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PROJECT REPORTS

How to design a value-based Chatbot for the manufacturing industry: An empirical study of an internal assistance for employees

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Abstract
With regard to AI as a key technology, this scientific paper deals with the identification of user drivers on the purchase decision of a cooperative AI (as explainable AI—XAI), as well as the analysis of the willingness to pay in the context of value-based pricing. Besides the economic dimension with regard to usefulness and usability of the system, the focus is mainly on the (innovative) explainable character. The analysis is carried out by a choice-based conjoint analysis (CBC) using the example of an intelligent assistance system for employees that supports internal business processes and workflows in business organizations. For this purpose, fictitious purchase offers were created under which decision-makers in manufacturing business organizations in Germany made simulated purchase decisions. The analysis shows that the target group attach great utility value to transparency in the sense of explanatory content, in addition to a high degree of interactivity and a high level of reliability.

1 Introduction

As a key technology, artificial intelligence (AI) offers new development potential in terms of process and/or product innovations as well as (service) business models for industrial products that are enhanced with intelligent (digital) services (e.g., intelligent monitoring, process regulation, process flexibility in order to push industry 4.0 to a new level) [8]. Nevertheless, the diffusion of AI-use in German manufacturing business organizations is relatively low [29]. Limited resources such as capital, technical expertise and further training opportunities for employees inhibit the integration and diffusion in the manufacturing sector [25].

The fact that AI systems are abstracted for users in a "black box" is also frequently mentioned. That means that results are no longer comprehensible or can only be comprehended with a disproportionately high effort and perceived as non-transparent [4]. Especially in sensitive application areas in industry (e.g. in (strategic) decision support), the comprehensibility and transparency of AI-generated proposals for action can be a central criterion for the use of AI [11]. As a result, factors such as trust and acceptance are gaining central importance in the implementation and operation of AI systems in an industrial context [9].

Related to this background, development methods such as cooperative AI are being implemented on the supplier side to counteract this inhibiting factor [34]. Key features of cooperative AI are that those learning systems explain themselves ("Explainable AI – XAI"), and can adapt to humans' usage behavior by interacting as collaborators ("Interactive AI") [1, 14]. This cooperative character has been known and studied in the academic context of research since the 1970s but it is considered as an innovative new feature in the current economic-commercial context. Nevertheless, there is little empirical evidence on whether these cooperative features influence or drive purchase decisions.

The purpose of this article is to identify relevant value drivers of cooperative AI systems as well as to analyze how those system influence manufacturing business organizations

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in Germany regard to their willingness to pay.[1] Within the framework of a choice-based conjoint analysis (CBC) using the example of an intelligent assistance system for employees, the value preferences and the willingness to pay have been analyzed with reference to relevant characteristics of cooperative AI systems for employees in manufacturing business organizations in Germany.[2]

2 Theoretical Foundations

The term AI describes development approaches that intend to teach machines cognitive abilities with the goal of being able to solve certain problems better and better through an independent learning process [5]. On the user side, however, the configuration or training of machine learning methods is currently a major challenge that often can be done by specialized experts only.

On one hand, there are strict framework conditions in such application areas that must be adhered to by the systems. On the other hand, the selection of optimal models is a big challenge. One approach for solving this problem is the development of cooperative AI. A key feature of a cooperative AI should contain the possibility of enabling employees to train the learning system without the need of advanced knowledge in the field of AI. Furthermore, those systems should be able to explain themselves [33, 37] as well as adapt to humans by interacting with employees [3, 28, 35]. This will make it possible, depending on the activity and profile of an employee, to dynamically create learning systems that optimally support the employee in his or her activity. In the best case also terms of trust and acceptance will increase [12, 26].

However, the increasing automation and (individual) adaptivity of the value proposition through AI also challenges the provider side. Classical pricing methods are reaching their limits due to, among others, non-existent marginal costs of data and algorithms [21]. Comparative studies by Liozu and Hinterhuber [23] show that in contrast to cost-based or market-based pricing models, companies with a value-based pricing model demonstrate a stronger price organization. It means that they can develop better pricing due to price controlling and recurring revenue. The basis for (customer) value-based pricing models is a stronger systematic methodology because experience and personal assessments are more likely to form the basis for pricing [23].

