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Development Of Intelligent Decision Support Systems in Small Business Consulting

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Abstract: In the present study a novel conceptual framework for an intelligent decision support system (IDSS) is proposed, specifically designed with consideration of the unique operational requirements of small enterprises. The primary objectives of the research are twofold: first, to conduct an in-depth analysis and critical evaluation of existing theoretical approaches to decision support in the small and medium-sized enterprise segment; second, to develop a specialized IDSS model tailored to advisory services for this class of organizations. The methodological foundation of the research consisted of a scrupulous systematic review of scientific publications from the last 5 years devoted to the implementation of artificial intelligence methods in the management processes of small and medium-sized enterprises, as well as to the key directions of development in explainable AI (XAI). As a result, the principal architectural design principles and technological components ensuring the effective functioning of such systems were identified. In conclusion, illustrative case studies of the application of the developed IDSS in tasks of strategic market positioning and financial diagnostics of small businesses are presented. These examples may serve as practical guidelines for IT solution developers, consulting firms, and academic researchers oriented toward the digital transformation of small and medium-sized enterprises.

Keywords: intelligent decision-support system, small business, business consulting, artificial intelligence, machine learning, explainable AI, hybrid models, decision-making, digitalisation, conceptual model.

Introduction

Within the current international economic landscape, small and medium-sized enterprises (SMEs) constitute the fundamental pillar underpinning sustainable growth, fostering innovation, and broadening employment opportunities. However, this cohort remains particularly susceptible to failure: empirical studies indicate that a considerable share of nascent SMEs ceases operations within the formative years. The chief catalyst for this high attrition rate is the escalating intricacy of managerial decision-making in contexts characterized by pervasive uncertainty, finite resources, and intensifying competitive dynamics. Concurrently, the digitalization of markets unveils novel pathways for expansion while amplifying operational complexity through the necessity to assimilate and interpret vast quantities of heterogeneous and unstructured information. Although the need for expert advisory services has surged, conventional consulting paradigms frequently prove prohibitively expensive for smaller firms. Consequently, there emerges a pressing methodological and practical imperative: the development and deployment of scalable, cost-effective, high-performance IT solutions capable of democratizing access to top-tier consultancy.

In this milieu, intelligent decision-support systems (IDSS) leveraging artificial-intelligence methodologies present a compelling avenue for redressing these challenges. Projections suggest that by 2027, the segment of the AI market dedicated to SMEs will attain a valuation of approximately USD 90.68 billion, expanding at a compound annual growth rate of 22.10 % over the 2022–2027 interval, a trend principally fueled by the SME sector's accelerated adoption of cloud-computing infrastructures and the proliferation of Internet-of-Things (IoT) deployments across industrial settings [1]. Within the banking, financial services, and insurance (BFSI) domain—often serving as the vanguard for AI integration in SME contexts—artificial intelligence underpins sophisticated customer-relationship-management platforms. For instance, data from Personetics, a global leader in personalized, data-driven engagement solutions for financial institutions, reveal that 67 % of small businesses seek from their banking partners digital instruments for cash-flow oversight, analytics, forecasting, and budgeting, aimed at enhancing financial visibility and optimizing liquidity management. This pronounced demand trajectory is anticipated to markedly elevate the AI market share within the SME ecosystem over the coming years.

Moreover, the education sector is undergoing transformation through the introduction of facial-recognition technology aimed at enhancing student engagement and safety, an initiative now being assessed as a pathway for AI adoption in the SME market in the coming years [11]. Despite vigorous research activity in AI, existing developments are predominantly tailored to large corporations with extensive datasets and mature IT infrastructures, whereas the specific requirements of small businesses—limited and low-quality data, a shortage of qualified personnel, and an acute need for transparent, comprehensible recommendations—remain largely overlooked.

The aim of the study is to analyze the theoretical foundations and to develop a conceptual model of an adapted Intelligent Decision Support System (IDSS) for SME consulting.

The scientific contribution lies in proposing a hybrid, explainable IDSS that systematically addresses the dual challenge of limited data access and the requirement for transparent, practically applicable recommendations in small-business consulting.

The author's hypothesis asserts that the synergy of hybrid AI models—combining data-driven machine learning and rule-based expert systems—with the principles of Explainable AI (XAI) will yield a reliable and effective IDSS that fundamentally enhances the quality of consulting services.

