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Pricing Powered by Artificial Intelligence: An Assessment Model for the Sustainable Implementation of AI Supported Price Functions

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Abstract. Artificial Intelligence (AI) in the price management process is being applied in business practice and research to a variety of pricing use cases that can be augmented or automated, providing opportunities as a forecasting tool or for price optimization. However, the complexity of evaluating the technology to prioritize implementation is challenging, especially for small and medium enterprises (SMEs), and guidance is sparse. Which are the relevant stakeholder criteria for a sustainable implementation of AI for pricing purpose? Which type of AI supported price functions meet these criteria best? Theoretically motivated by the hedonic price theory and advances in AI research, we identify nine criteria and eight AI supported price functions (AISPF). A multiple attribute decision model (MADM) using the fuzzy Best Worst Method (BWM) and fuzzy combined compromise solution (CoCoSo) is set up and evaluated by pricing experts from Germany and Spain. To validate our results and model stability, we carried out several random sensitivity analyses based on the weight of criteria exchange. The results suggest accuracy and reliability as the most prominent attribute to evaluate AISPF, while ethical and sustainable criteria are sorted as least important. The AISPF which best meet the criteria are financial prices followed by procurement prices.

Key words: price management, artificial intelligence,, human-AI interactions, sustainable AI, multiple attribute decision model.

1. Introduction

Price management within the digital environment is increasingly becoming technology based and data driven, with prices being completely or partially set by algorithms (Klein, 2021). In this context, Artificial Intelligence (AI) finds increasing application for sales forecast and price or revenue prediction problems and optimization. To date, a wave of AI point solutions has been proposed (Agrawal *et al.*, 2022), but only few studies provide

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a structured framework for AI decisions in marketing (Wu and Monfort, 2022), and to the best of our knowledge, there is no comparative assessment of existing AI support for concrete use cases in price management. Several classification criteria of AI systems have been used (by type of AI, industry usage, mode of human-AI cooperation, primary role of AI, etc.) to investigate which type turns out more attractive in terms of use intention (Kelly *et al.*, 2023; Cabrera-Sánchez *et al.*, 2021; Li *et al.*, 2022; Kim *et al.*, 2021), and the assessment of AI in terms of ethical and sustainable criteria is the focus of the European Commission (2020, 2024), as well as academic research (Dwivedi *et al.*, 2023). However, decision support for investing in such new technologies or data processes is sparse and especially challenging for small and medium-sized enterprises (SME), as managers may not be aware of the ethical and moral implications in a hybrid human-AI decision making process (Sanchez-Hughet *et al.*, 2022; Feuerriegel *et al.*, 2022). AI for process optimization has been studied for industrial processes (Al-Dhaimesh and Taib, 2023), for blockchain networks (Hombalimath *et al.*, 2023), and for financial risk management (Agarwal *et al.*, 2024), all of which highlight the need to explore automation and digitization in an increasingly complex and competitive environment, which can be broken down into several real-world problems to be studied. While research on the criteria and incentives that lead managers to adopt AI in Marketing processes is still sparse, much can be learned from the increasing insights of consumer behaviour towards AI. The use of AI from a consumer perspective is mainly studied building on technology acceptance models and has identified important drivers of people's behaviour intention towards AI (e.g. Kelly *et al.*, 2023; Cabrera-Sánchez *et al.*, 2021; Gursoy *et al.*, 2019). Especially functional AI systems are positively perceived (Kim *et al.*, 2021), and people prefer to collaborate interdependently with AI to reach their goal (Li *et al.*, 2022). The identified behavioural drivers can broadly be classified in economic cost-benefit analysis and social considerations, and to the best of our knowledge, there are so far no studies considering explicitly these criteria in management processes with human-AI interactions.

The objective of the present study is to contribute to the decision making of AI implementation for a responsible and successful pricing process, enhancing the use of AI for SME. For this purpose, theoretically motivated by the hedonic pricing theory (Lancaster, 1966; Rosen, 1974), we focus on the implementation of concrete use cases in the form of AI supported price functions (AISPF). In line with Al-Dhaimesh and Taib (2023), we identify concrete real-world pricing problems where disruptive technologies like AI can improve the task and consequently overcome potential problems or increase competitiveness. Concretely, two main research questions are set up: Which are the most relevant criteria for a sustainable use of AI for pricing? Which existing AI supported pricing functions meet these criteria best?

To address these questions, we make use of multi-criteria techniques for decision making, which find increasing application in the assessment of disruptive technologies (Fallahpour *et al.*, 2021). Concretely, we build on expert opinions setting up a multiple attribute decision model (MADM), using the Best Worst Method by Rezaei (2015) for criteria assessment, and combined compromise solution (CoCoSo) to rate and rank price functions. We identify nine assessment criteria for AISPF, which are differentiated in legal aspects (data protection, non-discrimination, transparency, safety-risk for users) and economic criteria (enhance customer value, accuracy and reliability, cost savings and efficiency, automation, ease of use). For the assessment, eight concrete AISPF are assumed (AI supported procurement prices, AI supported energy prices, AI supported international prices, AI supported personalized pricing, AI supported dynamic pricing, AI supported auction prices, AI supported prices in financial markets, AI supported price index). Pricing experts from Germany and Spain were interviewed and provided their assessment of the defined criteria and the rank of the criteria for each of the AISPF.

The paper contributes to research on AI use for decisions in marketing, especially in sales, and the increasing academic interest in technology based value assessment and pricing, and complements the knowledge on peoples' using intention of AI from a perspective of functional business use. The expert choice, as a tool of active listening of decision makers, is to the best of our knowledge, emloyed for the first time with pricing professionals, as a rising specific profile in sales and marketing. The results provide decision support for firms in implementing and prioritizing AI-supported use cases given the current state of knowledge.

Artificial intelligence is one of the top priorities in both research and business practice. Dwivedi *et al.* (2024) highlights the need to identify stakeholder benefits and tangible measures of the impact of the technology, and to align research and practice, and Agarwal *et al.* (2024) emphasizes the need to prioritize use cases based on different dimensions. Our research contributes to this alignment and addresses the complexity of AI implementation decision making for a specific domain, professional pricing.

However, there are several barriers to delegating pricing decisions to AI, such as risk management framework and governance structure to address the weak accountability of AI (Feuerriegel *et al.*, 2022), with regulatory compliance being one of the main barriers for SMEs (Sanchez-Hughet *et al.*, 2022). In addition, the inability of SMEs to reach the necessary manpower (Sanchez-Hughet *et al.*, 2022) requires a very specific prioritization of the AI implementation in pricing to target the right professionals, not necessarily with highly specialized knowledge in all aspects of pricing, but especially in specific pricing functions that are strategic for the AI implementation.

The aforementioned alignment between research and practice, is particularly critical for Small and Medium-sized Enterprises (SMEs), which often face distinct barriers when integrating AI into their operations. Feuerriegel *et al.* (2022) underscore, for instance, the risk management framework and governance structure to address the weak accountability of AI systems. At the same time, AI for financial tasks and risk management finds plenty of use cases (Agarwal *et al.*, 2024). This challenge, the regulatory compliance in the context of leveraging data through disruptive technologies, has been identified by Sanchez-Hughet *et al.* (2022) as a principal barrier for SMEs. Moreover, the limited access to necessary manpower exacerbates these challenges, making it imperative for SMEs to adopt a highly strategic approach to AI implementation in pricing, to target the right professionals, not necessarily with highly specialized knowledge in all facets of pricing, but especially in specific pricing functions that are strategic for the AI implementation. Such a focused approach ensures that SMEs can navigate the complexities of AI integration, and enhancing their competitive positioning and pricing excellence while aligning the investment with a broad and sustainable stakeholder perspective.

The paper is organized as follows: Section two introduces the challenges SMEs face in implementing AI, stakeholder criteria, and introduces the study case of evaluating AI within the price management process based on identified use cases. Section three outlines the multiple-attribute decision-making approach. Section four presents the results for the ranking of AI pricing functions and the relative importance of the identified criteria. Section five discusses the results and their implications, and concludes the paper.