The basic assumption of (customer) value-based pricing models is based on the customers evaluation of the product and service offerings which leads to the creation of a perceived performance value (benefit). Based on this evaluation customers establish the willingness to pay a certain price for the product or service. This willingness to pay must be determined in order to set an optimal price. This involves focusing on various aspects of value from the customer's point of view [18]. The maximum price that a consumer is willing to pay for a product or a service corresponds directly to the perceived customer benefit that the customer has assigned to the product [18]. Willingness to pay can be understood as a monetary expression of the perceived customer benefit [18].

An extensive literature review of relevant benefit drivers of cooperative AI systems in B2B contexts has identified different attributes in the categories of general system properties (AI); explainability; interactivity; autonomy; transparency; data processing; monetary dimension of (AI-based) software [6, 13, 15, 16, 20–22, 27, 30–33, 37] (Fig. 1).

2.1 Choice-Based Conjoint Analysis (CBC)

The methodological implementation is carried out by a choice-based conjoint analysis according to Louviere and Woodworth [24]. It has the goal to explain purchase decisions of consumers via a decompositional estimation of the evaluation of product features [2]. It differs methodologically from the traditional conjoint analysis (TCA).

Compared to TCA the CBC does not make ordinal or metric preference judgments about attributes or attribute characteristics. It rather analyzes (fictitiously) discrete purchase decisions of existing product profiles (choice tasks/stimuli) [2]. The precondition is the choice of the alternative that provides the consumer with the relatively highest utility value (= net utility). In this context, the observed choice decisions are used to infer consumers utility perceptions of individual product features.

From a theoretical point of view, CBC has therefore a higher incentive compatibility with regard to the revelation of the actual purchase intention and willingness to pay [7]. The actual purchase decision is ultimately made based on the performance of a service or product. The determination of the utility and partial utility values of the attributes and their characteristics is done via hierarchical Bayesian estimation (maximum likelihood method).

The likelihood function (aggregated probability function) describes the relationship between objective attribute characteristic values (of different performance packages) and the subjective utility [10]. The following quality criteria need to be followed to design a suitable choice set [7]:

[1] The study was conducted as part of KompAKI (https://kompaki.de/) focusing manufacturing business organizations in Germany.

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Fig. 1 Purchase-relevant attributes of (cooperative) AI-based software

Category	Attribute		
General system attributes of AI-based software	**Training frequencies**	**Degree of individualization (of the software)**	**Learning model**
	Training effort (= time + computing power)	**Algorithm performance**	**Evaluation/ overview of metrics**
	Latency/ computing time per request	**System activation**	**Systems availability**
	Functionalities	**Value propositions of AI based Software**	**Simulation function**
Explainability	**Explanation specification/ transparency of the AI model**		**Explainable methods of the algorithm (XAI methods)**
Interactivity	**Type of interaction (User & System)**	**Degree of Interactivity**	**Degree of gamification**
	Usability (user-friendliness)		
Autonomy	**Algorithm autonomy/ degree of proactivity**	**Self-supervision**	
Transparency	**Scope of data collection**	**Display of data usage (to employees)**	**Data access (internal)**
Data processing	**Data processing (local/ cloud)**	**Data transmission for cloud solutions**	**Provider capacity for cloud solutions**
Monetary dimension of (AI-based) software	**Integration effort**	**Costs of implementation**	**Revenue models & pricing strategies**

Fig. 2 Conditional pricing of an AI-based assistance system

Attribute	Characteristic 1	Characteristic 2	Characteristic 3	Indicator
Interaction	Verbal **(25€)**	Written (resp. icon-based) **(25€)**	Verbal + written (resp. icon-based) **(50€)**	*Interactivity*
Interactivity (adaption of interaction to the user)	No user adaption (statically) **(25€)**	Adaption to employee domain (medium) **(50€)**	Personalized user adaption (high) **(100€)**	*Interactivity*
Degree of individualization (of the software)	Standard model (low) **(100€)**	Industry sector model + organization-specific training data (medium) **(150€)**	Customized model + organization-specific training data (high) **(225€)**	*Effectiveness; process compatibility; effort complexity*
Transparency of the AI model	Model does not explain itself (none) **(25€)**	Basic statistical explainable methods (low) **(50€)**	Inferential conclusion of the algorithm (high) **(100€)**	*Explainability/ Transparency*
Algorithm performance (reliability)	Low (89%-90%) **(25€)**	Moderate (94%-95%) **(25€)**	High (99%) **(75€)**	*Effectiveness; efficiency*
Price (per 1000 request)	= Basic price (25€) + sum of partial cost/price shares per characteristic			