Materials and Methods

Research on the development of intelligent decision support systems (DSS) in consulting for small businesses can be grouped into several themes: application of artificial intelligence (AI), issues of interpretability and explainability of decisions, business analytics methods, and digital transformation of small and medium-sized enterprises (SMEs).

In recent years there has been a substantial increase in publications devoted to the application of artificial intelligence and machine learning in small and medium-sized enterprises. According to the IndustryARC review study, AI is becoming one of the main driving factors for the development and strengthening of competitive advantages of SMEs through process automation, efficiency improvement and stimulation of innovative solutions. Mishrif A. and Khan A. [2] note that AI and automation technologies proved decisive for the survival of small companies during the COVID-19 pandemic, which underscores the importance of flexible strategies and digital transformation. In this context Rane N. L. et al. [4] extend the analysis by considering deep and machine learning as a basis for constructing advanced business strategies and highlighting the potential of integrating intelligent systems into everyday management. The study by Rao K. T. V. et al. [9] complements this perspective by proposing the combination of deep learning methods with decision support systems in the field of financial management, which contributes to enhancing the adaptability of organizations to external challenges and internal changes.

Another important research vector focuses on ensuring the explainability and interpretability of conclusions generated by intelligent systems. Martino D. et al. [7] propose a comprehensive approach that combines mechanisms for explaining algorithmic decisions with flexible knowledge exchange schemes within business process management — an aspect particularly significant for SMEs where resources and competencies are often limited. Band S. S. et al. [5] together with Roundtree A. K. [6] emphasize the critical role of decision transparency and data protection, accentuating ethical, fairness and confidentiality issues on which the reputational resilience of small enterprises largely depends.

A further group of studies explores business analytics and decision support through data processing and decision-making methods. Alsibhawi I. A. A., Yahaya J. B., Mohamed H. B. [3] present a conceptual model for implementing business analytics in SMEs, underlining its importance for management optimization and enhanced competitiveness. Kgakatsi M. et al. [10] analyze the impact of big data technologies on SME performance, illustrating how data processing and analysis facilitate strategic adaptation and business growth. In this context, the application of multicriteria decision-making methods such as the Analytic Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), as presented by Marzouk M., Sabbah M. [8], proves especially valuable for supplier selection and supply-chain decisions, demonstrating the versatility and adaptability of DSS.

Publications on the digital transformation of SMEs constitute a distinct direction. An OECD report [11] identifies digital transformation as a vital factor for SME survival and successful operation, ensuring business resilience through the integration of modern digital technologies and data management. This aspect is particularly significant for intelligent DSS, which form part of a comprehensive digitalization strategy by enhancing managerial flexibility and accelerating adaptation to market changes [1].

Despite extensive discussion of AI and intelligent DSS in small business contexts, contradictions and research gaps persist. On the one hand, numerous studies highlight the importance and benefits of intelligent-technology adoption in small business [1, 2, 4, 9]. On the other hand, questions regarding accessibility, cost-effectiveness, and the readiness of SMEs to employ complex systems remain underexplored. Practical aspects of integrating varied DSS methods—such as AHP and TOPSIS—into the specific conditions of SMEs also receive limited attention [8].

Furthermore, issues related to the long-term use and support of intelligent DSS in small businesses, as well as the staff training and organizational culture required for their effective deployment, are scarcely covered. The challenge of balancing decision explainability against the technical complexity of models remains unresolved, representing an essential avenue for future research and the practical implementation of intelligent decision support systems in small business.

Results and Discussion

An analysis of the theoretical premises and the identification of research gaps led to the development of a conceptual model for an intelligent decision-support system tailored to the consulting needs of small-enterprise entities. The model’s architectural diagram (see Figure 1) rests on a hybrid integration of machine-learning techniques and expert rule sets, complemented by built-in explainability mechanisms. This configuration provides a comprehensive response to the principal challenges: limited and fragmentary source data, the necessity of incorporating expert knowledge, and stringent requirements for transparency in the generated recommendations [2, 3, 10].