2. Literature Review

The use of technology and data to create value and monetize marketing efforts has been accelerated by the adoption of artificial intelligence in the form of pre-trained, large-scale language models that find many different use cases (Rossi *et al.*, 2024). This increasing importance of big data analytics as competitive advantage has encouraged researchers to provide guidance for SMEs on how to approach the use of big data (Sanchez-Hughet *et al.*, 2022) and prioritize applications (Agarwal *et al.*, 2024). It has been demonstrated that the practice of technological innovation is significantly associated with business performance and SME survival (Rahman and Gogate, 2016), but there are few SMEs that claim to use artificial intelligence and include these technologies as part of their business model (Stentoft *et al.*, 2021). The existence of several barriers to delegating decisions to AI hinders the implementation of, for example, the risk management framework and governance structure to address the weak accountability of AI (Feuerriegel *et al.*, 2022), with regulatory compliance being one of the main barriers for SMEs (Sanchez-Hughet *et al.*, 2022). In addition, the inability of SMEs to reach the necessary manpower (Sanchez-Hughet *et al.*, 2022) requires a very specific prioritization of the AI implementation in processes like pricing to target the right professionals, not necessarily with highly specialized knowledge in all aspects of pricing, but especially in specific pricing functions that are strategic for AI implementation. Hence, it is important to ensure that SMEs can access and use AI (EU Commission, 2020), since they have fewer resources and experience in managing new technologies, however, there is no clear guidance and support. Researchers have studied various determinants of SMEs' technology adoption strategies, nevertheless, there is a small number of published studies which introduces a comprehensive framework to implement these findings (Darban and Wan Ismail, 2012).

To assess the use of AI, ethical and legal aspects need to be taken into account, as established in the whitepaper by the European Commission (2020). This need has also been confirmed by academic research, with managers often being unaware of ethical and moral implications when using hybrid human-AI processes for decision making (Feuerriegel *et al.*, 2022). Moreover, first studies in this line have revealed incentives for unethical practices in human resource management which calls for explicit requirements (Méndez-Suárez *et al.*, 2023), and others have studied AI assessment in this line in financial management or market research (Agarwal *et al.*, 2024; Dwivedi *et al.*, 2023). However, considering concrete marketing functions, an explicit study on the role of these challenges and corresponding decision support has not yet been studied.

With respect to the actions taken by the European Union, a great effort has been made in regulating issues related to data protection in the use of emerging technologies and

AI, within the legislative framework set out in the General Data Protection Regulation (GDPR), and this field remains a challenge, especially when most AI users are unaware of and do not exercise control over the use of their data (Wachter and Mittelstadt, 2019) and the role of AI is under attack with customers questioning the abuse of their private data (Mazurek and Małagocka, 2019). As the main raw material of any AI system is data, there is a concern and interest in the use of data, with AI systems having a high capacity for processing large amounts of personal data. It is not just a matter of being aware of whether AI complies with data protection legislation, but of knowing what data is being used and for what purposes (EU Commission, 2020). Authors from academia and industry use this variable in the framework that will help stakeholders evaluate commercial AI solutions (Omoumi *et al.*, 2021).

Another basic aspect about AI is the programming that its algorithms must have so that they do not generate discrimination on the basis of gender, sex, etc. (EU Commission, 2020). Algorithmic decision-making can threaten human rights, such as the right to non-discrimination. We need to bear in mind that legal instruments have severe weaknesses when applied to artificial intelligence. Demetzou (2020) proposes a framework, based on Data Protection Impact Assessment (DPIA) to assess the right to non-discrimination as one of the key fundamental rights that GDPR aims to safeguard.

Furthermore, transparency in the context of AI is an important concern, with the literature often referring to explainability, with reference to both interpretability, as well as trust in the systems (Saura *et al.*, 2022). Transparency has also been increasingly highlighted in regulatory development, company policies, as well as ethical guidelines over the last few years. For example, the EU adopted a strategy on AI in April 2018, and appointed the High-Level Expert Group (AI HLEG) to give advice on both investment strategies, as well as ethical issues with regards to AI in Europe (Larsson and Heintz, 2020). With the use of AI solutions, we cede a certain decision-making capacity to software, derived from its high data processing capacity and machine learning. Therefore, transparency is present in several AI assessment models.

Moreover, risk assessment plays a key role in Safety Management Systems. The introduction of artificial intelligence within autonomous systems makes it hard to reason about the probability and consequences of adverse events when control applications must use previous training sets to guide their response to novel situations (Johnson *et al.*, 2018). Especially when there are repercussions on the life and safety of users it is essential to know how these systems will assume or disregard risks for users (EU Commission, 2020). In this way, the regulation developed by the European Union on Artificial Intelligence establishes four levels of risk. The essence of this rule is to regulate AI according to its capacity to cause harm to society following a "risk-based" approach: the higher the risk, the stricter the rules (EU Commission, 2024).

Considering economic- and management criteria, the use of AI in general allows to improve the value proposition of the firm, through customization, value co-creation, search optimization or optimization of processes (Moreno-Izquierdo *et al.*, 2018), which allows to enhance the customer value, understood from the customer perspective, as well as from the firm perspective on customer value. Furthermore, the accuracy of forecasts is a critical element for decision making of investment and using AI can significantly improve the valuation accuracy, but often needs to be traded off with interpretability and does not always return profitable covering the realized investment (Sakri and Ali, 2022; Liu *et al.*, 2018; Moreno-Izquierdo *et al.*, 2018). The cost saving of predictions using AI algorithms comes especially in terms of time savings in the price prediction, which happens fast or even in real-time (Agrawal *et al.*, 2022). Moreover, the need for automation and scaling is increasingly emphasized in the context of sales and revenue management (Skiera, 2022), with an important aspect of AI technologies being the supervised and unsupervised learning, which allows to create sales artifacts to autonomously perform parts or the whole process (Singh *et al.*, 2018). Finally, considering the insights from consumer research with respect to the acceptance of AI, which has most commonly built on technology acceptance models (in particular TAM and UTAUT) to identify relevant factors, the perceived ease of use and effort expectancy, as well as perceived usefulness, are the most relevant factors inducing a positive behaviour towards AI use (Kelly *et al.*, 2023). The ease of use of AI solutions (or effort expectancy) is also considered a potential barrier for the user intention of AI technologies by managers. However, the results are ambiguous, since recent results on technology adoption of AI based products find that ease of use is not necessarily relevant for adoption (de Blanes Sebastián *et al.*, 2022). This may be explained with the respondents being digital natives or particular user profiles. In this line, first studies provide guidance for segmentation of AI users (Cabrera-Sánchez *et al.*, 2021). Concretely, these authors find that trust in the technology and technology fear moderates the relation between behavioural intention and use behaviour of AI, and hence is considered a crucial aspect in defining user segments which allows to guide investment in particular features, value communication or promoting trust, depending on the target segment, for a successful implementation. Likewise, Kelly *et al.* (2023) state that age differences in capabilities and difficulties of using AI have been identified by previous research to influence the attitude towards AI (Kelly *et al.*, 2023). Altogether, this effect of personal traits of consumers using AI is expected to be reflected in the user intention by management.

Considering the complexity in the assessment of intelligent technology, several authors have used a differentiation in different blocks of appraisal. For instance, Gursoy *et al.* (2019) recently proposed the AIDUA model (AI Device Use Acceptance Model), which builds on the cognitive appraisal theory. The model assesses consumers' perception in three appraisal stages, namely importance and relevance to themselves in the social context and the cost-benefit analysis, which both determine the outcome in terms of intended behaviour. In the same line, Cabrera-Sánchez *et al.* (2021) highlight two dimensions, the hedonic motivation and expected performance, as the greatest influence on consumers' behavioural intention with respect to AI. Hence, when considering the behaviour of professionals (not consumers) coping with AI technology, in line with the findings from the technology adoption by consumers, we differentiate the identified criteria in (1) social and ethical aspects and (2) economic considerations (Table 1).

Considering the price management process, the digitalization of the sales process implies opportunities and threats for sales professionals, who find themselves in a plurality of roles, often acting like brokers who orchestrate assets and resources, and may have a disruptive impact on the profession in how value is created and functions executed (Singh *et al.* 2019, 2018). Pricing consultants often limit themselves to what can be done in Excel, but pricing in the digital, technological, and socioeconomic context is becoming more and more complex, and the most successful companies are leveraging technology for transformative pricing management (PPS, 2023; Erdmann, 2024). This means that companies are encouraged to make smart pricing investments, and hybrid human-machine solutions offer new opportunities in this transition, which require first to understand how technology contributes to all aspects of pricing, from the cost-perspective to the customer-centric value perspective, and respond to competitors, pursuing opportunities and business growth while minimizing costs.

