerged as the most common quality related issue, while Pareto analysis indicated that dimensional errors and surface burns together contributed to 80% of the defects. Machine wise defect analysis showed variations between machines that could not be fully interpreted without corresponding process data, emphasizing the need for systematic process data collection. Trends in financial losses and the examination of major quality defects provided further insights to guide process improvement.

Overall, this study demonstrates that crankshaft grinding quality is based not only on grinding process parameters. Maintenance and quality are inter-related towards a better product output as well as for the smooth operation of the process. It emphasizes the interactions between each different functions inside the organization are more important to deliver a product in good quality. Further, it summarize the importance of process data collection towards analyzing, prediction and prescription purposes.

Bibliography

[1] Kamal Kishore et al. “A comprehensive review on the grinding process: Advancements, applications and challenges”. In: *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science* 236.22 (2022), pp. 10923–10952. DOI: 10.1177/09544062221110782. eprint: https://doi.org/10.1177/09544062221110782. URL: https://doi.org/10.1177/09544062221110782.

[2] Peter Krajnik et al. “Grinding and fine finishing of future automotive powertrain components”. In: *CIRP Annals* 70.2 (2021), pp. 589–610. ISSN: 0007-8506. DOI: https://doi.org/10.1016/j.cirp.2021.05.002. URL: https://www.sciencedirect.com/science/article/pii/S0007850621001189.

[3] P. V. Golinitskii et al. “Digitalization of fault detection in crankshafts”. In: *Journal of Machinery Manufacture and Reliability* 53.3 (May 2024), pp. 263–270. DOI: 10.1134/s1052618824700031. URL: https://doi.org/10.1134/s1052618824700031.

[4] Qingyu MENG et al. “Modelling of grinding mechanics: A review”. In: *Chinese Journal of Aeronautics* 36.7 (2023), pp. 25–39. ISSN: 1000-9361. DOI: 10.1016/j.cja.2022.10.006. URL: http://dx.doi.org/10.1016/j.cja.2022.10.006.

[5] P. Comley et al. “A High Material Removal Rate Grinding Process for the Production of Automotive Crankshafts”. In: *CIRP Annals* 55.1 (2006), pp. 347–350. ISSN: 0007-8506. DOI: https://doi.org/10.1016/S0007-8506(07)60432-6. URL: https://www.sciencedirect.com/science/article/pii/S0007850607604326.

[6] Peter Krajnik et al. “Advances in modeling of fixed-abrasive processes”. In: *CIRP Annals* 73.2 (2024). Cited by: 10; All Open Access, Green Open Access, Hybrid Gold Open Access, pp. 589–614. DOI: 10.1016/j.cirp.2024.05.001. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85199785549&doi=10.1016%2fj.cirp.2024.05.001&partnerID=40&md5=653df3b47b5f7d880d24369c1cb8a56a.

[7] Siyuan Wang et al. “Research and process optimization of crankshaft grinding parameters based on Gaussian heat source model”. In: *The International Journal of Advanced Manufacturing Technology* 132.1-2 (Mar. 2024), pp. 601–611. DOI: 10.1007/s00170-024-13331-2. URL: https://doi.org/10.1007/s00170-024-13331-2.

[8] Junjie Tang, Zhongjun Qiu, and Tianyi Li. “A novel measurement method and application for grinding wheel surface topography based on shape from focus”. In: 133 (Feb. 2019), pp. 495–507. ISSN: 0263-2241. DOI: 10.1016/j.m

easurement.2018.10.006. URL: http://dx.doi.org/10.1016/j.measurement.2018.10.006.

[9] Jack Palmer et al. "An experimental study of the effects of dressing parameters on the topography of grinding wheels during roller dressing". In: *Journal of Manufacturing Processes* 31 (Jan. 2018), pp. 348–355. ISSN: 1526-6125. DOI: 10.1016/j.jmapro.2017.11.025. URL: http://dx.doi.org/10.1016/j.jmapro.2017.11.025.

[10] Toms Torims et al. "A Study on how Grinding Technology Parameters Affect the Surface Texture Formation of Marine Diesel Engine Crankshafts". In: *Advanced materials research* 538-541 (June 2012), pp. 1413–1421. DOI: 10.4028/www.scientific.net/amr.538-541.1413. URL: https://doi.org/10.4028/www.scientific.net/amr.538-541.1413.

[11] Bhaskar Botcha et al. "Process-machine interactions and a multi-sensor fusion approach to predict surface roughness in cylindrical plunge grinding process". In: *Procedia Manufacturing* 26 (Jan. 2018), pp. 700–711. DOI: 10.1016/j.promfg.2018.07.080. URL: https://doi.org/10.1016/j.promfg.2018.07.080.

