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Value-Based Feature Design for Smart Services in Computerized Numerical Control Machine Tools: A Case Study on Measuring Perceived Value Using a Choice-Based Conjoint Analysis

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Abstract

Artificial intelligence (AI) has emerged as a key technology, transforming the manufacturing industry by enabling new business models and reshaping existing ones through smart services. However, due to a lack of expertise in some companies, there are challenges in understanding how AI can be effectively integrated to create value and how products can be further developed into smart service products. Against this background, this paper contributes to the value-driven design of intelligent machine tools. In an exploratory research study, the self-explicated method was used with 23 industry experts to evaluate different service types and a variety of possible features. The results identify intelligent quality improvement as the smart service with the highest perceived value from the user's perspective. Based on these results, fictional service offerings were created and examined in a choice-based conjoint analysis with a sample of n = 245 industry professionals involved in procurement and retrofitting decisions for machine tools. The evaluation of feature selection is based on the analysis of willingness to pay, and additionally, the paper identifies optimal feature combinations for different target groups to maximize willingness to pay.

Categories: Computational Intelligence and Information Management, Consumer Behavior, Decision Support
Keywords: ai, smart services, cnc maschine tools, value-based pricing, willingness to pay, conjoint analysis, choice-based conjoint

Introduction

Artificial intelligence (AI) as key technology unlocks new opportunities for process and product innovations, as well as for the development of (service) business models. Integrating intelligent (digital) services, such as smart monitoring, process regulation, and increased process flexibility takes industry 4.0 to a new level (Ahmmed et al., 2024). While AI has been a familiar concept since the 1950s, recent advances in model approaches and computing power have enhanced its readiness for the market. These advancements became particularly evident during the 2010s with the milestones in generative AI, which demonstrated its transformative capabilities (Krizhevsky et al., 2012).

As a result, businesses began adopting AI as a powerful tool to redesign and enhance various aspects of their business models by using the capacity to optimize and innovate internal and external operations like enhancing quality, increasing efficiency, and boosting effectiveness. Moreover, AI facilitates the repositioning of value propositions and lead to innovation from traditional products through the addition of supplementary (smart-) services (von Garrel and Jahn, 2023).

Business models in the manufacturing industry significantly perceived value from the use of AI by transforming traditional products into smart service products, such as intelligent machine tools. These tools enable continuous monitoring of operations, automatic optimization, and early detection of maintenance requirements. This helps increase machine availability, minimize downtime, and lower production costs, while also improving workpiece quality. As a result, production processes become more efficient, and entirely new business models emerge (Makar, 2023) (von Garrel and Jahn, 2023). However, the benefits of smart services are highly dependent on a company's specific operations and strategic objectives. For instance, predictive maintenance is a widespread AI-powered application for machine tools, but its implementation and integration generally differ between companies. To derive value from a smart service, it must be tailored to the individual production environment, operational goals, and customer requirements (Makar, 2023), (Schmidgal et al., 2022), and (von Garrel and Jahn, 2023).

Against this background, the objective of this article is to identify key value drivers of smart services through a choice-based conjoint (CBC) analysis. Using the example of a Computerized Numerical Control (CNC) machine tool, the study examines how the design of smart services influences perceived value, as measured by customers' willingness to pay. Therefore, the research addresses two key perspectives: on the

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one hand, the supplier side, represented by machine and equipment manufacturers as developers, and on the other hand, the customer side, encompassing manufacturing companies that implement these technologies in their operations.

Case Description

State of the art

AI encompasses development approaches which are designed to enable machines cognitive abilities based on data, with the goal of autonomously improving their ability to solve specific problems through a modeled learning process (Kaplan and Haenlein, 2019). In the mechanical engineering industry, machines are enhanced through AI-based or data-driven approaches, transforming them into smart service products. These are physical products combined with digital services to create greater value for the customer. Typically equipped with sensors, actuators, and communication technologies, these products are connected through the Internet of Things (IoT), which enables them to collect and analyze data in their operating environment and to autonomously execute operations or make decisions (Jin et al., 2018).

These products typically offer not only physical functionality but also value-added services, such as predictive maintenance, personalized user experiences, or real-time optimizations, all of which ultimately aim to improve quality or optimizing processes. Table *1* summarizes the most common smart services in the mechanical engineering industry. Predictive maintenance and quality improvement are the most frequently cited, while other approaches such as setup time optimization and alarm systems illustrate how AI-based solutions extend beyond production efficiency to support employees directly. The value creation can occur in different ways depending on the use case. Accordingly, in practice, there are various approaches of how value can be generated by data-driven methods. The most common value creation in practice focuses on the following service values outlined in Table *1*.

Smart Service	Value Creation and Description	References
Predicative Maintenance	Condition-based maintenance based on continuously collected machine data	(Liu, 2010) (Zuth et al., 2021) (Zhu et al., 2020) (Jia et al., 2022) (Liu and Xu, 2017) (Luo et al., 2018) (Guo et al., 2020)
Quality Improvement	Detection of non-conforming parts and adherence to tolerances	(Liu, 2010) (Zhu et al., 2020) (Jia et al., 2022) (Liu and Xu, 2017) (Luo et al., 2018) (Guo et al., 2020)
Production Time Optimization	Maximizing drive performance and reducing rapid traverse (G0) movement	(Liu, 2010) (Jia et al., 2022) (Luo et al., 2018)
Setup Time Optimization	Optimal tool placement in the magazine and efficient timing for workpiece or tool changeovers	(Liu, 2010) (Niemi, 2003) (Khakpour et al., 2024)
Employee Information & Alarm System	Warning notifications for unusual machining or machine noises; cloud-based knowledge sharing assistance	(Liu, 2010) (Zuth et al., 2021) (Jia et al., 2022) (Liu and Xu, 2017) (Luo et al., 2018) (Guo et al., 2020)

TABLE 1: Common smart services in mechanical engineering industry

Author computation

Every value proposition has a price. Technically, the price describes, based on a pricing mechanism, the conversion of a non-monetary value into a monetary form. This, in turn, is shaped by the revenue model that is planned for value generation (Hinterhuber, 2004). The following revenue models are commonly applied to smart service products and data-based services. Table *2* provides an overview, showing that recurring service fees and usage-based approaches dominate in practice, while single payments are rarely mentioned in the literature. Gain-sharing models, although less established, highlight the potential for performance-based pricing.