The hedonic price theory has long been the framework to study price functions as packages of a variety of attributes and relationships between prices (Lancaster, 1966; Rosen, 1974). The use of AI algorithms for price functions based on observed data (attributes, behaviour, external conditions, etc.) changes the approach to price functions, suggesting the pattern instead of imposing a particular (linear) algorithm, but is based on the same input elements as the hedonic pricing models. Several studies have compared the performance of hedonic pricing and AI based methods and find improved accuracy of the value forecast and a reduced price prediction error (Sakri and Ali, 2022; Moreno-Izquierdo *et al.*, 2018; Liu *et al.*, 2018). The trade-off comes often in terms of interpretability, which remains a black-box in many AI algorithms, while being easy for a hedonic approach.

Given the complexity of pricing, academics and pricing professionals differentiate the development of particular stages or the whole process across firms and categories (Simon and Fassnacht, 2019; Frohmann, 2023). Especially at the price implementation stage, AI technology can support a set of different price functions. To date, research has considered different price functions which can be powered by AI, however, there is no joint consideration or comparative assessment respectively in order to provide decision support. We know that the attitude towards AI usage depends on the primary role of the AI system in the context of human-machine interactions, and that functional AI systems are more positively perceived compared to social AI, which can be explained by the mediating effect of perceived usefulness (Kim *et al.*, 2021). Furthermore, the interaction between human and AI can take different forms. Li *et al.* (2022) define four human AI-cooperation modes, based on the cooperation theory, differentiating between forms of cooperative behaviour (independent versus interdependent) and the goal of the cooperation (exploration versus exploitation/optimization of existing resources). Given the strong and weak aspects of humans and AI, respectively (e.g. large scale tasks versus emotional judgement and random events), the authors identify that people prefer to collaborate interdependently with AI. Concretely, it turns out that people are most positively receptive for human-AI collaboration in a context of interdependent exploitative collaboration. In the context of AI price functions, this implies that a particular AI supported price function may be less or more favoured depending on the type of human-AI interaction.

The main use cases of AI supported pricing can be categorized in (1) forecasting tools in form of AI-based price prediction models, with use cases being financial prices, auction prices, energy prices, procurement prices, exchange rates, or consumer price index and (2) price optimization tools in form of AI-based pricing strategies based on market conditions, with use cases being personalized pricing or segmentation and dynamic pricing.

AI-Based Price Forecasting Use Cases:

Stock market prices are increasingly being predicted using AI algorithms, encompassing machine learning and deep learning techniques. Ferreira *et al.* (2021) show how market forecasting has shifted from traditional methods to complex AI algorithms that can handle large amounts of data and have demonstrated significant financial gains in stock trading through advanced data analysis and pattern recognition capabilities, suggesting a central role for AI in financial decision-making processes.

Auction prices can also be accurately forecasted using AI, with various algorithms such as genetic algorithms, artificial neural networks, and regression analysis proving to significantly enhance the precision of real estate auction price predictions, as demonstrated by Kang *et al.* (2020). The authors emphasize that this advancement aids investors and fund managers in making more informed decisions, highlighting AI's growing impact on improving economic outcomes in real estate auctions.

Electricity prices are subject to complex and volatile market dynamics, making accurate forecasting essential. Zaroni *et al.* (2020) show how several AI-based models can be used to forecast day-ahead electricity prices in the Finnish market. The complexity and volatility of energy underscores the need of prediction accuracy and the AI models show a superior performance to improve forecasting with great precision.

Procurement prices for agricultural products like strawberries can greatly benefit from AI-based forecasting models. Jafari *et al.* (2020) demonstrate that using daily time-series data on price and yield variables, their AI models can significantly enhance the accuracy of 1- to 7-day ahead price forecasts for strawberries in Canada. This improved forecasting capability offers substantial commercial advantages by providing more accurate market signals and better decision-making tools for procurement processes, thereby optimizing procurement pricing strategies.

International price setting can be significantly enhanced by the application of AI models, as investigated by Chen and Hu (2019). They focus on the exchange rate pass-through (ERPT) effect on Chinese export price indices, demonstrating AI's capability to offer superior forecasting performance. This advancement aids stakeholders in navigating the complexities of international trade and economics with more accurate and informed decision-making processes, highlighting the critical role of AI in global pricing mechanisms.

Consumer Price Index (CPI) forecasting has greatly benefitted from advancements in AI, with Ambukege *et al.* (2017) demonstrating a marked improvement in prediction accuracy. Their research integrates neural networks and fuzzy logic to create a potent machine learning model that efficiently utilizes data from the Tanzania National Bureau of Statistics for CPI prediction. This progress not only exemplifies AI's capability in enhancing economic forecasting but also underlines its value in refining decision-making processes, offering a robust tool for strategic planning in various economic sectors. Similar results hold for the AI based prediction of house price index (Xu and Zhang, 2022).

AI-Based Price Optimization Use Cases:

Personalized pricing, as detailed by Gerlick and Liozu (2020), highlights the pivotal role of AI and algorithmic decision-making in creating price settings that adjust specifically to individual consumer behaviours and preferences. AI based personalized pricing allows to analyse vast consumer data sets, enabling dynamic, real-time price adjustments for

Table 1
Assessment criteria for AI use and AI supported pricing functions.

Assessment criteria	AI supported Price Functions (use cases)
Legal aspects	1. AI supported procurement pricing (Jafari *et al.*, 2020)
1. Data protection (EU Commission, 2020, 2024; Wachter and Mittelstadt, 2019; Mazurek and Małagocka, 2019)	2. AI supported forecasting of energy prices (Zaroni *et al.*, 2020)
2. Non-discrimination (EU Commission, 2020, 2024; Demetzou, 2020)	3. AI supported international pricing (Chen and Hu, 2019)
3. Transparency (EU Commission, 2020, 2024; Saura *et al.*, 2022; Larsson and Heintz, 2020)	4. AI supported personalized pricing (Gerlick and Liozu, 2020)
4. Safety-risk for users (EU Commission, 2020, 2024)	5. AI supported dynamic pricing (Moreno-Izquierdo *et al.*, 2018)
	6. AI supported prediction for financial markets (Ferreira *et al.*, 2021)
Economic/Management aspects	7. AI supported auction prices (Kang *et al.*, 2020)
5. Enhance customer value (Moreno-Izquierdo *et al.*, 2018)	8. AI supported price index (Ambukege *et al.*, 2017; Xu and Zhang, 2022)
6. Accuracy and Reliability of the forecast (Sakri and Ali, 2022; Liu *et al.*, 2018; Moreno-Izquierdo *et al.*, 2018)	9. AI based ads pricing for web advertising (Park, 2020)
7. Cost savings and efficiency (Agrawal *et al.*, 2022)	
8. Automation and scaling (Skiera, 2022; Singh *et al.*, 2018)	
9. Ease of use (no-code or low-code applications) (Kelly *et al.*, 2023; de Blanes Sebastián *et al.*, 2022)	

a tailored shopping experience. Such advancements in pricing strategy benefit businesses by optimizing profitability and potentially enhance customer satisfaction with prices that accurately reflect each consumer's perceived value. In this context, Gautier *et al.* (2020) studies the technological, economic, and legal perspective on AI's role in personalized pricing, particularly through the lens of algorithmic price discrimination and tacit collusion. The AI algorithms, exploiting massive volumes of personal data, allow for finer-grained price discrimination, enhancing the accuracy of personalized pricing strategies. However, first concerns respective potential regulatory needs are raised in this context.

Dynamic pricing in the tourism sector, as studied by Moreno-Izquierdo *et al.* (2018) for Airbnb listings, is significantly enhanced through AI, notably machine learning models. The authors show that AI can analyse extensive databases to optimize pricing strategies effectively. Such data-driven insights enable dynamic adjustment of prices in real-time according to market demand, improving competitiveness and profitability by leveraging sophisticated pattern recognition and data analysis techniques.

Table 1 provides a summary table of the identified use cases, which are denoted as AI supported price functions (AISPF) to be evaluated, and the discussed assessment criteria. The AI algorithms that find applications for the indicated price functions are specified in Table A1 in Appendix A of the paper, with Supervised Machine Learning Algorithms and Reinforcement learning algorithms being the most used.

All these AI-based price functions are promising in improving accuracy at low costs or speed up price adjustments and promotions adapting to customer value perceptions

Table 2
Research contribution embedded in the literature.