[12] Xinyan Ou et al. "First time quality diagnostics and improvement through data analysis: A study of a crankshaft line". In: vol. 49. Cited by: 11; All Open Access, Gold Open Access. 2020, pp. 2–8. DOI: 10.1016/j.promfg.2020.06.003. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85090497558&doi=10.1016%2fj.promfg.2020.06.003&partnerID=40&md5=8aecfc2080f9b433518f602a48ba239d.

[13] C. Salame et al. "MULTI-SENSOR MONITORING OF WHEEL WEAR DURING CBN GRINDING OF CRANKSHAFT STEEL". In: *MM Science Journal* 2025.6 (Dec. 2025). DOI: 10.17973/mmsj.2025\{_}12\{_}2025166. URL: https://doi.org/10.17973/mmsj.2025_12_2025166.

[14] Tangbin Xia et al. "Online Analytics framework of Sensor-Driven Prognosis and Opportunistic Maintenance for mass customization". In: *Journal of Manufacturing Science and Engineering* 141.5 (Mar. 2019). DOI: 10.1115/1.4043255. URL: https://doi.org/10.1115/1.4043255.

[15] Konrad Wegener et al. "Intelligent Grinding". In: *International Journal of Automation Technology* 20.1 (2026), pp. 57–77. DOI: 10.20965/ijat.2026.p0057.

[16] Hong-Seok Park, Yuandi Wang, and Ngoc-Hien Tran. "A Data and Connectivity Based Process Control for Grinding Brake Disc". In: *Lecture Notes in Mechanical Engineering* (2023). Cited by: 0, pp. 617–626. DOI: 10.1007/978-3-031-34821-1_67. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85172335499&doi=10.1007%2f978-3-031-34821-1_67&partnerID=40&md5=7cb7bc3dd5941ae1af6f73895451d33e.

[17] Lishu Lv et al. "Intelligent technology in grinding process driven by data: A review". In: *Journal of Manufacturing Processes* 58 (2020). Cited by: 67, pp. 1039–1051. DOI: 10.1016/j.jmapro.2020.09.018. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85090912011&doi=10.1016%2fj.jmapro.2020.09.018&partnerID=40&md5=47b5758438572e4cd2f6bf3ad9870709.

[18] T. Kaufmann et al. "AI-based Framework for Deep Learning Applications in Grinding". In: Cited by: 15. 2020, pp. 195–200. DOI: 10.1109/SAMI48414.2020.9108743. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85087055139&doi=10.1109%2fSAMI48414.2020.9108743&partnerID=40&md5=b625b53887cbd5c6780f39ac91deacaf.

[19] Xin Chen and Kai Cheng. "Cutting tool remaining useful life prediction using Multi-Sensor data fusion through graph neural networks and transformers". In: *Machines* 13.11 (Nov. 2025), p. 1027. DOI: 10.3390/machines13111027. URL: https://doi.org/10.3390/machines13111027.

[20] Tao Yang et al. "Intelligent Manufacturing for the Process Industry Driven by Industrial Artificial Intelligence". In: *Engineering* 7.9 (2021). Cited by: 243; All Open Access, Gold Open Access, Green Open Access, pp. 1224–1230. DOI: 10.1016/j.eng.2021.04.023. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85116422946&doi=10.1016%2fj.eng.2021.04.023&partnerID=40&md5=c8e4b089b1ca33a4a2f160df85243053.

[21] Kaveh Amouzgar et al. "Smart process planning of crankshaft machining through multiple objectives optimization". In: vol. 134. Cited by: 0; All Open Access, Gold Open Access, Green Open Access. 2025, pp. 241–246. DOI: 10.1016/j.procir.2025.03.018. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-105009400889&doi=10.1016%2fj.procir.2025.03.018&partnerID=40&md5=82d5a2d3656920f8fa4f67dcc66b1bea.

[22] Rodrigo de Souza Ruzzi et al. "Influence of grinding parameters on Inconel 625 surface grinding". In: *Journal of Manufacturing Processes* 55 (2020). Cited by: 54, pp. 174–185. DOI: 10.1016/j.jmapro.2020.04.002. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85083079283&doi=10.1016%2fj.jmapro.2020.04.002&partnerID=40&md5=c5cef076d3b008ebd8e45cfdfc32837d.

[23] Ivan Pavlenko et al. "Parameter identification of cutting forces in crankshaft grinding using artificial neural networks". In: *Materials* 13.23 (2020). Cited by: 64; All Open Access, Gold Open Access, Green Open Access, pp. 1–12. DOI: 10.3390/ma13235357. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85096686313&doi=10.3390%2fma13235357&partnerID=40&md5=b635fb55043e9f5692079cdf9bac0e40.

[24] Wei Cao et al. "The influence of wear volume on surface quality in grinding process based on wear prediction model". In: *The International Journal of Advanced Manufacturing Technology* 121.9-10 (July 2022), pp. 5793–5809. DOI: 10.1007/s00170-022-09575-5. URL: https://doi.org/10.1007/s00170-022-09575-5.