Revenue Model	Description	References
Single Payment	Single payment for a product or service.	(Schüritz et al., 2017)
Service Fee	Recurring payments made on a regular cycle (e.g. monthly, quarterly, annually) for continuous access to a service.	(Classen and Friedli, 2021) (Jefimova and Nabseth, 2018) (Schüritz et al., 2017) (Curry et al., 2021)
Usage-based	Customer pays based on a measurable metric (e.g. number of requests, data volume, etc.).	(Classen and Friedli, 2021) (Jefimova and Nabseth, 2018) (Schüritz et al., 2017) (Curry et al., 2021)
Gain Sharing	Payment amount is based on measured success defined through established indicators (KPIs), in which the provider is typically given a percentage share.	(Classen and Friedli, 2021) (Jefimova and Nabseth, 2018) (Schüritz et al., 2017) (Curry et al., 2021)

TABLE 2: Common revenue models for smart services

Author computation

The service types outlined in Table *1* and the revenue models presented in Table *2* can be systematically combined to configure a smart service. The specific value contribution of such a service depends on the integration and design of additional functional features, which can vary significantly and thereby influence the overall perceived utility value by the user. Due to the wide range of combinations and design possibilities, this paper deals with the following questions:

1. How can value-based AI services be designed for CNC machine tools?

2. Which attributes and features positively or negatively influence the perceived value and willingness to pay for an AI-supported CNC machine tool?

3. What is the optimal product combination to maximize willingness to pay, depending on various business characteristics?

Exploratory research - Self-Explicated Method (SEM)

In order to achieve the objective of the study, the operationalization is divided into an exploratory and main study. The exploratory research focuses on collecting general attributes and features, while identifying the most relevant evaluation criteria in the procurement and decision-making process using the self-explicated method (SEM).

For an appropriate operationalization, specific attribute features are needed to enable decision-making and the evaluation of perceived utility value of smart services. By comparing the portfolios of four German mechanical engineering manufacturers, a variety of distinct features were identified, which can be categorized into 10 attributes that characterize smart services for CNC machine tools (State of the Art, Table *1*). A detailed explanation and the specific implementation of the following features can be found in Table *15* in the Appendix. The 10 attributes identified are as follows:

· Operation (AI-Service On/Off)

· Recording Automation

· Scope of Use Cases

· Integration & Implementation

· Transparency (AI model)

· Accuracy

· Data History Range

· Variety of Data Sensors

· Evaluation & Data Access

· Price

For the operationalization of the CBC, the scope must be reduced to six attributes due to excessive complexity caused by too many comparable options. Therefore, the presented attributes were assessed for six of the most relevant features from a customer value perspective. To obtain insights from the customer's perspective, experts and practitioners from Marketing & Sales and Customer Support were surveyed. The Marketing & Sales side represents relevant features in the procurement process, while Customer Support provides statements about the usability.

The preliminary study was conducted using the self-explicated method, in which participants were placed in a fictitious customer-perspective scenario (Table *3*). They were given the opportunity to retrofit their machine tools with a smart service and could choose one of the service types listed in Table *1*. They were additionally asked to rank the six selected attributes based on their relevance to the intended use cases and to select a preferred revenue model from those summarized in Table *2*. Table *3* provides an overview of the questions and answer formats used in this scenario, illustrating how participants evaluated service offerings, features, and pricing models from a customer standpoint.

Question	Answer Format
“Imagine that, as a customer, you receive an offer to optimize your CNC machine(s) with an additional service. Please rank the listed service products in terms of the additional value they provide for your CNC machine (using drag & drop).”	Highest value (01) lowest value (05)
“As a customer, you have decided on an additional service product and would like to acquire it. You receive an offer for this AI service and are now evaluating its features. Please rank the listed features in terms of their relevance (using drag & drop).”	Highest value (01) lowest value (10)
“Which of the following revenue models would you prefer most from a customer perspective?”	Multiple selections possible

TABLE 3: Self-explicated method placed in fictitious customer-perspective scenario

Author computation

Experts from the industry were contacted and invited to participate. The screening of the target group was based on a self-assessment at their own discretion in the survey:

"Are you in direct contact with your customers? Do you believe you can represent a customer and make statements about their needs, desires, or expectations?"

Exploratory research - results

In total, n = 29 participants expressed interest in taking part in the survey. After the self-assessment, n = 23 experts participated. This included n = 13 from Marketing & Sales and n = 9 from Customer Support. Using the SEM, “Quality Improvement” was identified as the smart service offering the highest value for a CNC machine tool from the customer's perspective. In addition, the five most important features and a preferred revenue model were determined. In the procurement and decision-making process, aside from price and integration & implementation, the most important evaluation criteria for such systems are as follows:

· Operation

· Data Evaluation & Data Access

· Scope of Use Cases

· Accuracy

· Transparency (AI model)

The experts estimate that when paying for a smart service, their customers mostly prefer a “usage-based” revenue model. Ultimately, the determined attributes address the central dimensions of benefit and usability in a purchase situation for data-based smart services for a CNC machine tool.