Authors	AI in marketing	AI in finance	AI in process/task	Pricing automation with AI	Guidance for SMEs	AI assessment using MADM
Ambukege *et al.* (2017)		✓	✓	✓	✓	
Moreno-Izquierdo *et al.* (2018)	✓		✓	✓	✓	
Ferreira *et al.* (2021)		✓	✓	✓		
Cabrera-Sánchez *et al.* (2021)	✓		✓		✓	
Darban and Wan Ismail (2012)	✓		✓		✓	
de Blanes *et al.* (2022)	✓		✓		✓	
Sanchez-Hughet *et al.* (2022)	✓		✓		✓	
Gursoy *et al.* (2019)	✓					
Singh *et al.* (2018)	✓		✓			
Xu and Zhang (2022)	✓			✓		
Khan and Nazir (2023)	✓					✓
Gerlick and Liozu (2020)			✓	✓	✓	
Demetzou (2020)			✓		✓	
Feuerriegel *et al.* (2022)			✓		✓	
Kim *et al.* (2021)	✓		✓			
Li *et al.* (2022)			✓			
Omoumi *et al.* (2021)			✓			
Wachter and Mittelstadt (2019)			✓			
Jafari *et al.* (2020)		✓	✓			
Agrawal *et al.* (2022)	✓		✓			
Kelly *et al.* (2023)	✓					
Liu (2024)		✓	✓			✓

and market conditions, leading to improved decision making and providing a competitive advantage.

Identifying optimal AI pricing functions, where optimal is defined as meeting the set of identified stakeholder criteria, is relevant for prioritizing investments from a sustainable perspective. That is, while AI-based personalized pricing is highly attractive and beneficial for marketing, care must be taken not to violate privacy or introduce unintended biases (e.g. Rossi *et al.*, 2024). Starting with the implementation of AI in the pricing process, AI point solutions for cost-considerations in the price setting task are identified as a "safe haven", meeting the overall stakeholder criteria, and therefore may be prioritized in getting started with AI in pricing, especially if firms have difficulties to keep up with legal aspects and compliance of new laws such as the AI act and/or are more risk averse in this aspect lacking financial and/or legal support in case of mistakes.

Table 2 highlights the increasing work on the use of AI in task or process automation or augmentation in marketing, as well as in finance for isolated tasks (AI point solutions). This type of complexity in decision making or implementation of disruptive technologies has been addressed in different contexts using multivariate decision models, and the novelty from the methodological approach in this context is the application to AI use for

Price setting, as one of the crucial decision variables in the Marketing Mix, considering all encompassing pricing related tasks where AI point solutions have been identified in the literature, which allows to provide guidance to SMEs in AI investment for pricing meeting not only short term needs but overall stakeholder criteria. In addition, the fuzzy approach takes into account the uncertainty of pricing experts in assessing the performance of AI in different pricing functions, since pricing experts are generally not AI experts and the state of AI performance for marketing tasks is currently still a subject of research. The AI implementation in marketing, as well as finance, is rising at an impressive speed, promising a competitive advantage, but at the same time caution is required to implement the technology, and researchers have warned not to rely blindly on pre-trained AI models (Rossi *et al.*, 2024). This requires an assessment of the technology in a broader context, and this paper contributes by evaluating pricing use cases for prioritizing AI investments. For further research, this approach of an assessment of AI point solutions in a particular field using MADM, can be applied to the other variables of the Marketing Mix, as well as finance.

3. Methodology

To address the complex decision problem of implementing AI supported price functions, we use multiple criteria decision making (MCDM) approach, in form of multiple-attribute decision making (MADM) approach, which allows to establish rankings of the identified criteria and the assessment of the contribution by alternative AISPF. This methodological approach has been used in a variety of complex decision-making problems associated with economic return. For example, Liu (2024) evaluates the financial risk of high-tech companies in a complex financially volatile environment and managers' uncertainty in decision making using MADM with CoCoSo method illustrated with a case study, emphasizing the widespread attention of this approach in engineering, as well as management science. Rezaei (2015) introduced the BWM to determine weight coefficients of criteria for an MCDM problem through an optimization model and various extensions of the traditional BWM have been developed in recent years. Fuzzy BWM (Guo and Zhao, 2017) is an example. Moreover, BWM attracted a lot of attention from researchers dealing with complicated MCDM problems in different fields and industries such as waste management, supply chain management (Lahri *et al.*, 2021), and transportation management (Rezaei *et al.*, 2018). The algorithm and full description of Fuzzy BWM can be found in Torkayesh *et al.* (2022) and briefly Fuzzy BWM is explained here:

Step 1. First of all, decision criteria are identified. For an MCDM problem, we define several criteria with n criteria, and we show them as $C_1, C_2, \ldots, C_n$.

Step 2. We determine the best criterion (most important) and worst criterion (least important).

Step 3. Performing the Fuzzy pairwise comparison for the best criterion. A fuzzy pairwise comparison is produced for all included criteria using the fuzzy linguistic scale (Table 3). A best-to-others vector must be shown as a vector: $(\tilde{a}_{B1}, \tilde{a}_{B2}, \ldots, \tilde{a}_{Bn})$ where $\tilde{a}_{Bj}$ represents the preference of the best criterion over the criterion j.

Table 3
Fuzzy linguistic scale for FBWM.

Trinagular fuzzy numbers	Linguistic terms
(1, 1, 1)	Equally important (EI)
(2/3, 1, 3/2)	Weakly important (WI)
(3/2, 2, 5/2)	Fairly important (FI)
(5/2, 3, 7/2)	Very important (VI)
(7/2, 4, 9/2)	Absolutely important (AI)

Step 4. Performing the Fuzzy pairwise comparison for the worst criterion. Results are called as the other-to-worst vector. An other-to-worst vector is shown: $\tilde{A}_W = (\tilde{a}_{1W}, \tilde{a}_{2W}, \dots, \tilde{a}_{nW})$ where $\tilde{a}_{jW}$ represents the preference of the criterion j over the criterion worst criterion W.

Step 5. The optimal weightings of criteria can be defined as the formula below:

$$\min \max_j \left\{ \left| \frac{\tilde{W}_B}{\tilde{W}_j} - \tilde{a}_{Bj} \right|, \left| \frac{\tilde{W}_j}{\tilde{W}_W} - \tilde{a}_{jW} \right| \right\} \tag{1}$$

s.t:

$$\sum_j R(\tilde{W})_j = 1,$$

$$\alpha_j^w < \beta_j^w < \gamma_j^w,$$

$$l_j^w \geqslant 0 \quad \text{for all } j,$$

where $\tilde{W}_B = (\alpha_B^w, \beta_B^w, \gamma_B^w)$, $\tilde{W}_j = (\alpha_j^w, \beta_j^w, \gamma_j^w)$, $\tilde{W}_W = (\alpha_W^w, \beta_W^w, \gamma_W^w)$, $\tilde{a}_{Bj} = (\alpha_{Bj}^w, \beta_{Bj}^w, \gamma_{Bj}^w)$, and $\tilde{a}_{JW} = (\alpha_{jW}^w, \beta_{jW}^w, \gamma_{jW}^w)$

The other method for producing the alternatives score is CoCoSo or combined compromise solution (Yazdani *et al.*, 2019). This method has been investigated in many research applications and its algorithm is different from BWM. Various type of fuzzy CoCoSo are being used as Ecer and Pamucar (2020) use it in supplier selection. However, the classic fuzzy model is used in this study and Peng and Huang (2020) developed fuzzy version of CoCoSo. CoCoSo includes a powerful novel approach to handling complicated MCDA problems. The algorithm is based on an integrated exponential weighted product and several combined strategies. It can be used as a distance measure based on the gray relational coefficient that makes it more flexible. The CoCoSo approach introduces three aggregation strategies (scores) to obtain more confidential outcomes. As a consequence, each score enhances the decision quality and finally reveals a full ranking index (Fernàndez-Portillo *et al.*, 2023; Yazdani *et al.*, 2019). The method increases the decision-making quality in big decision problems (when a high amount of alternatives exist) due to its simplicity and accuracy. In this paper, we apply a fuzzy extension of CoCoSo to deal with uncertainty in supply chain risk. The entire process of formulating a ranking of AI price functions can be observed in Fig. 1. It starts with a deep literature review and expert interview to encounter the relevant alternatives and criteria. Then a decision analysis platform, combined