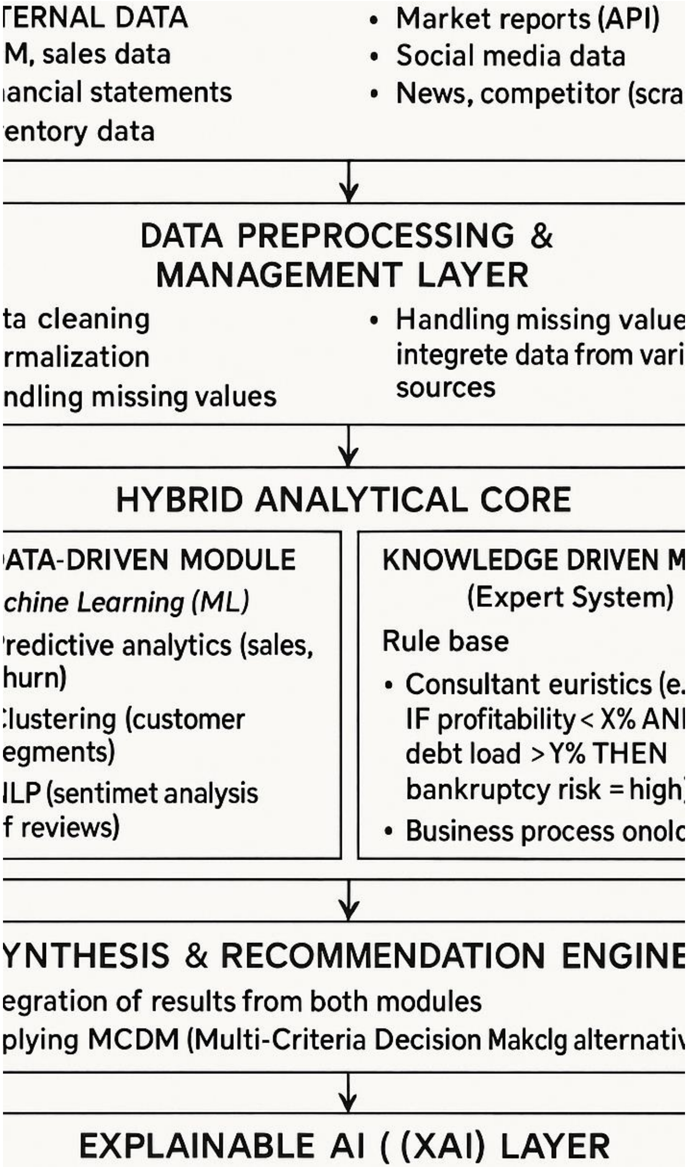

Fig. 1. Conceptual architecture of a hybrid explainable IDSS for small business consulting (compiled by the author based on the analysis of [2, 3, 10]).

The architecture is organized as a multi-layered, interconnected system. The upper layer aggregates heterogeneous sources, encompassing internal corporate data—such as financial metrics and CRM records—and external information streams, including market trends, competitor activity, and user feedback on social media. The subsequent preprocessing layer performs cleansing, normalization, and semantic enrichment of the incoming datasets, thereby improving their intrinsic quality and partially mitigating issues of incompleteness and noise [10].

At the core of the architecture lies a hybrid analytical engine that integrates two complementary modules. The first module, grounded in machine-learning methods, is designed to uncover latent correlations and patterns. For instance, regression models are used to estimate sales-volume dynamics while accounting for seasonal factors and advertising expenditure, and natural-language-processing algorithms perform sentiment analysis of customer reviews to identify product strengths and weaknesses [11]. The second module implements an expert system based on formalized rules derived from the accumulated experience of professional business consultants—for example, the rule "IF profit margin < 5 % AND current ratio < 1.0, THEN recommend a high-priority audit of operating expenses." According to several studies, the synergistic combination of quantitative analysis and qualitative expertise mitigates the limitations imposed by a shortage of purely statistical data [7].

The outputs of both modules are fed into a unified recommendation engine, where multi-criteria decision-making (MCDM) techniques—specifically the Analytical Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)—can be applied to evaluate and rank alternative strategies against criteria such as expected profit, risk level, and required investment [8]. As a result, the system produces not a single "benchmark" scenario but rather a set of well-grounded proposals that clearly indicate each option's strengths and weaknesses.

A key innovation of the proposed architecture is the integration of an explainable-AI (XAI) layer. Instead of functioning as an opaque black box, the model delivers human-oriented justifications for its recommendations. For example, when a marketing strategy is suggested, the system can visualise the contribution of each factor—such as an increase in search-query volume on a related topic or negative sentiment in competitors' product reviews—thereby fostering trust among users who may lack deep data-science expertise [5, 6]. The final results are presented through intuitive dashboards and reports that ensure straightforward interpretation for consultants or entrepreneurs.

For illustrative purposes of the model's practical application, consider a scenario involving the assessment of financial health and the forecasting of cash-flow gaps. A small enterprise uploads its financial statements for the preceding two years into the system, after which the following stages are executed:

1.Analysis: The rule-based module, built on an expert knowledge base, verifies the principal indicators—liquidity, profitability, and asset turnover—against regulatory benchmarks.