Main study - CBC

Building on the findings of the exploratory research, the main study allows getting an isolated view of these attributes using a CBC method to analyze their relevance and perceived utility in relation to willingness to pay.

The CBC was conducted using a quantitative survey via an online questionnaire. This methodological approach is used to simulate consumer decision-making by presenting fictitious purchasing situations (Bauer et al., 2015). Introduced by Louviere and Woodworth in 1983, it aims to decompose and estimate the consumers' perceived value on various product attributes (Louviere and Woodworth, 1983). Respondents are presented with several product combinations (referred as "choice tasks" or stimuli) with different characteristics, from which they select their preferred product proposal.

The central idea behind CBC is to simulate a real decision process where the options presented are fictitious, but the consumer's choice reflects their underlying preferences. The utility or value of the product combinations is calculated based on the choices made, typically using a hierarchical Bayesian estimation following the maximum likelihood method. The likelihood function captures the relationship between the objective attribute (including features) and the subjective utility perceived by the consumer (Goeken et al., 2021). This allows to estimate both the total utility and the partial utilities (partial values) of individual product attributes, which helps to understand the trade-offs consumers are willing to make between different product attributes and their willingness to pay. To ensure suitable choice sets, the following quality criteria must be met:

1. Empirical independence → no empirical related effect between characteristics

2. Relevant attributes of purchase decisions

3. Variation of characteristics → variation of features per attribute

4. Limitation of the characteristics per attribute → complexity reduction

5. Compensatory relationships of characteristics → e.g. high quality → high price

In this context, attribute features were assigned in a workshop with industry experts to develop a realistic simulation that corresponds to a smart service for quality improvement. Table *4* presents the resulting feature combinations, showing how each attribute is operationalized with specific levels and associated costs. As part of this design, the attribute Scope of Use Cases was adapted to Scope of Quality Monitoring, and the revenue model was applied as a usage-based mix of "pay-per-function" and "pay-per-use," with a price range of €2-€12 per hour of machine running time. The price is allocated proportionally across the attributes and features, depending on the estimated costs and efforts. This approach considers both the relationships between the individual features of an attribute and the relationships between the attributes themselves. For example, the development and training of AI models for Scope of Quality with high accuracy involves significantly higher efforts and costs compared to implementing the operation of the model within the machine. Similarly, developing a service with preventive optimization during the machining process requires greater effort and costs than a quality assessment after program execution.

Attribute	Feature 1	Feature 2	Feature 3
Operation (AI-Service On/Off)	User Interface **(0.00€)**	NC Program Code **(0.50€)**	
Evaluation & Data Access	Machine Interface (without data storage) **(0.50€)**	Cloud/App (with data storage) **(1.00€)**	
Scope of Quality Monitoring	Quality Assessment after Program (pass/fail) **(0.50€)**	Controlled Interruption during the Processing **(1.50€)**	Preventive Optimization in the Processing **(3.50€)**
Accuracy	Low Accuracy (approx. 90%) **(1.00€)**	Moderate Accuracy (approx. 95%) **(2.00€)**	High Accuracy (approx. 99%) **(4.50€)**
Transparency (AI model)	No Explanation/Only Result **(0.00€)**	Explanation of AI Decision **(2.50€)**	
Price (per hour of machine running time)	= sum of partial cost/price shares per feature		

TABLE 4: Possible feature combinations of a quality improvement smart service based on pay-per-use and pay-per-function revenue model

Author computation

Based on Table 4 of the various features and their possible combinations, the following smart service products can be created:

· *Operation:* The AI service can be activated manually at the machine or by a command in the program code.

· *Scope of Quality Monitoring:* The quality is evaluated either after each workpiece or continuously during the machining process.

o In the case of piecewise evaluation, the quality of the machining process is displayed after a run, eliminating the need for evaluating during the machining process. However, this only works for series production. Parameters for a qualitative workpiece must be determined in advance during a reference run.

o For single-piece production, each workpiece is individually assessed, and the machine's position parameters are continuously compared against the target positions. If deviations occur, the machining can either be interrupted or the machining parameters are automatically adjusted and optimized.

· *Evaluation & Data Access:* The results are directly accessible at the machine or on a cloud-based website (including data history).

· *Accuracy:* As is common in practice, occasional misjudgments may occur. Various levels of accuracy are offered with regard to error rates.

· *Transparency*: Additionally, the system can provide an explanation of the AI decisions, ranging from simple pass/fail responses to detailed parameter information.

To generate a dataset with a valid data foundation, it is necessary to specify the target group. For this study, the target group is limited to the German manufacturing industry, characterized by the ability to integrate machine tools into their processes, a certain degree of technical and operational know-how, and involvement in decision-making and procurement processes. To generate such a specific data set with a sufficient sample size, recruitment and data collection is assigned to a panel of the Schlesinger Group/SAGO. Participants were placed in six fictional purchase decision scenarios, where they were asked to choose the offer with the highest perceived subjective value in each scenario. After that they were asked to decide whether they would purchase a particular offer at the stated price-performance ratio. Figure 1 represents a fictional purchase decision scenario with three different offers.