1. Empirical independence → no empirical related effect between characteristics
2. Relevant attributes of purchase decisions
3. Variation of the characteristics → variation of the characteristics per attribute
4. Limitation of the characteristics per attribute → complexity reduction
5. Compensatory relationships of characteristics → e.g. high quality → high price

In order to maintain the quality criteria, six purchase relevant attributes of cooperative AI-based software have been condensed. These attributes were identified by expert interviews on the supplier and developer side and operationalized with regard to their characteristics for the object of investigation (Fig. 2). The selected attributes refer on the one hand to the economic dimension [36], which is central in the B2B context, and on the other hand to the essential attributes of AI cooperativity. Additionally, the evaluation basis of the economic dimension refers to the price usefulness and usability of a cooperative AI-based system [36]. The usefulness evaluation targets the indicators of effectiveness and efficiency which are relevant in performance control. The usability evaluation refers on the one hand to the process compatibility of the software and on the other hand to the effort complexity of the user-oriented development.

For a realistic simulation the price is distributed percentagewise on the characteristic of attributes in dependency of the caused efforts and costs. The revenue model[3] as well as the price strategy[4] are set in the sense of this conditional pricing.[5] In principle, pricing policy in B2B is considered as a sensitive topic and is not publicly accessible (or only to a limited extent). In most cases, there are no final target groups of pricing policy. Usually, organizations negotiate a specific price depending on the use case [16].

Despite the limited availability of public price accessibility, three products have been identified to guide the simulation under a market-based strategy.[6] Based on these, the price range for the use case is 300–500€ with an average market price of $((300 \times 2) + 500)/3 = 366.67 \rightarrow 370$€ per 1000 requests. The presented attribute characteristics carry price shares, which sum up and represent a finished product package that is in the determined price range.[7] The pricing of a complete product package is based on a base price of 25€ per 1000 requests, plus the partial cost/price shares of individual functional components of the software.[8]

The CBC was implemented by an intelligent assistance system as an internal business organization chatbot that can support employees in internal processes. This AI-based system can be linked to various internal systems (e.g. ERP, IoT systems, predictive analytics, project management tools) via APIs and optimize workflows. It is able to interact with employees and assist with activities based on cross-departmental information, such as:

- “Send mail X to employees involved in process Y.”
- “Make an appointment with XY for *date*/*time*.”
- “Show me live monitoring of process C.”
- “Display me the colleagues/processes that need support.”
- “Show me material inventories and related products (including sales).”

Based on Fig. 2 ($3^5 = 243$ possible combinations), a reduced orthogonal experimental design was created with a required sample size of n = 100. To generate a data set with subjects suitable for evaluation, the target group “decision-makers in manufacturing business organizations in Germany”[9] has been identified. A total of 162 participants which are corresponding to the target group mentioned above were taking part in the quantitative online study. The participants were recruited by the panel of the service provider Kantar Group [19]. The participants were shown 10 fictitious purchase decision situations where they were asked to choose 1 of 3 offers in each decision situation (Fig. 3).

3 Results

The sample is made up of 59.0% (n = 95) SMEs (Small and Medium Enterprise) and 41.0% (n = 66) major business organizations. These include the following industries by NACE codes (see Fig. 4). In total, participants with various positions took part in the survey (managing directors = 14.4%/n = 23; employees with management responsibility = 70%/n = 112; employees without management responsibility = 15.6%/n = 25). Among these three quarters

[3] The revenue model is a combination of “pay-per-use” (per 1000 requests) and “pay-per-function” [13; 39; 21; 16]. The price variations in the “pay-per-function” result depending on incurred efforts and costs of functionalities. The relationship of the respective characteristics of attributes to each other as well as the attributes among each other are considered. For example, the development and training of AI models would cause considerably higher efforts and costs than a transparent representation/reproduction of the explanation methods. The development of an individual model would involve higher coding and training efforts and therefore ultimately cause more costs than a regular standard model.