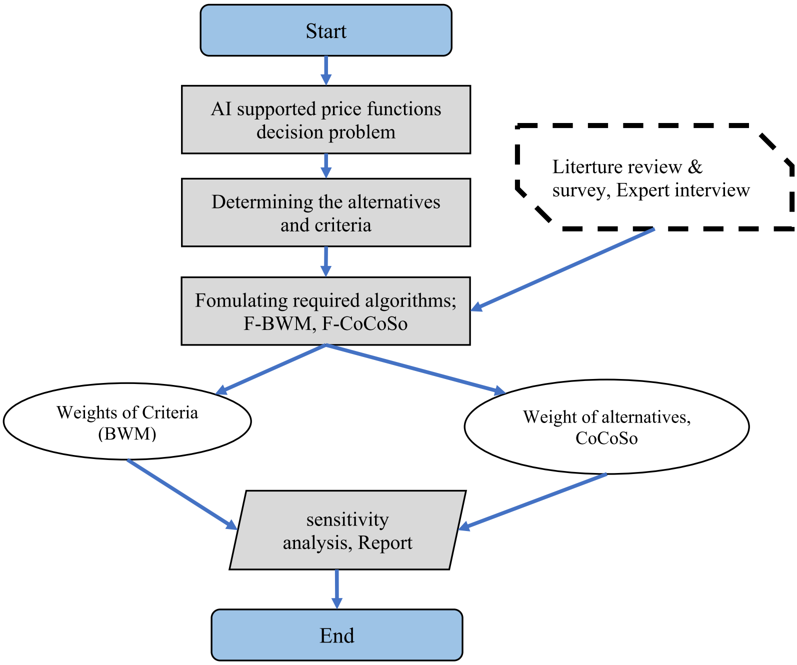

Fig. 1. The procedure for decision making and pricing function system.

Table 4
Linguistic scale for ranking evaluation.

TFN	Linguistic term
(0.222, 0.25, 0.286)	Absolutely less significant (ALS)
(0.25, 0.286, 0.333)	Dominantly less significant (DLS)
(0.286, 0.333, 0.4)	Much less significant (MLS)
(0.333, 0.4, 0.5)	Really less significant (RLS)
(0.4, 0.5, 0.667)	Less significant (LS)
(0.5, 0.667, 1)	Moderately less significant (MoLS)
(0.667, 1, 1)	Weakly less significant (WLS)

Source: Demir *et al.* (2022).

by Fuzzy BWM and Fuzzy CoCoSo, will address the best alternative with respect to fundamental objectives (criteria). Finally, a sensitivity analysis of the results and reporting is carried out.

The F-CoCoSo method is applied based on the following steps.

Step 1. Identifying the decision-making matrix including criteria, alternatives, decision-making team, questionnaire preparation, etc.

Step 2. Experts will offer the opinion for evaluation. They are asked to form a decision matrix using a fuzzy linguistic scale (Table 4) according to:

$$\tilde{X}_{ij} = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix}, \quad \text{for } i = 1, \dots, m \text{ and } j = 1, \dots, n. \tag{2}$$

Step 3. The normalized matrix is developed based on the nature of the criteria as equations (3)–(4).

$$\tilde{r}_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}}, \tag{3}$$

$$\tilde{r}_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}}, \tag{4}$$

where equation (3) is used for benefit criteria, and equation (4) is used for cost criteria.

Step 4. The sum of the weighted comparability sequence (SW_i) and the power-weighted comparability sequences (PW_i) for each alternative are determined based on equations (4)–(5).

$$\widetilde{SW}_i = \sum_{j=1}^{n} (\tilde{w}_j \tilde{r}_{ij}), \tag{5}$$

$$\widetilde{PW}_i = \sum_{j=1}^{n} (w_j)^{r_{ij}}. \tag{6}$$

Step 5. Then the aggregated appraisal scores are applied to calculate the relative weights of alternatives.

$$\tilde{Q}_1 = \frac{\widetilde{PW}_i + \widetilde{SW}_i}{\sum_{i=1}^{m} (PW_i + \widetilde{SW}_i)}, \tag{7}$$

$$\tilde{Q}_2 = \frac{\widetilde{SW}_i}{\min_i \widetilde{SW}_i} + \frac{\widetilde{PW}_i}{\min_i \widetilde{PW}_i}, \tag{8}$$

$$\tilde{Q}_3 = \frac{\lambda \left(\widetilde{SW}_i\right) + (1 - \lambda)(\widetilde{PW}_i)}{\lambda \max_i \widetilde{SW}_i + (1 - \lambda) \max_i \widetilde{PW}_i}, \tag{9}$$

where $0 \leqslant \lambda \leqslant 1$ and is usually considered 0.5 ($\lambda = 0.5$ is taken in this study).

Step 6. Ultimately, the integrated value for each alternative is obtained based on equation (9).

$$\tilde{Q}_i = (\tilde{Q}_1 \times \tilde{Q}_2 \times \tilde{Q}_3)^{\frac{1}{3}} + \frac{1}{3}\left(\tilde{Q}_1 + \tilde{Q}_2 + \tilde{Q}_3\right). \tag{10}$$

4. Use Cases, Data and Analysis

Our paper considers a specific professional area to study existing AI point solutions and provide an assessment considering stakeholder criteria, which are ranked and evaluated for each AI pricing point solution, taking into account the uncertainty in the assessment by experts. Price managers, at the intersection of marketing and finance, are core to monetizing the firm's efforts, and managers are under pressure to react quickly, foresee changes in any type of costs, and predict consumer perception and price reactions for a large number of stock keeping units and consumer segments. In this context, AI offers a competitive advantage in several dimensions, and there are several AI point solutions, but there is little evidence on which criteria matter for implementation and which AI-based pricing functions meet these criteria best to be prioritized. That is, instead of directly implementing AI in pricing at any point with promising short-term benefits, it is considered crucial first to assess which are the relevant criteria for all stakeholders (firms, consumers, government) and assess the importance for pricing professionals when considering AI use for particular price functions, as well as which of the AI price functions (point solutions) meet the overall stakeholder criteria best.

Our approach is illustrated with a detailed case study on pricing use cases (AI pricing functions), although it's worth noting that our methodology is adaptable to other marketing mix variables or broader business areas. With AI in processes being one of the rising research fields (e.g. Liu, 2024; Hombalimath *et al.*, 2023; Al-Dhaimesh and Taib, 2023), multivariate decision-making models have proven very useful in assessing disruptive technologies to improve decision-making (Khan and Nazir, 2023; Liu, 2024).

We contacted eight international pricing experts from Germany and Spain for their participation in the study, which is a usual size for expert sample (e.g. Azadeh *et al.* (2015) use six experts to assess the lean performance of organizations using AHP and fuzzy scales; Suner *et al.* (2012) use an AHP setting with five experts to determine priorities of criteria for a decision support on cancer treatment methods). The experts received a questionnaire asking them to rate criteria and alternatives. The expert profiles are summarized in Table 5.

The computation is divided in two stages, one is to deliver the criteria weight (the importance factor for each of the considered drivers) by fuzzy BWM and lingo program, and second is to obtain each alternative score using fuzzy CoCoSo software. BWM results are provided in Table 6, which indicates that C6 and C5 are the best criteria. The consistency of the computation has been checked and seems placed in an acceptable area. For the next stage, it is necessary to utilize those weights for CoCoSo as inputs. The algorithm for Fuzzy CoCoSo (F-CoCoSo) can be found in Peng and Huang (2020). After finalizing the computation, Table 7 is generated, showing the alternative score and each alternative ranking. Higher score addresses the better alternative and A6 and A1 are categorized as 1st and 2nd ranked options, while A4 shows the worst alternative. The order of alternatives is as follows:

$$A6 > A1 > A2 > A3 > A5 > A8 > A7 > A4.$$

The computation detail for Fuzzy CoCoSo can be seen in Appendix A, in the Tables A2–A5. In the CoCoSo method, the value of λ is a measure to check the sensitivity

Table 5
Selection of experts.