	Offer 1	Offer 2	Offer 3
Operation (AI-Service On/Off	NC Program Code	User Interface	User Interface
Evaluation & Data Access	Machine Interface (without data storage)	Cloud/App (with data storage)	Cloud/App (with data storage)
Scope of Quality Monitoring	Preventive Optimization in the Processing	Controlled Interruption during the Processing	Controlled Interruption during the Processing
Accuracy	High Accuracy (approx. 99%)	Moderate Accuracy (approx. 95%)	Low Accuracy (approx. 90%)
Transparency (AI model)	Explanation of AI Decision	No Explanation/ Only Result	No Explanation/ Only Result
Price (per hour of machine running time)	11.50€	4.50€	3.50€

Would you buy the selected option?

Yes

No

FIGURE 1: Example of a fictional purchase decision scenario with three different offers

Interface of Qualtrics questionnaire (Qualtrics, 2025). Excerpt of a figure from the software tool.

Main study - results

A total of *n* = 1370 individuals accessed the study through the panel. According to the screening process, *n* = 378 participants matched the target group criteria and were admitted to the survey:

· "Is your company location in Germany? (→ applies)”

· "In which economic sector is your company active? (→ among others Production)"

· “Is a CNC machine tool integrated into at least one of your manufacturing processes, or is integration possible? (→ applies)"

· "Are you involved in corporate decision-making and procurement processes? (→ applies)”

After a subsequent quality check, the sample was reduced to *n* = 245 by assessing the minimum proportion of questions answered (75%), completion time (> 6 minutes), and the logic of response behavior.

Among the *n* = 245 participants, small and micro-enterprises are represented with 12.24%, medium-sized enterprises with 59.59%, and large enterprises with 28.16%. The sample shows a diverse distribution of industries with a large portion of companies operating across multiple sectors. Figure *2* illustrates the distribution of industries based on European NACE codes. The majority of companies are active in mechanical engineering (*n* = 114), followed by manufacture and processing of metal products (*n* = 69), repair and maintenance of machinery (*n* = 55), and manufacture of electrical equipment (*n* = 55). The participants come from various company departments but many work across departments. More than half of the sample (57.55 %) work in production, among other areas, and therefore have an application- and usage-oriented perspective.

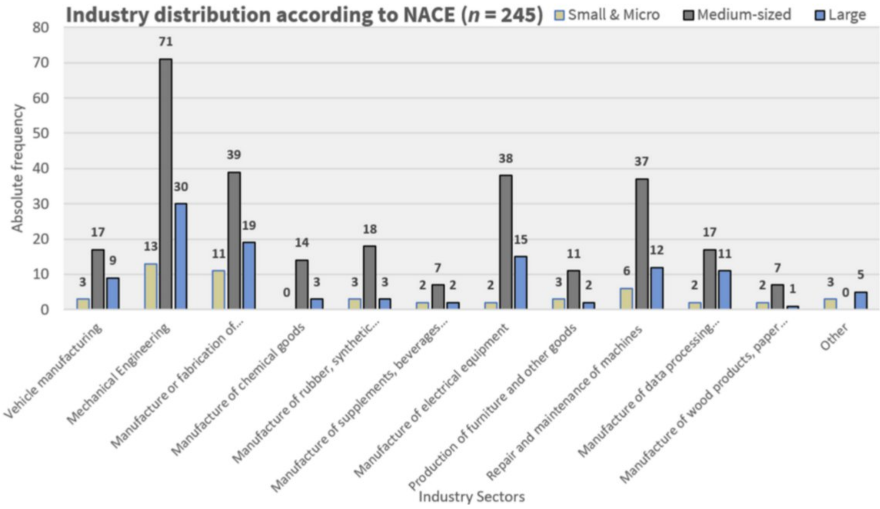

FIGURE 2: Distribution of industries by NACE codes (n = 245)

Author computation. x-axis: Industry sectors; y-axis: Absolute frequency

The companies are also broadly positioned in terms of the complexity of the goods they produce with CNC machine tools playing a central role in their production processes. According to their own statements, 49.39% of the sample produce simple products (e.g., components or supply parts), 41.63% produce products of medium complexity (e.g., modules), and 54.29% produce complex products (e.g., machines and systems). More than one-third of the sample shows single-piece production (39.59%) as well as mass production (38.37%) as an organized production. In over half of the companies series production (63.27%) is present. The most common are companies producing simple products (33.47%) or complex products (32.65%).

Furthermore, 73.88% (*n* = 181) responded that they are already using AI in their company. At 95.10% (*n* = 233), almost all participants have been involved at least once in the procurement process or the retrofitting of a machine tool. Table *5* summarizes the distribution of participant involvement in machine tool procurement or retrofitting, distinguishing between companies using AI and those that do not. In all, 73.06% of the participants work in a company that uses AI and have been involved at least once in a procurement process or the retrofitting of machine tools.

Involvement in Machine-Tool Procurement/Retrofitting	Organization Uses AI	Organization Does Not Use AI
Involved in procurement process or retrofitting of machine tools.	73.06%	22.04%
Not involved in the procurement process or retrofitting of machine tools.	0.82%	4.08%

TABLE 5: Distribution of participant involvement in machine tool procurement or retrofitting by AI usage versus no AI usage

Author computation. AI, artificial intelligence

In total, 60.82% (*n* = 149) of the participants would purchase one of the three offers in each purchase decision situation and 87.76% (*n* = 232) purchased one of the three offers in three out of six decision situations. Figure *3* illustrates the absolute frequencies of positive purchase decisions across all participants, highlighting overall engagement and purchase intent in the simulated scenarios.