[4] The pricing strategy is based on “market-based pricing” [16; 15].

[5] Conditional pricing enables a more realistic determination of the willingness to pay of individual attributes and characteristics.

[6] These are: “Conversational AI” (SAP Store); “Azure Bot” (Azure-Microsoft Store); “Amazon Lex” (AWS Marketplace). Prices are from March 2022 and may have changed.

[7] Few product executions are outside of the identified price range with a minimum price of 225€ per 1000 requests and a maximum price of 575€ per 1000 requests.

[8] At this point it is not possible to calculate exact costs/price shares (e.g. the option of verbal interaction has exactly a partial price share of 25€.) But this is also not relevant in the overall context, since customers buy finished products and do not obtain single attribute characteristics. Ultimately, the matter of investigation is the extent to which the target group is willing to pay higher amounts on specific product packages, under consideration of the various costs and efforts involved.

[9] The target group is defined as persons with the power to act in operational decision-making processes in German manufacturing business organizations.

Fig. 3 Example of a simulated purchase decision situation (qualtrics.^{XM} temp)

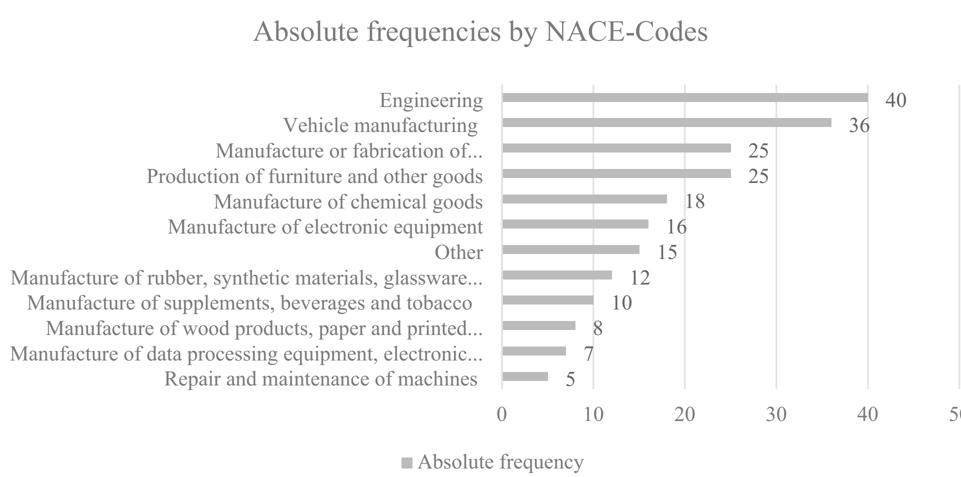
	Offer 1	Offer 2	Offer 3
Interaction	Written (resp. icon-based)	Written (resp. icon-based)	Written (resp. icon-based)
Interactivity (adaption of interaction to the user)	Personalized user adaption (high)	Adaption to employee domain (medium)	No user adaption (statically)
Degree of individualization (of the software)	Customized model + organization-specific training data (high)	Industry sector model + organization-specific training data (medium)	Standard model (low)
Transparency of the AI model	Basic statistical explainable methods (low)	Inferential conclusion of the algorithm (high)	Basic statistical explainable methods (low)
Algorithm performance (reliability)	Moderate (94%-95%)	High (99%)	Moderate (94%-95%)
Price per 1000 requests	450€	425€	250€
	○	○	○

Would you buy the selected option?

Yes

No

Fig. 4 Represented industries by NACE codes



(74.7%) indicated to be involved in the purchase process of software in the business organization. As the following Fig. 4 implies, certain business organizations are active across different industries (industry distribution → n = 217).