Expert	Professional profile
Expert I (Germany)	Consultant for Pricing and Digital Business Transformation, with 30 years of experience at an international price consultancy company, as well as freelance. Book author. 56 years old, economist.
Expert II (Germany)	Advisor for Pricing and Revenue Management at an international management consultancy firm, with 15 years of experience. Book author and conference speaker. PhD in Operation Management (Revenue Management).
Expert III (Germany)	Academic in the field of value assessment and pricing, with 14 years of experience in pricing research, conferences in the field and teaching of price management at an Executive MBA programme and a university. 40 years old, PhD in Economics.
Expert IV (Germany)	Professor, Advisor and Speaker on Marketing, in particular consumer behaviour and pricing. Director of a management research centre, collaboration with an international pricing consultancy. Author of academic articles and pricing case studies. PhD in Business Studies.
Expert V (Spain)	Revenue and Pricing Manager in an international hotel group, especially dynamic pricing and revenue management IT systems. MBS and EMBA.
Expert VI (Spain)	Managing Director at an international telecommunication company, specialized in customer value and revenue management.
Expert VII (Spain)	Academic in AI applications in different sector. Lecturer in national and international universities. 39 years old. PhD in Science and Technology applied to Industrial Engineering.
Expert VIII (Spain)	Pricing practitioner and CEO of SME technology company. Graduated in marketing and lecturer of price management courses since 1992.

Table 6
The weight produced by Fuzzy BWM for 9 criteria based on expert opinion.

Criteria	Ex. 1	Ex. 2	Ex. 3	Ex. 4	Ex. 5	Ex. 6	Ex. 7	Ex. 8	Av. Weights
C1	0.110	0.070	0.081	0.149	0.039	0.134	0.066	0.183	**0.1040**
C2	0.075	0.027	0.047	0.059	0.048	0.037	0.033	0.028	**0.0443**
C3	0.054	0.093	0.081	0.089	0.086	0.027	0.098	0.042	**0.0713**
C4	0.026	0.055	0.032	0.119	0.033	0.134	0.049	0.042	**0.0612**
C5	0.110	0.147	0.142	0.102	0.214	0.214	0.197	0.156	**0.1602**
C6	0.128	0.253	0.142	0.268	0.179	0.160	0.230	0.226	**0.1982**
C7	0.154	0.059	0.133	0.095	0.146	0.134	0.131	0.156	**0.1260**
C8	0.214	0.097	0.133	0.089	0.113	0.107	0.098	0.056	**0.1136**
C9	0.128	0.199	0.208	0.030	0.142	0.053	0.098	0.110	**0.1210**

of the results, so based on Table A6 in Appendix A, we can see that while changing λ, the ranking will not alter. Another point is the ranking and alternative score in three different ranking strategies in equations (7), (8) and (9). Once again, our results show the high stability comparing to final ranking by equation (10). In total, the fuzzy CoCoSo method validates the stable and confidential assessment.

In addition, to validate the accuracy of the results and observe how sensitive is the CoCoSo algorithm in this study, we performed twenty-one sensitivity analysis tests. Tests 1 to 21 include the criteria weight replacement one by one randomly. For example, among them, T2 and T21 are the weight replacement of "*ease of use*" criterion with highest (best) and lowest importance (worst) criteria, respectively. With each test, CoCoSo ranking will change and then ranking comparison allows us to examine the stability and sensitivity of the results. The extracted ranking results are observed in Table 8. Except for the tests 3,

Table 7
AI pricing function score and their ranking according to F-CoCoSo method.

	Alt. score	Ranking
A1	3.6811	**2**
A2	3.6507	**3**
A3	3.5936	**4**
A4	2.9159	**8**
A5	3.4842	**5**
A6	3.7062	**1**
A7	3.2474	**7**
A8	3.4742	**6**

Table 8
Sensitivity analysis test and alternative rankings.

	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	T13	T14	T15	T16	T17	T18	T19	T20	T21
A1	2	2	1	2	4	2	2	2	2	2	2	4	4	2	2	2	3	4	3	2	3
A2	3	3	3	3	2	3	3	3	3	3	1	3	2	3	3	3	1	2	2	3	2
A3	4	4	4	4	3	4	4	4	4	4	4	2	3	4	4	4	4	3	4	4	4
A4	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8
A5	6	6	5	6	6	6	5	5	5	6	6	6	6	6	6	5	6	6	6	6	6
A6	1	1	2	1	1	1	1	1	1	1	3	1	1	1	1	1	2	1	1	1	1
A7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7
A8	5	5	6	5	5	5	6	6	6	5	5	5	5	5	5	6	5	5	5	5	5

11 and 17, where A6 obtained 2nd and 3rd ranking, the rest of the experiments reflected that A6 is the best alternative. The worst alternative (A4) maintained its position in all the experiments. Moreover, alternatives 5, 7 and 8, except for slight changes, remained within the ranking position. This confirms that our model and obtained results are stable enough and experts can rely on them. Based on the Table 8, we have produced Fig. 2 that shows the ranking stability schematically.

5. Discussion, Management Implications and Conclusion

5.1. *Discussion of the Results*

The assessment model reveals that accuracy and reliability of the forecast (C6), followed by enhancement of customer value (C5) and cost saving and efficiency (C7) are the most relevant criteria for the evaluation of AI in price management. That is, in light of unpredictable surrounding external economic conditions and the critical impact of pricing and revenue management on a firm's economic growth, accuracy and reliability emerge as crucial evaluation metrics. Moreover, accuracy often needs to be traded off with interpretability (Liu *et al.*, 2018) and profitability of the technical investment (Moreno-Izquierdo *et al.*, 2018), which emphasizes the need to focus on this criterion. Likewise, the trend of a value-based approach to price setting and the monetization of this value (Hinterhuber and Liozu, 2019) justifies the importance of the effect on customer value. Finally, in third place, a technological innovation in the management process should not only reduce costs

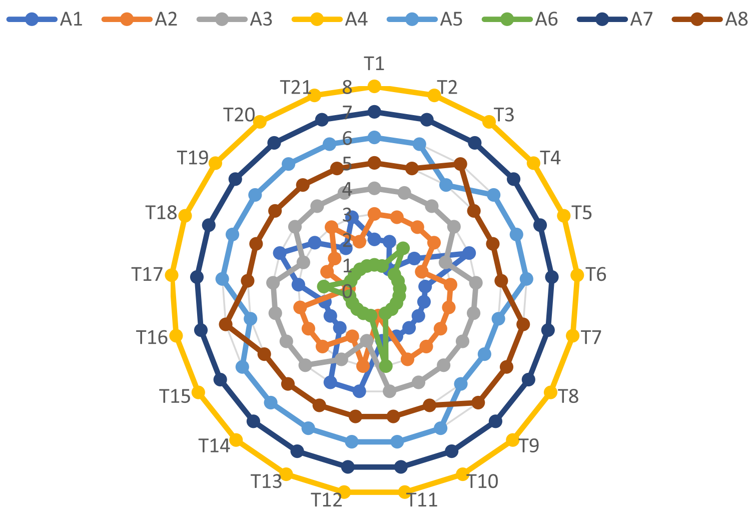

Fig. 2. The random sensitivity analysis experiments for alternatives.

but also be efficient, which confirms this aspect being considered one of the main benefits of AI in a different context (Agrawal *et al.*, 2022).

The four least important criteria are all within the same category of ethical and sustainable aspects. Concretely, non-discrimination (C2) ranks as least relevant, and slightly higher are safety risk (C4), transparency (C3) and data protection (C1). Note that all these criteria are discussed in the whitepaper by the European Union (2020), which confirms the existence of market failure in terms of ethical and sustainable implementation of AI, and emphasizes the need for regulatory guidelines.

Finally, the results reveal that the AI supported price functions which rank highest in the contribution to the established set of stakeholder criteria are the prediction of financial prices (A6), followed by procurement prices (A1). Especially AI supported financial price prediction is already finding broad application in the business practice (Ferreira *et al.*, 2021). On the opposite side, AI supported personalized pricing (A8) ranks lowest in the expected contribution to the established criteria. The latter is the result of the low importance that is given to C1–C4, which mainly aim to protect customers. Our research result was tested through several sensitivity analysis for approval and accuracy.

However, some results are inconsistent, since some experts evaluate ease of use as very important while for others it is one of the least important criteria. We argue that this may depend on the level of management as pricing professionals where the expert operates or on his or her technical knowledge. This is in line with recent articles of technology adoption of AI, which do not identify ease of use as a relevant factor (de Blanes Sebastián *et al.*, 2022), which may be due to certain cohorts being used for digital operations. Hence, this gives rise to further research, segmenting the assessment of pricing professionals by age or the executive level of the expert. In any case, this limitation of the study is in line with Singh *et al.* (2018), who find that practitioners and scholars differ in their prediction on how much digitalization technologies like AI will cause disruptions and how salespeople and AI will work together. Note that this is in agreement with the segmentation of consumers towards their AI user intention, suggested by Cabrera-Sánchez *et al.* (2021).