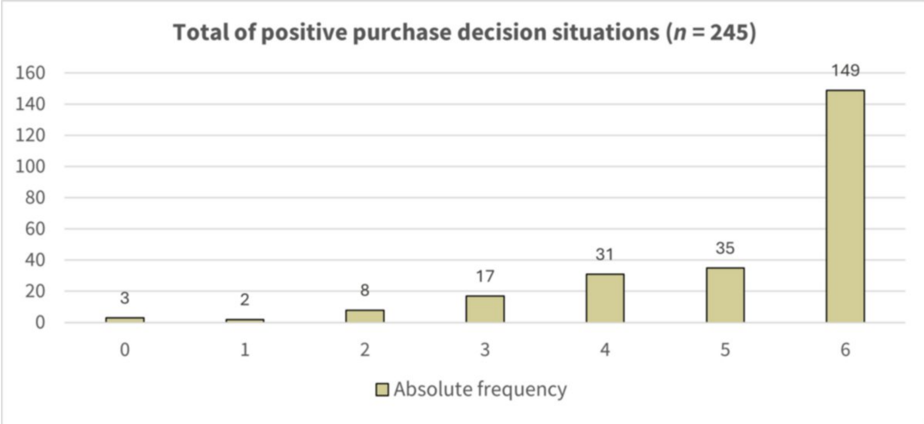

FIGURE 3: Absolute frequencies of positive purchase decisions situations (n = 245)

Author computation. x-axis: Purchase decision; y-axis: Absolute frequency

After finishing the CBC, the participants were explicitly asked which attributes were most important to them when evaluating the AI service. In comparison, these deviate on average by 3.14% from the estimated utility shares of the likelihood method, but this barely affects the ranking of perceived value. The greatest discrepancy is seen for the attribute “Evaluation & Data Access," which is in fourth and fifth place respectively. Figure *4* illustrates the comparison between explicit and estimated utility shares for all attributes, highlighting the consistency and minor differences between the two assessment methods.

„Which attributes of the presented AI service are or were most important to you in your evaluation?”

Simulated purchase decisions

Rank	Explicit Utility Perception Share (Survey)	Attributes	Estimated Utility Share (CBC)	Rank
1	28.3 %	*Accuracy*	33.9%	**1**
2	21.4 %	*Scope of Quality Monitoring*	23.7%	**2**
3	19.1 %	Transparency (AI model)	18.5%	**3**
4	17.0 %	Evaluation & Data Access	11.7%	**5**
5	14.2 %	Operation (AI-Service On/Off)	12.3%	**4**
	100.0%		100.0%	

FIGURE 4: Explicit and estimated utility shares of attribute ranking (n = 245)

Author computation

All proportions of perceived utility value (= estimated utility share) that are in the positive range of the y-axis indicate a perceived value, while those in the negative range indicate no perceived utility. Even if only a few attributes show a bigger gab, the features with a positive utility value are represented for each attribute. It clearly can be seen that accuracy is perceived as a highly valuable benefit. While an accuracy of approximately 99% strongly supports a purchase decision, a lower accuracy of 90% inhibits such a decision. The exact distribution can be seen in Figure *5*.

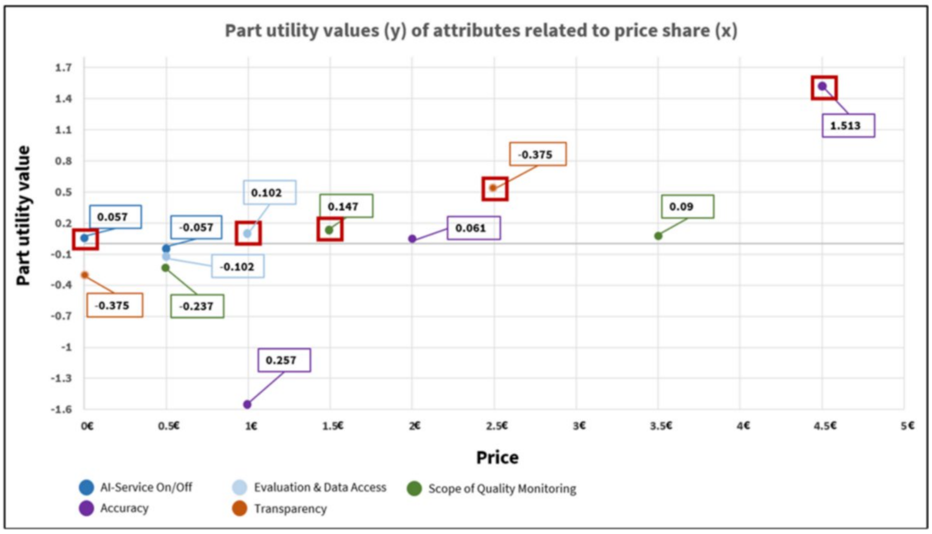

FIGURE 5: Plot of estimated part utility values related to price share (n = 245)

Author computation. x-axis: Price; y-axis: Part utility value

When analyzing the individual features, an optimal product combination emerges based on the utility perception shares. The features with the highest part utility value per attribute, in combination, correspond to the optimal product combination with the highest expected net utility value and the maximum willingness to pay. It represents the product development with the highest purchase probability. Figure 5 illustrates the estimated part utility values for each feature, while Table 6 summarizes the specific optimal product combination and the associated willingness to pay of €9.50 per hour of machine running time.