2.Forecasting: A machine-learning component (for example, ARIMA or LSTM models) produces a six-month cash-flow projection that incorporates seasonal fluctuations and historical trends.

3.Synthesis and recommendation: The system identifies a high risk of a cash-flow shortfall three months ahead (see Fig. 2).

4.Explanation: The XAI layer details the contribution of each factor—for instance, 60 % of the projected shortfall is attributed to the seasonal decline in sales observed in historical data, whereas 30 % results from the sharp increase in accounts receivable during the last quarter—and proposes concrete actions: a) prioritize reinforcement of the debt-collection process; b) consider obtaining a short-term loan.

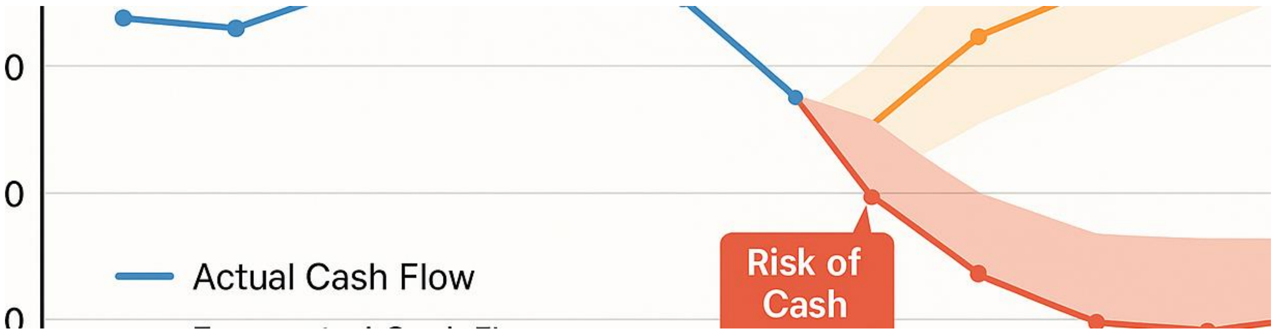

Fig. 2. An example of visualization of the cash flow forecast (compiled by the author based on the analysis of [1, 4, 9, 11]).

Scenario 2: Selection of a market-positioning strategy to increase revenue for a small coffee shop:

1.Data collection and creation. The system automatically extracts quantitative and qualitative information from diverse sources: reviews of the coffee shop itself and of its competitors on online maps and social networks, together with sales history from the CRM. This multi-source approach guarantees information completeness and minimizes noise in unstructured data.

2.Comprehensive content and segment analysis. Advanced NLP techniques perform a semantic assessment of customer reviews, revealing that coffee quality receives high ratings, whereas a shortage of gluten-free desserts is consistently cited as a pain point. Concurrently, a clustering algorithm identifies a "health-conscious" segment that is most responsive to gluten-free offerings. A rule embedded in the knowledge module states: *IF* an unoccupied niche exists *AND* internal competencies allow it to be developed, *THEN* a niche-specialization strategy is recommended.

3.Multi-criteria synthesis of alternatives. At the final stage, an MCDM mechanism generates and ranks three alternative positioning strategies according to expected revenue growth, resource requirements, and operational risk level (see Table 1). This provides the coffee-shop owner not with a single "best" option but with a balanced set of recommendations, each accompanied by its respective strengths and weaknesses.

Table 1. Example of a multicriteria evaluation of strategic alternatives (TOPSIS method) (compiled by the author based on analysis [1, 3, 6, 7, 11]).

Strategic Alternative	Expected Revenue Growth (Weight = 0.4)	Implementation Cost (Weight = 0.3)	Risk Level (Weight = 0.2)	Brand Alignment (Weight = 0.1)	Final Score	Rank
A. Expansion of the gluten-free menu	0.85	0.70	0.75	0.90	0.80	1
B. 15 % price reduction	0.60	0.90	0.40	0.50	0.64	2
C. Launch of an aggressive advertising campaign	0.50	0.40	0.50	0.70	0.50	3

4. Explanation. The XAI module justifies the selection of Strategy A by generating a report with the following statement: "The recommendation is based on the substantial potential for revenue growth resulting from entry into a new segment (contribution +45 %), identified during the analysis of customer reviews, as well as on the moderate level of the associated risk (contribution +20 %)." For intuitive understanding, the system presents a diagram showing the distribution of factor contributions.