Overall, approximately three-quarters (72.84%) of participants selected one of the presented offers for purchase in 7–10 of the purchase decision situations. Almost half of them (49.3%) did so in every purchase decision situation. Only 7.4% (n = 12) did not make a purchase in any of the simulated purchase decision situations (see Fig. 5).

See Fig. 6

Positive purchase decision	Frequencies
0	*n= 12*
1	*n= 3*
2	*n= 3*
3	*n= 4*
4	*n= 4*
5	*n= 5*
6	*n= 13*
7	*n= 17*
8	*n= 11*
9	*n= 10*
10	*n= 80*

Fig. 5 Amount of positive purchase decisions

The evaluation of the results[10] in Fig. 6 shows the part utility values[11] in dependency of the costs (price shares) and describes the willingness to pay of individual attribute characteristics. In total, 8 of the 15 attribute characteristics are assigned a positive net utility value in dependency of the price share.

The attribute characteristics with the highest part utility value per attribute in combination, corresponds to the optimal product combination with the highest expected net utility value to the maximum willingness to pay (Fig. 7). It represents the product development with the highest purchase probability (Fig. 6 red boxes).

NUA[12] **> NUB**[13] **+ U**[14]

If attribute characteristics are considered with a positive part utility value, the "industry sector model + organizational-specific training" has the highest part utility value in every possible product combination. At the same time this attribute characteristic has in relation the highest price share. It is noticeable that the participants show the highest willingness to pay for the expected benefit of this attribute characteristic (150€ per 1000 requests).

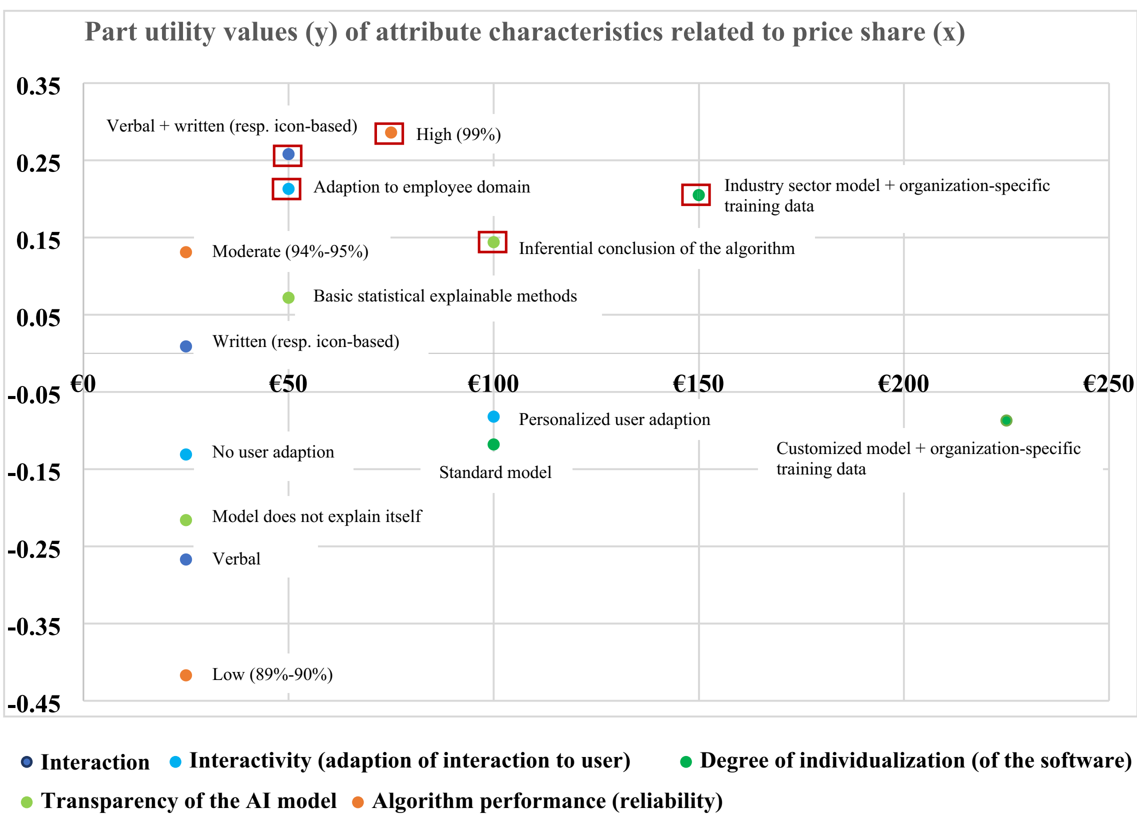


Fig. 6 Plot of estimated part utility values related to price share (n = 162)

[10] The technical implementation, execution and evaluation were done with the survey and statistics tool *qualtrics*^{XM}.