Attribute	Optimal Product Combination (n = 245)
Operation (AI-Service On/Off)	User Interface
Evaluation & Data Access	Cloud/App (with data storage)
Scope of Quality Monitoring	Controlled Interruption during the Processing
Accuracy	High Accuracy (approx. 99%)
Transparency (AI model)	Explanation of AI Decision
Price (per hour of machine running time)	9.50€ (per hour of machine running time)

TABLE 6: Optimal product combination (total sample, n = 245)

Author computation

The perceived value of the features differs between groups, which is reflected in their preferred product combinations. These group differences represent different application purposes, operating environments, as well as the use of and experience with AI.

Application purpose encompasses the complexity of the manufactured product, which was categorized into three groups: Table 7 presents the optimal product combination for companies producing simple products (e.g., components or supplier parts), Table 8 shows the combination for products of medium complexity (e.g., modules), and Table 9 illustrates the combination for complex products (e.g., machines and systems). The results indicate that companies selling complex products prefer a more advanced scope of quality monitoring with “Preventive Optimization in Processing” and demonstrate a higher willingness to pay compared to companies producing less complex products.

Attribute	Optimal Product Combination (Simple Complexity, n = 121)
Operation (AI-Service On/Off)	NC-Program Code
Evaluation & Data Access	Cloud/App (with data storage)
Scope of Quality Monitoring	Controlled Interruption during the Processing
Accuracy	High Accuracy (approx. 99%)
Transparency (AI model)	Explanation of AI Decision
Price (per hour of machine running time)	10.00€ (per hour of machine running time)

TABLE 7: Optimal product combination (simple complexity, n = 121)

Author computation

Attribute	Optimal Product Combination (Medium Complexity, n = 102)
Operation (AI-Service On/Off)	User Interface
Evaluation & Data Access	Cloud/App (with data storage)
Scope of Quality Monitoring	Controlled Interruption during the Processing
Accuracy	High Accuracy (approx. 99%)
Transparency (AI model)	Explanation of AI Decision
Price (per hour of machine running time)	9.50€ (per hour of machine running time)

TABLE 8: Optimal product combination (medium complexity, n = 102)

Author computation

Attribute	Optimal Product Combination (Complex, n = 133)
Operation (AI-Service On/Off)	User Interface
Evaluation & Data Access	Cloud/App (with data storage)
Scope of Quality Monitoring	Preventive Optimization in the Processing
Accuracy	High Accuracy (approx. 99%)
Transparency (AI model)	Explanation of AI Decision
Price (per hour of machine running time)	11.50€ (per hour of machine running time)

TABLE 9: Optimal product combination (complex, n = 133)

Author computation

The operating environment refers to the structure of the production organization, which was categorized into single-unit production, series production, and mass production. Table *10* presents the optimal product combination for single-unit production, Table *11* for series production, and Table *12* for mass production. It becomes evident that companies engaged in mass production prefer an advanced scope of quality monitoring as well as control through program code. For such capabilities, they show a higher willingness to pay, reaching 12.00 per hour of machine running time.

Attribute	Optimal Product Combination (Single Production, n = 97)
Operation (AI-Service On/Off)	User Interface
Evaluation & Data Access	Cloud/App (with data storage)
Scope of Quality Monitoring	Controlled Interruption during the Processing
Accuracy	High Accuracy (approx. 99%)
Transparency (AI model)	Explanation of AI Decision
Price (per hour of machine running time)	9.50€ (per hour of machine running time)

TABLE 10: Optimal product combination (single production, n = 97)

Author computation

Attribute	Optimal Product Combination (Series Production, n = 155)
Operation (AI-Service On/Off)	User Interface
Evaluation & Data Access	Cloud/App (with data storage)
Scope of Quality Monitoring	Controlled Interruption during the Processing
Accuracy	High Accuracy (approx. 99%)
Transparency (AI model)	Explanation of AI Decision
Price (per hour of machine running time)	9.50€ (per hour of machine running time)

TABLE 11: Optimal product combination (series production, n = 155)

Author computation

Attribute	Optimal Product Combination (Mass Production, n = 94)
Operation (AI-Service On/Off)	NC-Program Code
Evaluation & Data Access	Cloud/App (with data storage)
Scope of Quality Monitoring	Preventive Optimization in the Processing
Accuracy	High Accuracy (approx. 99%)
Transparency (AI model)	Explanation of AI Decision
Price (per hour of machine running time)	12.00€ (per hour of machine running time)

TABLE 12: Optimal product combination (mass production, n = 94)

Author computation

Companies that consciously integrate AI into their operations differ from those that do not. In this context, “consciously” refers to AI being deliberately procured as an application to enhance effectiveness or efficiency, rather than merely acquired as an additional feature of a product or service. Table 13 presents the optimal product combinations for companies already using AI, while Table 14 shows the combinations for companies not using AI. The results indicate that companies already utilizing AI tend to prefer an advanced scope of quality monitoring and the storage of their data history through cloud-based solutions.

Attribute	Optimal Product Combination (No AI Utilization, n = 64)
Operation (AI-Service On/Off)	User Interface
Evaluation & Data Access	Machine Interface (without data storage)
Scope of Quality Monitoring	Controlled Interruption during the Processing
Accuracy	High Accuracy (approx. 99%)
Transparency (AI model)	Explanation of AI Decision
Price (per hour of machine running time)	9.00€ (per hour of machine running time)

TABLE 13: Optimal product combination (no AI utilization, n = 64)

Author computation

Attribute	Optimal Product Combination (AI Utilization, n = 181)
Operation (AI-Service On/Off)	User Interface
Evaluation & Data Access	Cloud/App (with data storage)
Scope of Quality Monitoring	Preventive Optimization in the Processing
Accuracy	High Accuracy (approx. 99%)
Transparency (AI model)	Explanation of AI Decision
Price (per hour of machine running time)	11.50€ (per hour of machine running time)

TABLE 14: Optimal product combination (AI utilization, n = 181)

Author computation

Discussion

AI has transformed business models in manufacturing industries. It has become an integral component for enabling process, product, and service innovations. AI-powered smart service, for e.g., for CNC machine tools, enhance process efficiency and effectiveness, increase machine availability, minimize downtime, and reduce production costs.