Analysis of the proposed model reveals several limitations. First, being essentially a conceptual construct, it imposes stringent requirements on software implementation, the organization of high-quality representative datasets, and—most challenging—the formalized representation of expert knowledge. Second, the system's operational effectiveness correlates directly with the volume and reliability of the underlying information, and the processing mechanisms provided cannot fully neutralize the adverse effects of insufficient data coverage. Third, there is a risk of algorithmic bias when latent distortions are present in the training sets or in the rule base [11].

Nevertheless, the approach proposed constitutes a promising tool that shifts the emphasis from mere data accumulation toward the creation of an intelligent decision-making partner for SMEs. The integration of explainable artificial intelligence (XAI) methods is not a nominal add-on but a core component that enables practical implementation and reinforces trust, as corroborated by recent studies [5]. The digital transformation of SMEs is often depicted as a funnel in which only a small fraction of enterprises progress from initial awareness to practical adoption. In this context, the proposed IDSS can act as a catalyst, removing barriers at the stages of assessment and pilot deployment of technological solutions.

The next stage of research should focus on developing and field-testing a prototype of the proposed system in real consulting practice. Central objectives include creating highly effective techniques for eliciting and formalizing consultants' expert knowledge and conducting an in-depth analysis of the ethical consequences of deploying such solutions, particularly the issue of accountability for the system's recommendations [4, 6].

In conclusion, the conceptual architecture of the intelligent decision-support system provides a sound scientific foundation for a new generation of intelligent tools tailored to small-business tasks. The model integrates and systematizes state-of-the-art advances in artificial intelligence while addressing the specific needs and constraints of the most numerous yet least protected sector of the economy.

Conclusion

The study introduced a platform for constructing intelligent decision-support systems aimed at consulting for small businesses. A review of contemporary scientific literature demonstrated the high relevance of the topic and revealed a key research gap: the absence of comprehensive models adapted to the characteristics of small-enterprise data that integrate quantitative and qualitative analytical methods while simultaneously ensuring transparency of the generated recommendations.

The present study articulates an advanced, multi-tiered blueprint for an intelligent decision-support system that unites data-driven learning with rule-based reasoning, all while preserving full transparency of its inferences. At the foundation lies a data-acquisition and cleansing stratum, charged with aggregating heterogeneous inputs—from transactional logs to expert annotations—and bringing them into a harmonized, analysis-ready form. Above this, a hybrid inference core fuses machine-learning models (e.g., ensemble predictors, deep neural networks) with a formalized expert-system shell, enabling the system to both learn patterns from historical data and apply codified domain-knowledge rules. A subsequent synthesis engine ingests outputs from these analytic channels, reconciling potential conflicts and coalescing them into coherent recommendations. Finally, an explicit explainability layer exposes the internal decision paths—through feature-attribution maps, rule-trace logs, or counterfactual scenarios—so that end users can inspect, validate, and contest any suggestion the system produces.

What distinguishes this work at a scientific level is the systemic orchestration of these four modules into a seamless meta-architecture: we define precise modular interfaces, formalize the communication protocols by which data and inference results are exchanged, and present algorithmic schemas that govern both synchronous and asynchronous interactions among components. The theoretical contribution lies in demonstrating that such a unified framework—where hybrid analytic constructs are inextricably linked to explainable-AI principles—constitutes a robust conceptual foundation for engineering decision aids characterized by methodological rigor and operational transparency. To validate our approach, we develop two exemplar applications tailored to the needs of small and medium-sized enterprises: one implements a comprehensive financial-health diagnostic tool employing composite ratio analysis and anomaly detection, while the other models strategic entry scenarios into new markets via multi-criteria evaluation and adaptive scenario-planning algorithms. These case studies not only substantiate the practical viability of our architecture but also illustrate how its explainable outputs facilitate informed, accountable decision making.

From an applied standpoint, the articulated conceptual architecture functions as a strategic blueprint for software engineers and consulting firms intent on pioneering cutting-edge solutions for the SME segment. Deploying such systems is expected not only to elevate the precision and democratize access to consulting expertise but also to strengthen the competitive agility and resilience of small enterprises—outcomes that carry substantial socio-economic weight.

In closing, the next frontier of high-impact consulting resides in the seamless integration of human expert judgment with AI's computational prowess, whereby intelligent systems augment, rather than supplant, the consultant's specialized acumen.

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