[11] The preference of individual attribute characteristics is represented by the estimated part utility values (= net utility → NU). These describe the probability (depending on the price share) with which the attribute characteristic would (probably) improve or worsen a product combination with regard to a purchasing intention.

[12] $\mathbf{NN_A}$ = Net utility value of purchase offering A.

[13] $\mathbf{NN_B}$ = Net utility value of purchase offering B.

[14] **U** = Status quo (current net utility value).

Optimal product combination (*n*= 162)
Verbal + written (resp. icon-based)
Adaption to employee domain (medium)
Industry sector model + organization-specific training data (medium)
Inferential conclusion of the algorithm (high)
High (99%)
450€ (per 1000 requests)
Effect size: High

Fig. 7 Optimal product combination

In addition, Fig. 6 shows that the participants prefer an interactive system that adapts to the users within a certain framework (employee domain) and offers various ways of interaction (verbal + written). The highest utility value is perceived by the participants for a high reliability (algorithm performance) of the system. This can be understood among other things, through the revenue model component "pay-per-use", because low performance (more misclassified requests) leads to higher usage costs in the long term.

Furthermore, Fig. 6 clarifies that the participants prefer a transparent AI. While "Basic statistical explanations" and "Inferential of the algorithm" produce a positive part utility value, the attribute characteristic "Model does not explain itself" generates a negative one. Accurately, the participants perceive the highest benefit (utility value) for an inferential (self-explaining) system in terms of transparency and they are willing to pay 100€ per 1000 requests for it.

4 Discussion, Conclusion and Outlook

From the authors point of view, the lack of generalization of the results for other AI-based software solutions is a matter for discussion with regard to the validity and expressiveness of the results. Furthermore, the CBC analysis (due to the necessary reduction of complexity) only includes a very small number of included attributes, which does not cover all relevant attributes of purchasing decisions. Likewise, a hypothetical bias is conceivable because no real transactions were associated with the purchase decisions. Reliability is to be criticized in the context of pricing, because pricing in the context of B2B is mostly dependent on use cases and difficult to generalize. The high number of positive purchase decisions indicates either that the offers were created to low or that a high demand for such AI-based software solutions on the market exist. However, it could also be explained by the number of major business organizations represented in the sample, which have higher financial resources and therefore consider the costs to be a lower risk compared to the benefits (utility value).

AI-based software solutions are among the key technologies of our time and offer innovative approaches in solving complex problems. Despite scientific findings from theory and practice, diffusion in German business organizations still shows great potential. The increasing number of AI applications in the future requires employees who can train and control such systems. The labor market for these skilled workers is extremely tight and makes it very difficult for (small) manufacturing organizations to acquire them. However, for practical and human-oriented use, it is essential to develop forms of AI that can be operated and understood by non-experts. According to empirical findings, the abstraction of AI systems in "black boxes", due to non-transparent decision-making of the algorithms, seems to inhibit their use. A possible solution approach to compensate for this is represented by cooperative AI as explainable AI, which should additionally increase people's trust in AI-based systems (in the broad mass) and thus strengthen the acceptance for AI use in German business organizations. The evaluation of the CBC analysis shows that decision-makers in manufacturing business organizations in Germany attach great utility value to transparency in the sense of explanatory content, in addition to a high degree of interactivity and a high level of reliability.

The presented results create the starting point for further analyses. The goal is to introduce factors such as "experience with AI systems" but also "enterprise size" as independent variables in the further analyses and identify further factors determining the utility value. In addition, further CBC analyses are planned with further AI systems, which will also provide further information on value-based pricing related to transparency of cooperative AI-based software.

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