However, the perceived value that customers associate with smart services strongly depends on how well these services are tailored to their use cases. In this regard, it is crucial to gain a deeper understanding of the customers' perceived value. Therefore, this article aims to explore the key value drivers for CNC machine tools from a user perspective and analyze which specific features influence perceived value and willingness to pay. The following research questions were answered in the course of the study.

1. How can value-based AI services be designed for CNC machine tools?

2. Which attributes and features positively or negatively influence the perceived value and willingness to pay for an AI-supported CNC machine tool?

3. What is the optimal product combination to maximize willingness to pay, depending on various business characteristics?

To answer the first question, insights from n = 23 experts in customer support and marketing & sales were considered. The results show that AI-based Quality Improvement is currently considered the data-driven service with the highest customer value. Aside from Price and Integration & Implementation, other key evaluation criteria in procurement and purchase decision-making include Operation, Data Evaluation & Access, Scope of Use Cases, and the Accuracy and Transparency of the AI model. These factors are regarded as particularly important when assessing such systems. A usage-based revenue model is perceived as providing the greatest value for data-driven services in the B2B sector. The identified attributes relate to the key dimensions of benefit and usability, offering guidance on prioritizing data-driven services for machine tools.

With respect to the second question, the features of each attribute were adapted to a smart service for quality improvement. The following price shares were allocated to the features based on incurred costs and efforts. Even though the price shares were estimated rather than precisely calculated, this is not considered problematic in the overall context, since respondents in the choice-based conjoint analysis always evaluate and choose a complete product package rather than individual features. Ultimately, the focus lies in investigating to what extent the target group is willing to pay higher amounts for specific product packages by considering development costs and other associated efforts.

For the analysis, the sample size was reduced from n = 1370 to n = 245 through screening and quality checks. Approximately three-quarters of the surveyed companies are SMEs, with the majority classified as medium-sized enterprises (59.59%). Companies in the mechanical engineering sector dominate the sample by almost half (46.53%). The data also show that the manufacture of complex products (54.29%) in series production (63.27%) is the most frequently represented. Furthermore, more than half of the respondents are active in the production sector of their company (57.55%), which indicates a sample with a heightened user perspective. Nearly all respondents (95.10%) have been involved at least once in procurement processes or the retrofitting of machine tools, highlighting their practical experience. A significant proportion (73.88%) already consciously use AI in their companies, indicating that AI has become increasingly prevalent in German manufacturing SMEs.

The conjoint analysis revealed valuable insights into the perceived value of AI-based service features and their impact on willingness to pay across different groups. The participants' explicit evaluations of important attributes deviated only slightly (3.14% on average) from the estimated utility shares derived from the CBC, indicating consistency in perceived value rankings. The largest discrepancy was observed for the "Evaluation & Data Access" attribute. While this led to a shift in the selection decision, it had a minimal impact on the overall insights. The attributes with the highest perceived utility are "Accuracy," "Scope of Quality Monitoring," and "Transparency." "Accuracy" and "Scope of Quality Monitoring" consistently show the highest levels at "High Accuracy (approx. 99%)," along with the "Explanation of AI Decisions" across all groups. The groups differ significantly in their preferences for the "Scope of Quality Monitoring."

However, from the authors' point of view, the generalizability of the results in terms of validity and reliability needs to be considered. Due to the required reduction in complexity, the CBC analysis was able to cover a limited number of attributes only and does not cover all relevant features involved in the purchasing decisions. Since the purchase decisions were not associated with real transactions, it is not possible to prevent the occurrence of biases. Nevertheless, an optimal product combination for the entire sample can be identified based on the features with the highest part utility values for each attribute. This combination includes operation via a "User Interface," evaluation through a "Cloud/App with Data Storage," controlled interruption during the processing, "High Accuracy (approximately 99%)," and a transparent AI model. On average, for the given combination, the companies in the sample are willing to pay €9.50 per hour of machine runtime.

Businesses that manufacture less complex products and smaller quantities also share this optimal product combination and are willing to pay €9.50 to €10.00 per hour of machine running time. In contrast, businesses that consciously use AI and manufacture complex products prefer "Preventive Optimizations in Processing," which reflect a higher level of quality improvement. Businesses engaged in mass production with higher production volumes comparatively strive for a fully digitized solution. Moreover, they also prefer "Operation via NC Program Code." These three groups are willing to pay €11.50 to €12.00 per hour of machine running time. In contrast, businesses that have not yet consciously integrated AI into their organizational structure do not prioritize a digitized solution and high level of quality monitoring. They avoid "Cloud/App-based (with data storage)," indicating that the perceived value of data is lower for businesses that have not yet adopted AI. However, the frequency distribution (AI: n = 181, no AI: n = 64) shows that this only applies to a small number of businesses. Since around 60% of the sample consists of SMEs, AI also appears to be widespread in medium-sized companies.