5.2. *Management Implications*

The increasing interest in generative AI among leading tech giants highlights its perceived economic and strategic importance. However, this enthusiasm also raises ethical concerns, emphasizing the need for a balanced approach to AI implementation in price management. As Kotler (2024) asserts, the strategic application of AI in marketing decisions is crucial for company success in the coming years. Research by Hagendorff *et al.* (2023) and Jansen *et al.* (2023) demonstrates how AI can outperform traditional problem-solving tasks in certain contexts, suggesting its potential for enhancing decision-making processes.

These aspects have also been highlighted in the context of AI-based pricing management, as shown by the results of the evaluation by professional pricing consultants, with the most important evaluation criteria by the professionals being superior performance in terms of accuracy, value and cost. However, the prevailing focus on immediate business outcomes (short-term perspective) has so far given little attention to the need for research on AI that promotes a sustainable (long-term) perspective, which requires consideration of a broader stakeholder perspective.

In this regard, our study underscores the importance of integrating professional expertise and judgment with respect to AI use cases with ethical and legal considerations, to advance the future of price management. AI models are particularly noted for their role in predictive analysis, and their potential to be cheaper and easier to use compared to pure human analysis, offering an alternative or complement to conventional methods. Despite these advances, the ethical implications of AI in decision-making require a careful in-depth examination (Dwivedi *et al.*, 2023). That is, when using AI for pricing, the low ranking of ethical aspects for certain pricing functions requires special care in implementing AI for these tasks, building on the AI model as co-intelligence rather than pure automation to achieve intelligent pricing solutions while respecting ethical requirements.

Echoing the call from McKinsey of the need to prioritize AI use cases in finance (Agarwal *et al.*, 2024), we highlight the critical need for a holistic assessment of AI use cases in pricing — an interdisciplinary field between marketing and finance — to ensure a comprehensive understanding of their impacts. This approach allows for an informed prioritization of AI applications by SMEs, taking into account not just economic benefits but also ethical and legal considerations.

The need for ethical and human criteria is less relevant for AI-based price forecasting use cases, but more relevant for AI use cases that consider price optimization, such as personalized pricing and dynamic pricing. This requires special care for the latter, and the need to train and hire professionals to work with AI, with particular attention to data use, transparency, and security threats, as well as algorithmic biases that may lead to unethical discrimination. That is, in line with Agarwal *et al.* (2024) for financial risk management and Dwivedi *et al.*, our contribution is to provide a detailed assessment of the complex context of using AI in price management, balancing technological innovation that promises economic gain with ethical responsibility.

5.3. *Conclusion*

The present research has provided first directions in the assessment and implementation of concrete AI solutions for pricing, provides evidence of market failure for a sustainable implementation of AI in price management and opens directions for further research. The study brings a combination of MCDM methods and expert opinions to address required solution for decision problems on the use of AI technology, which is a novel approach in this context and can be recommended to researchers to advance their findings. In addition, utilizing other fuzzy set models, MCDM methods like MABAC (Multi-Attributive Border Approximation Area Comparison), MARCOS (Measurement of alternatives and ranking according to COmpromise solution), EDAS (Evaluation based on Distance from Average Solution) and stratified decision-making tools can enhance the accuracy of the results in decision analysis for the implementation of disruptive technologies in marketing processes, as they are part of future research lines.

A. Appendix

AI algorithms are classified into three types, (1) Supervised Machine Learning Algorithm (SMLA), which identifies the relationship between input variables and output variables (Regression, chatbot). (2) Unsupervised Learning Algorithm (USLA), which has no output variables and all variables play the same role (Principal Component Analysis (PCA)). (3) Reinforcement learning algorithm (RLA), which makes decisions based on experience and learning from mistakes (Artificial neural network (ANN), neuro fuzzy system (NFS)). Table 2 provides an overview of the dominant algorithm for each AISPF.

Table A1
SML and RLA as frequently used AI algorithms in AISPF.

AI supported Price Functions (AISPP) to be evaluated	AI Algorithm
1. AI supported procurement pricing	SMLA as a Regression (Jafari *et al.*, 2020) and as a Chatbot (Cui *et al.*, 2022)
2. AI supported forecasting of energy prices	RLA as an ANN (Alshater *et al.*, 2022; El Hag Hassan and El-Khawaga, 2024; Kumari and Tanwar, 2021; Jasiński, 2020)
3. AI supported international pricing	RLA as an ANN (Safari and Ghavifekr, 2021) and as NFS (Petković *et al.*, 2020)
4. AI supported personalized pricing	RLA as an ANN (Zhang *et al.*, 2020; Häckel *et al.*, 2022)
5. AI supported dynamic pricing	RLA (Tiwari *et al.*, 2021) with geolocations (Pandey and Caliskan, 2021) or Blockchain (Tiwari *et al.*, 2021)
6. AI supported prediction for financial markets	USLA as PCA (Yu *et al.*, 2021) SMLA (Regression) (Le Gallo, 2021) RLA (Antunes *et al.*, 2021)
7. AI supported auction prices	RLA as an ANN (Munro and Rassenti, 2019; Ghosh *et al.*, 2022)
8. AI supported price index	SMLA as a Regression) (Jafari *et al.*, 2020) as a chatbot (Cui *et al.*, 2022)
9. AI based ads pricing for web advertising	RLA as a NFS (Sarkar and Pal, 2021) and ANN (Modarresi and Diner, 2019)

Table A2
Initial fuzzy decision matrix.

	C1			C2			C3			C4			C5			C6			C7			C8			C9		
A1	5.00	7.00	8.63	3.75	5.75	7.63	3.75	5.75	7.50	5.75	7.75	9.25	2.75	4.50	6.38	6.00	8.00	9.50	6.00	8.00	9.50	5.75	7.75	9.25	4.50	6.50	8.38
A2	5.50	7.50	9.00	4.75	6.75	8.38	5.25	7.25	8.75	6.00	8.00	9.38	2.13	3.75	5.75	5.75	7.75	9.13	5.50	7.50	9.00	6.00	8.00	9.50	5.00	7.00	8.75
A3	5.75	7.75	9.13	5.00	7.00	8.50	4.25	6.25	7.88	5.75	7.75	9.13	4.25	6.25	8.25	4.75	6.75	8.63	4.50	6.50	8.25	5.25	7.25	8.88	4.25	6.25	8.13
A4	1.88	3.75	5.75	2.25	4.25	6.25	1.63	3.50	5.50	4.25	6.25	8.13	6.00	8.00	9.38	6.25	8.25	9.63	3.50	5.50	7.25	4.50	6.50	8.38	3.25	5.25	7.25
A5	2.75	4.75	6.75	2.63	4.50	6.50	2.25	4.00	6.00	4.75	6.75	8.63	5.25	7.25	8.88	6.00	8.00	9.50	4.75	6.75	8.38	5.25	7.25	9.00	3.50	5.50	7.50
A6	5.25	7.25	8.88	4.25	6.25	8.13	5.50	7.50	9.13	4.75	6.75	8.50	3.88	5.75	7.50	5.50	7.50	9.13	5.00	7.00	8.75	5.75	7.75	9.25	4.75	6.75	8.50
A7	4.00	6.00	7.88	2.63	4.75	6.25	3.25	5.25	7.13	4.75	6.75	8.63	5.50	7.50	9.25	4.50	6.50	8.38	3.50	5.50	7.38	4.50	6.50	8.38	4.25	6.25	8.13
A8	5.25	7.25	8.88	5.00	7.00	8.63	5.50	7.50	9.13	5.25	7.25	9.00	3.25	5.00	6.75	5.50	7.50	9.25	3.00	4.75	6.50	5.25	7.25	9.00	4.75	6.75	8.50

Table A3
Normalized fuzzy matrix.

