AI ASSISTED DECISION MAKING FOR DISTRESSED AND RESTARTING PRODUCTION COMPANIES

Ștefania Chiribău-Vitlinger[1], Mihai Dragomir[2], Diana Dragomir[3] and Florin Popișter[4]
[1]Technical University of Cluj-Napoca, Cluj-Napoca, Romania, 103-105. Bd. Muncii, Cluj-Napoca, Romania
ORCID No. 0009-0003-5202-1356, stefania.vitlinger@campus.utcluj.ro
[2]Technical University of Cluj-Napoca, Cluj-Napoca, Romania, 103-105. Bd. Muncii, Cluj-Napoca, Romania
Corresponding author, ORCID No. 0000-0003-0561-4274, mihai.dragomir@muri.utcluj.ro
[3]Technical University of Cluj-Napoca, Cluj-Napoca, Romania, 103-105. Bd. Muncii, Cluj-Napoca, Romania
ORCID No. 0000-0001-6833-8815, diana.dragomir@muri.utcluj.ro
[4]Technical University of Cluj-Napoca, Cluj-Napoca, Romania
ORCID No. 0000-0003-2469-0643, florin.popister@muri.utcluj.ro

ABSTRACT: In the complex economic environments of the present, production companies are often faced with difficult decisions. Encountering financial, operational or market related distress and seeking restarting opportunities can be successfully approached if dynamic, incomplete, and uncertain information is processed and assessed correctly in short amount of time. AI systems, including LLM, ML and BI, are suitable solutions in this context. The paper proposes a structured combination of multi-criterial decision-making tools and AI instruments to navigate the specifics of these processes in production companies, taking into account their particular needs related to equipment failure, supply chains, inventories, distribution networks, etc. The framework put forward is modelled for effectiveness and efficiency and its impact is evaluated with the help of a case study in the field of machinery.

KEYWORDS: AI, MDCM, company distress, production company

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1. INTRODUCTION

In the field of manufacturing, even successful companies are often under duress, due to strong competition and external pressures to conform to regulations, to produce quality and cost-efficient products and to deliver them to the proper market niches in short times. However, there is a stark difference between the field of production and the more modern software development, AI solutions, or even service companies – manufacturing requires the physical transformation of raw materials and components using equipment, know-how and personnel, based on collaboration with suppliers, stakeholders, and distribution channels. There are inevitable costs and challenges associated with all of these, and companies can easily encounter financial, operational or market related distress, needing support and valuable information to be able to recover and return to profitability.

In this context, good decision-making becomes critical, and production managers can benefit from all the help they can get, which lately comes in the form of AI instruments that are fast, reasonably reliable and ensure confidentiality and consistency. Large language models (LLM) are useful in laying the foundation for good decisions and in improving communicability and explainability towards the stakeholders. Machine learning (ML) can detect trends and opportunities, either on the market or within the company's processes, providing excellent support for field-testing the changes that companies desire to implement, while, at the same time, ensuring the long-term monitoring of business processes for improvement. Also, there are specialized Business Intelligence (BI) tools that can provide more specific information concerning financial aspects, sales, taxes, and other topics, saving the production managers a considerable amount of time and offering tailored expertise.

In the current work, the authors have started with a simple but compelling research (and development) question: "Can effective AI solutions be integrated in the decision-making process of production managers seeking to restore a manufacturing company in distress?"

The reasoning behind this is to ensure that the instruments of Multi-Criterial Decision Making (MCDM) that are prevalent in the industry are prepared to accept inputs and provide outputs to some of the AI industries are becoming popular for companies. Enhancing the process with AI insights and providing AI with ranked criteria and results can

lead to the two approaches complimenting each other and the company reaching the final goal of solvency faster, as managers will be able to make better choices concerning their available funds and engagement with other market actors.

2. RESEARCH METHODOLOGY

In order to achieve the stated goal, a structured research methodology was developed starting from the conceptual approach proposed to combine AI and MCDM in the context described above (see Figure 1).