The number of purchase decisions also raises questions about the representativeness of the estimated price. The fact that more than half (60.82%) of the sample purchased one of the three offered options in every purchasing decision scenario, suggests that the offers may have been priced too low. Instead, considering the proportion of respondents (73.06%) who had at least once been involved in the procurement or retrofitting of machine tools and work in a company that uses AI, the results indicate a high market demand for such a smart service for CNC machines. A combination of both is also conceivable, as nearly half of the businesses in the sample operate in the mechanical engineering industry. This industry usually possesses greater financial resources and can therefore perceive the costs as a lower risk compared to the potential benefits. However, it should be noted that generalizing pricing for such a smart service is challenging, as pricing in the B2B market is a sensitive issue and is typically either not disclosed or only partially accessible. Prices are usually negotiated based on the specific use case and tailored to customer requirements within the respective application areas.

Conclusions

In summary, the analysis provides valuable insights into the integration of smart services in CNC machine tools for for developers, such as machinery and equipment manufacturers on the provider side, as well as for end users in manufacturing on the customer side. The results show across all groups that high accuracy is considered a key driver of purchase decisions, whereas low accuracy inhibits such decisions. This finding is not surprising, as precision plays a critical role in the operation and application of machine tools.

Although additional research is required to validate the findings, the results suggest that manufacturing companies in Germany perceive value from embedding smart services in CNC machine tools. Apart from accuracy, the design of individual features has a strong influence on perceived value and willingness to pay, and this is affected by structural characteristics of manufacturing and organizational context.

Appendices

Attribute	Description of Attribute	Manufacturer Examples (M1–M4) → Use Cases
Operation (AI-Service On/Off)	User interaction with the system, e.g. verbal or haptic user interface in the steering system.	M1: Pneumatic locking (foot), interface control device, Remote Control Panel, Programmable Control Unit (PCU). M2: Intelligence Human-Maschine-Interfaces (HMI). M3: Intelligence HMI for Operation, control, and machine connection. M4: Voice- and haptic-based control options (Touchpoint user interface).
Recording Automation	Data recording manually activated or always active.	M1: Continuous tool and machine monitoring (including camera system) M2: Continuous monitoring of the machine's condition and performance (including other automation systems). M3: Continuous monitoring and recording of various selectable operating and sensor data. M4: Continuous monitoring of operating times downtime and other process parameters.
Scope of Use Cases	Application possibilities.	M1: Monitoring and Predictive Maintenance, enhancement of machine performance, automatic setup and teardown process, automatic filling system for the coolant unit, cybersecurity measures (advanced firewall, etc.) interface for robotic loading. M2: Monitoring and Predictive Maintenance, digital twins and planning simulations, automated spindle calibration. M3: Monitoring and Predictive Maintenance, digital twins, digital tool management, intelligent network, 3D-Simulations M4: Monitoring and Predictive Maintenance, automated tool planning, robotic integration and intelligent network
Integration & Implementation	Integration options of measurement technology.	M1: Tool monitoring, software updates, adaptive control, coolant level, camera system, raw part measurement, axes condition, spindle condition. M2: Various OPC UA (Open Platform Communications Unified Architecture) interfaces for diverse integration possibilities of sensors. M3: Additive manufacturing technologies for versatile sensor integration in DMU 5-axis machining centers. M4: Wide range of sensors for monitoring the machine's internal and external environment, enabling comprehensive Smart Factory solutions.
Transparency (AI model)	Level of detail and transparency in how the algorithm reaches its results.	M2: SCADA system (Supervisory Control and Data Acquisition). M3: No-Code Manufacturing Execution Platform à Industrial digital No-Code/Low-Code Smart Factory software. M4: Camera-based assistance system → Traceability through images/video sequences.
Accuracy	Number of correctly classified anomalies by the algorithm.	Every smart service and its integrated AI models are based on a level of accuracy that determines how the algorithm can make predictions based on the training data.
Data History Range	Review and comparison period for the stored data.	M1: Long-term storage, comprehensive cloud access to network drives within a corporate network, machine and operational data M2: Traceability of manufacturing processes through process and production data, company-wide cloud solution (operational, production, and machine data), collaborative network of various machine manufacturers for machine data exchange. M3: Long-term data storage and analysis capabilities → Production planning, maintenance management, and real-time monitoring. M4: Extensive and long-term data storage (production planning, maintenance

		management, and real-time monitoring) available for analysis.
Variety of Data Sensors	Machine data of inside or outside of the machine.	M1: Tool demand planning and setup assistance, adaptive control, setup and teardown process, camera system → collision detection, coolant temperature control, axes condition, spindle condition. M2: Diverse sensor technology for machine status, production metrics, and process parameters for comprehensive IoT solutions. M3: Extensive data acquisition for additive manufacturing processes (thermal imaging cameras, melt pool analysis, powder flow monitoring, laser power, distance measurement, vibration, environmental conditions). M4: General monitoring functions, cameras, melt path monitoring, calibration system, temperature, vibration, performance, coherence tomography for weld seams.
Evaluation & Data Access	Provision and availability of data analysis.	M1: Remote Diagnostics, EES (Extended Energy Saving) → Energy consumption, display menu, Data Monitoring and Control Gateway, open interface for external systems, 3D models. M2: Remote monitoring and remote access to a collaborative network, various data analytics for autonomous data processing and anomaly detection. M3: NC simulation and 3D models, cloud platform for data storage and analysis, unified user interface across all systems. M4: Cloud platform for connecting machines and sensors to enable real-time production data, integration of various tools for monitoring production processes and identifying optimization potential, worldwide access available.
Price	Monetary value of the service.	Machine manufacturers charge prices for all products, retrofits, and services.

TABLE 15: Feature possibilities of smart service products in mechanical engineering (author computation)

M: Manufacturer

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Patrick Berger, Jörg von Garrel

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