	C1			C2			C3			C4			C5			C6			C7			C8			C9		
A1	0.43	0.71	0.93	0.24	0.55	0.84	0.28	0.55	0.78	0.29	0.68	0.98	0.09	0.33	0.59	0.29	0.68	0.98	0.46	0.77	1.00	0.25	0.65	0.95	0.23	0.59	0.93
A2	0.50	0.78	0.98	0.39	0.71	0.96	0.48	0.75	0.95	0.34	0.73	1.00	0.00	0.22	0.50	0.24	0.63	0.90	0.38	0.69	0.92	0.30	0.70	1.00	0.32	0.68	1.00
A3	0.53	0.81	1.00	0.43	0.75	0.98	0.35	0.62	0.83	0.29	0.68	0.95	0.29	0.57	0.84	0.05	0.44	0.80	0.23	0.54	0.81	0.15	0.55	0.88	0.18	0.55	0.89
A4	0.00	0.26	0.53	0.00	0.31	0.63	0.00	0.25	0.52	0.00	0.39	0.76	0.53	0.81	1.00	0.34	0.73	1.00	0.08	0.38	0.65	0.00	0.40	0.78	0.00	0.36	0.73
A5	0.12	0.40	0.67	0.06	0.35	0.67	0.08	0.32	0.58	0.10	0.49	0.85	0.43	0.71	0.93	0.29	0.68	0.98	0.27	0.58	0.83	0.15	0.55	0.90	0.05	0.41	0.77
A6	0.47	0.74	0.97	0.31	0.63	0.92	0.52	0.78	1.00	0.10	0.49	0.83	0.24	0.50	0.74	0.20	0.59	0.90	0.31	0.62	0.88	0.25	0.65	0.95	0.27	0.64	0.95
A7	0.29	0.57	0.83	0.06	0.39	0.63	0.22	0.48	0.73	0.10	0.49	0.85	0.47	0.74	0.98	0.00	0.39	0.76	0.08	0.38	0.67	0.00	0.40	0.78	0.18	0.55	0.89
A8	0.47	0.74	0.97	0.43	0.75	1.00	0.52	0.78	1.00	0.20	0.59	0.93	0.16	0.40	0.64	0.20	0.59	0.93	0.00	0.27	0.54	0.15	0.55	0.90	0.27	0.64	0.95

Table A4
Fuzzy weighted comparability.

	C1			C2			C3			C4			C5			C6			C7			C8			C9			Si		
A1	0.04	0.07	0.10	0.01	0.02	0.04	0.02	0.04	0.06	0.02	0.04	0.06	0.01	0.05	0.09	0.06	0.14	0.19	0.06	0.10	0.13	0.03	0.07	0.11	0.03	0.07	0.11	0.28	0.61	0.88
A2	0.05	0.08	0.10	0.02	0.03	0.04	0.03	0.05	0.07	0.02	0.04	0.06	0.00	0.04	0.08	0.05	0.13	0.18	0.05	0.09	0.12	0.03	0.08	0.11	0.04	0.08	0.12	0.29	0.62	0.88
A3	0.06	0.08	0.10	0.02	0.03	0.04	0.02	0.04	0.06	0.02	0.04	0.06	0.05	0.09	0.14	0.01	0.09	0.16	0.03	0.07	0.10	0.02	0.06	0.10	0.02	0.07	0.11	0.24	0.58	0.87
A4	0.00	0.03	0.06	0.00	0.01	0.03	0.00	0.02	0.04	0.00	0.02	0.05	0.09	0.13	0.16	0.07	0.15	0.20	0.01	0.05	0.08	0.00	0.05	0.09	0.00	0.04	0.09	0.16	0.50	0.78
A5	0.01	0.04	0.07	0.00	0.02	0.03	0.01	0.02	0.04	0.01	0.03	0.05	0.07	0.11	0.15	0.06	0.14	0.19	0.03	0.07	0.10	0.02	0.06	0.10	0.01	0.05	0.09	0.21	0.54	0.84
A6	0.05	0.08	0.10	0.01	0.03	0.04	0.04	0.06	0.07	0.01	0.03	0.05	0.04	0.08	0.12	0.04	0.12	0.18	0.04	0.08	0.11	0.03	0.07	0.11	0.03	0.08	0.12	0.28	0.62	0.90
A7	0.03	0.06	0.09	0.00	0.02	0.03	0.02	0.03	0.05	0.01	0.03	0.05	0.07	0.12	0.16	0.00	0.08	0.15	0.01	0.05	0.08	0.00	0.05	0.09	0.02	0.07	0.11	0.16	0.50	0.81
A8	0.05	0.08	0.10	0.02	0.03	0.04	0.04	0.06	0.07	0.01	0.04	0.06	0.02	0.06	0.10	0.04	0.12	0.18	0.00	0.03	0.07	0.02	0.06	0.10	0.03	0.08	0.12	0.23	0.55	0.84

Table A5
Fuzzy exponentially weighted comparability sequence.

	C1			C2			C3			C4			C5			C6			C7			C8			C9			Pi		
A1	0.92	0.96	0.99	0.94	0.97	0.99	0.91	0.96	0.98	0.93	0.98	1.00	0.68	0.84	0.92	0.78	0.93	1.00	0.91	0.97	1.00	0.85	0.95	0.99	0.84	0.94	0.99	7.75	8.49	8.87
A2	0.93	0.97	1.00	0.96	0.98	1.00	0.95	0.98	1.00	0.94	0.98	1.00	0.00	0.79	0.89	0.76	0.91	0.98	0.89	0.95	0.99	0.87	0.96	1.00	0.87	0.95	1.00	7.16	8.49	8.86
A3	0.94	0.98	1.00	0.96	0.99	1.00	0.93	0.97	0.99	0.93	0.98	1.00	0.82	0.91	0.97	0.55	0.85	0.96	0.83	0.92	0.97	0.81	0.93	0.98	0.81	0.93	0.99	7.58	8.46	8.86
A4	0.00	0.87	0.94	0.00	0.95	0.98	0.00	0.91	0.95	0.00	0.94	0.98	0.90	0.97	1.00	0.81	0.94	1.00	0.72	0.89	0.95	0.00	0.90	0.97	0.00	0.88	0.96	2.44	8.25	8.73
A5	0.80	0.91	0.96	0.88	0.95	0.98	0.84	0.92	0.96	0.87	0.96	0.99	0.87	0.95	0.99	0.78	0.93	1.00	0.85	0.93	0.98	0.81	0.93	0.99	0.69	0.90	0.97	7.39	8.38	8.81
A6	0.92	0.97	1.00	0.95	0.98	1.00	0.95	0.98	1.00	0.87	0.96	0.99	0.80	0.89	0.95	0.72	0.90	0.98	0.86	0.94	0.98	0.85	0.95	0.99	0.85	0.95	0.99	7.79	8.52	8.89
A7	0.88	0.94	0.98	0.88	0.96	0.98	0.90	0.95	0.98	0.87	0.96	0.99	0.88	0.95	1.00	0.00	0.83	0.95	0.72	0.89	0.95	0.00	0.90	0.97	0.81	0.93	0.99	5.95	8.31	8.78
A8	0.92	0.97	1.00	0.96	0.99	1.00	0.95	0.98	1.00	0.90	0.97	1.00	0.74	0.86	0.93	0.72	0.90	0.99	0.00	0.85	0.92	0.81	0.93	0.99	0.85	0.95	0.99	6.87	8.40	8.81

Table A6
Final ranking of alternatives.

	Fuzzy Q1			Crisp Q1	Fuzzy Q2			Crisp Q2	Fuzzy Q3			Crisp Q3	Final Score Qi	Qi	Final ranking
A1	0.10	0.13	0.18	0.14	4.92	7.27	9.13	7.11	0.82	0.93	1.00	0.92	3.68	3.6811	**2**
A2	0.10	0.13	0.18	0.13	4.77	7.35	9.13	7.08	0.76	0.93	1.00	0.90	3.65	3.6507	**3**
A3	0.10	0.13	0.18	0.13	4.62	7.06	9.04	6.91	0.80	0.92	0.99	0.91	3.59	3.5936	**4**
A4	0.03	0.12	0.17	0.11	2.01	6.47	8.46	5.65	0.27	0.89	0.97	0.71	2.92	2.9159	**8**
A5	0.10	0.12	0.18	0.13	4.34	6.81	8.81	6.66	0.78	0.91	0.99	0.89	3.48	3.4842	**5**
A6	0.10	0.13	0.18	0.14	4.95	7.32	9.22	7.17	0.82	0.93	1.00	0.92	3.71	3.7062	**1**
A7	0.08	0.12	0.17	0.13	3.44	6.50	8.62	6.19	0.62	0.90	0.98	0.83	3.25	3.2474	**7**
A8	0.09	0.12	0.18	0.13	4.25	6.90	8.87	6.67	0.73	0.91	0.99	0.88	3.47	3.4742	**6**

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