[25] Ruizhi Li, Zipeng Wang, and Jihong Yan. "Multi-Objective optimization of the process parameters of a grinding robot using LSTM-MLP-NSGAII". In: *Machines* 11.9 (Sept. 2023), p. 882. DOI: 10.3390/machines11090882. URL: https://doi.org/10.3390/machines11090882.

[26] Marcin Hinz, Lea Hannah Guenther, and Stefan Bracke. "A comprehensive parameter study regarding the neural networks based monitoring of grinded surfaces". In: *Proceedings of the 31st European Safety and Reliability Conference (ESREL 2021)* (Jan. 2021), pp. 2014–2021. DOI: 10.3850/978-981-18-

2016-8\{_}521-cd. URL: https://doi.org/10.3850/978-981-18-2016-8_521-cd.
[27] Javier Diaz-Rozo, Concha Bielza, and Pedro Larrañaga. "Machine-tool condition monitoring with Gaussian mixture models-based dynamic probabilistic clustering". In: *Engineering Applications of Artificial Intelligence* 89 (Jan. 2020), p. 103434. DOI: 10.1016/j.engappai.2019.103434. URL: https://doi.org/10.1016/j.engappai.2019.103434.
[28] Zewen Hu et al. "Small-sample machining quality prediction via a fuzzy broad learning system enhanced by prior knowledge". In: *Journal of Manufacturing Systems* 84 (Dec. 2025), pp. 601–613. DOI: 10.1016/j.jmsy.2025.12.021. URL: https://doi.org/10.1016/j.jmsy.2025.12.021.
[29] Faiza Anwer and Shabib Aftab. "Latest Customizations of XP: A Systematic Literature Review". In: *International Journal of Modern Education and Computer Science* 9.12 (Dec. 2017), pp. 26–37. DOI: 10.5815/ijmecs.2017.12.04. URL: https://doi.org/10.5815/ijmecs.2017.12.04.
[30] Claes Wohlin. "Guidelines for snowballing in systematic literature studies and a replication in software engineering". In: *Proceedings of the 18th International Conference on Evaluation and Assessment in Software Engineering*. EASE '14. London, England, United Kingdom: Association for Computing Machinery, 2014. ISBN: 9781450324762. DOI: 10.1145/2601248.2601268. URL: https://doi.org/10.1145/2601248.2601268.
[31] Matthew J Page et al. "The PRISMA 2020 statement: an updated guideline for reporting systematic reviews". In: *BMJ* 372 (Mar. 2021), n71. DOI: 10.1136/bmj.n71. URL: https://doi.org/10.1136/bmj.n71.
[32] Virginia Braun and Victoria Clarke. "Using thematic analysis in psychology". In: *Qualitative Research in Psychology* 3.2 (2006). Cited by: 142813, pp. 77–101. DOI: 10.1191/1478088706qp063oa. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-33750505977&doi=10.1191%2f1478088706qp063oa&partnerID=40&md5=0fcde27f20660ffc3f46fe23d4829658.
[33] Weng Marc Lim. "What is qualitative research? An overview and guidelines". In: *Australasian Marketing Journal (AMJ)* 33.2 (July 2024), pp. 199–229. DOI: 10.1177/14413582241264619. URL: https://doi.org/10.1177/14413582241264619.
[34] Anthony G Tuckett. "Applying thematic analysis theory to practice: a researcher's experience." In: *Contemporary nurse : a journal for the Australian nursing profession* 19.1-2 (2005). Cited by: 502, pp. 75–87. DOI: 10.5172/conu.19.1-2.75. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-27244434775&doi=10.5172%2fconu.19.1-2.75&partnerID=40&md5=d505ad67bf14331a568603ebbf710a97.
[35] Sirwan Khalid Ahmed et al. "Using thematic analysis in qualitative research". In: *Journal of Medicine, Surgery, and Public Health* 6 (2025), p. 100198. ISSN: 2949-916X. DOI: https://doi.org/10.1016/j.glmedi.2025.100198. URL: https://www.sciencedirect.com/science/article/pii/S2949916X25000222.
[36] David Byrne. "A worked example of Braun and Clarke's approach to reflexive thematic analysis". In: *Quality and Quantity* 56.3 (2022). Cited by: 2606; All

Open Access, Green Open Access, Hybrid Gold Open Access, pp. 1391–1412. DOI: 10.1007/s11135-021-01182-y. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85108827650&doi=10.1007%2fs11135-021-01182-y&partnerID=40&md5=a40c7319be5d5a144d6132caa2dd7664.

[37] Nastja Macerol et al. "Superabrasive applications in grinding of crankshafts: a review". In: *Proceedings of the 20 th International Symposium on Advances in Abrasive Technology, Okinawa, Japan911–919*. 2017.

[38] Christoph Schröer, Felix Kruse, and Jorge Marx Gómez. "A Systematic Literature Review on Applying CRISP-DM Process model". In: *Procedia Computer Science* 181 (Jan. 2021), pp. 526–534. DOI: 10.1016/j.procs.2021.01.199. URL: https://doi.org/10.1016/j.procs.2021.01.199.

A
Appendix 1

Below shows the sample interview questions asked from industry experts and academic researchers

Interview Questions for Industry Experts Warm-Up Questions

- Can you briefly describe your role and how long you have been working in crankshaft grinding section?
- What are the main tasks you typically responsible/do in crankshaft grinding section?
- What type of grinding methods do you use in the line?

Main Questions

1. When you or your team notice that "something feels off" during grinding, what is the first thing you check from a production point of view?
2. From a production perspective, which process parameters (e.g., feed rate, speed, coolant flow) are most critical to achieving the desired crankshaft quality?
3. When grinding quality starts to deviate, how do you determine whether the issue is related to production settings, machine condition, or material variation?
4. How do you coordinate with maintenance and quality teams when adjustments or corrective actions are required during production?
5. How do you use feedback from quality inspections or operators to adjust your production process and maintain stable grinding performance?

Production Related

1. From a production standpoint, what factors most strongly influence consistent grinding quality?
2. How do you ensure that the grinding process remains stable while meeting high production targets or higher output demands?
3. When production demand increases, what challenges or trade-offs do you observe in maintaining quality?
4. What process indicators or signals (e.g., surface finish, cycle time, sound, vibration) help you detect early signs of instability?
5. Grinding burns are a common issue—what production practices or controls do you follow to minimize this risk?
6. How do quality requirements influence your production planning, process adjustments, or operational decisions?
7. What routine checks or process controls do you perform to prevent grinding-related quality issues?

8. When a quality issue occurs, what production data or records do you typically review (e.g., process parameters, batch info, operator logs)?
9. When surface quality begins to deteriorate, what is the first process parameter you check or adjust?
10. What early warning signs do you observe (e.g., changes in sound, machine behavior, output quality) before a defect develops?
11. From a production perspective, which actions are most critical to maintain stable and repeatable grinding performance?
12. How do you identify that a grinding wheel or process condition is no longer producing acceptable results?
13. What tools, systems, or digital dashboards do you use to monitor process performance and support decision-making?
14. What are the data you record during crankshaft grinding process?
15. When a grinding defect occurs, how do you combine production data, operator experience, and feedback from quality/maintenance teams to identify the root cause?

Below shows the sample interview questions focused on academic experts

Warm-Up

1. Can you briefly describe your research experience in grinding, especially related to cylindrical or crankshaft grinding?

Identification of Key Process Parameters

1. From your research, what are the most influential grinding process parameters affecting (surface quality, dimensional accuracy, production efficiency)?
2. How would you prioritize these parameters in terms of impact?
3. (E.g., wheel speed, workpiece speed, feed rate, depth of cut, coolant flow, dressing conditions)
4. (Refer: Malkin book, Stephen Grinding Technology)

Parameter → Quality Relationships

1. Which parameters are most strongly linked to grinding burn and thermal damage, and why?

3. Parameter → Production/Productivity Relationships

1. How do grinding parameters influence cycle time and material removal rate (MRR)?

Interaction Effects

1. How do different parameters interact with each other (e.g., feed rate vs coolant, wheel speed vs depth of cut)?
2. Can you give examples where changing one parameter alters the effect of another?

Role of Tooling & Machine Conditions

1. How do grinding wheel properties (grain size, bond type, dressing) influence process outcomes?

Measurement & Indicators

1. Which process signals or measurements best reflect the influence of parameters on quality and production performance?
2. (E.g., forces, temperature, acoustic emission, vibration, power)

3. Which indicators are most reliable for detecting early deviations?

Data-Driven Understanding

1. How can multi-modal data (process + sensor + quality data) help identify relationships between parameters and outcomes?
2. What modeling approaches are most effective for understanding parameter effects?
3. What modeling approaches are most effective for predicting grinding performance?

Industrial Relevance

1. In your opinion, which critical parameter relationships are often misunderstood or overlooked in industry?
2. Where do industries struggle most when trying to balance quality and productivity?

Optimization & Future Direction

1. What strategies would you recommend to optimize grinding parameters for both quality and production?
2. What future developments (e.g., AI, adaptive control, digital twins) could improve parameter selection and control in grinding?

Wrap-Up

1. If you had to highlight 3–5 key parameters that every crankshaft grinding process must control carefully, what would they be, and why?

DEPARTMENT INDUSTRIAL AND MATERIALS SCIENCE
CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden
www.chalmers.se

CHALMERS
UNIVERSITY OF TECHNOLOGY