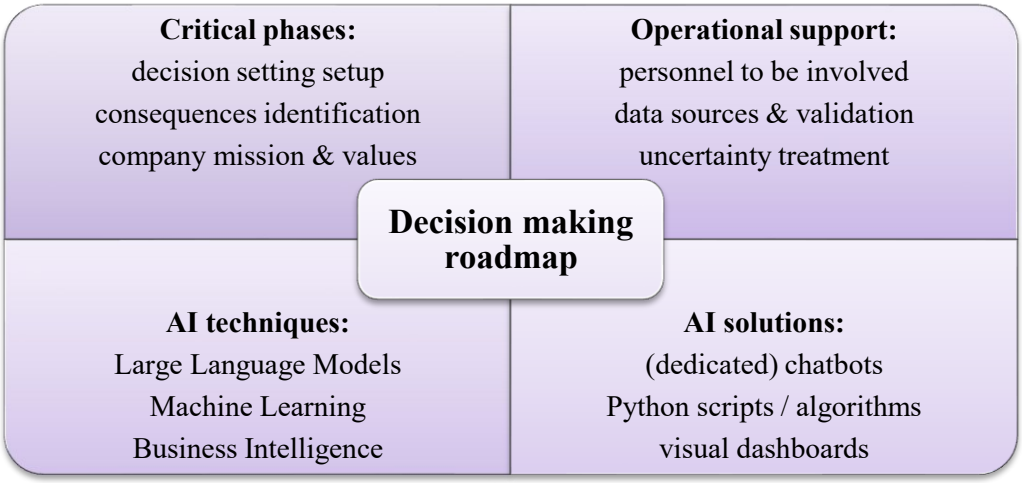

Figure 1. Conceptual decision-making enhancement roadmap

As can be seen in the figure above, the decision-making activity is characterized by the existence of 4 critical phases (criteria identification, solution generation, actual multi-criterial correlation, result ranking, and analysis) and requires operational support to the decision makers, in the form of data collection, communication, risk assessment and forecasting. The AI techniques mentioned in the previous chapter can further be deployed through specific chat, visual or algorithmic solutions to provide treatment of pre-MCDM data or analysis and implementation preparation for post-MCDM data.

The research methodology that is derived from deploying this concept has the following main steps that will be applied through a case study in the machinery industry for exemplification:

- identify and describe the problem and its component human, technical and financial elements with respect to company distress and need for intervention;
- determine and describe the exiting options and alternatives under ambivalence conditions resulting from market, regulatory and operational challenges;
- propose and refine decision-making criteria in line with the company, the industry and entrepreneurial needs to redress the current course and reinitiate the business model;
- select and implement the adequate pair of AI techniques and AI solutions to refine input, using freely available platforms and websites;
- carry-out the MCDM using specialized software and ranking approach, although in the current case this is not the main focus of the research demarche;
- feed outputs of MCDM to the proper AI solutions (also from the freely available ones) to refine the results and foster their application.

As mentioned in article [1], there number of possible uses for AI by entrepreneurs is already significant, and it is growing, including applications that process market related data, supporting product development and process improvement, and enhancing customer engagement in all interaction phases. Moreover, by deploying artificial intelligence as an entrepreneurship medium, new economic opportunities and business models are revealed in relation to sentiment analysis, distributed governance, and upskilling [2]. Other authors focus on the holistic impact of AI and other emerging technologies on the entrepreneurial process and mindset, by changing the way ideas and products are generated, produced, and sold, and bringing about new ethical challenges especially in the space of individual rights associated with the use of digital solutions [3]. Another important use of AI in the area of entrepreneurship and entrepreneurial ventures is in supporting the goals of sustainable development, both in the area of diminishing environmental impacts and in ensuring cohesive social dynamics [4].

Current approaches in specialty literature also describe the use of Explainable Artificial Intelligence, integrating hardware and software solutions, to support decision-making related to well-known managerial economics financial ratios in predicting

and avoiding bankruptcy [5]. At the same time, there are preoccupations to use specific techniques like machine learning to round up predictions based on financial ratios with other qualitative metrics related to management and governance systems and brand recognition [6]. More practical approaches involve the use of the DS-XGBoost model to develop an early warning mechanism for the financial aspects of start-ups, which can transform the distress management process through preventive activities and better solution timing [7].

3. RESULTS AND DISCUSSION

The following decision setup was created based on the collaboration of the authors with manufacturing companies in various domains. A machinery manufacturing company is facing low sales volumes, negative cashflow and migrating personnel. We proposed the following analysis criteria for decision making in this context: necessary resources, potential impact of the solutions in revenue, acceptability to employees, organizational capability for implementation. Next, we asked the AI LLM tool Gemini from Google version 2.5 Pro to refine this list (see Table 1). Similarly, the following 3 solutions for redress have been identified based on discussions with companies in this sector: contract a bank loan and use it for marketing and HR development, enter a joint venture / franchising contract, or reduce activity to minimum and wait for better demand. Again, Google Gemini was used for refining these proposals (see Table 1).

Table 1. Original brainstormed inputs to the MCDM analysis and refined results generated by Google Gemini 2.5 Pro

Original criteria (own work)	**Necessary resources**	**Potential impact of the solutions**	**Acceptability to employees**	**Organizational capability**
Refined criteria (Google Gemini)	*Financial investment* *HR required* *Technological & material resources* *Time to implement*	*Direct revenue generation* *Cost reduction* *Speed to impact revenue*	*Impact on morale & engagement* *Change management requirements* *Impact on workload and job security*	*Existing processes & systems* *Leadership & management capacity* *Risk assessment & mitigation capability*
Original solutions (own work)	**Contract a bank loan for marketing and HR**	**Enter a joint venture / franchising contract**	**Reduce activity and wait it out**	
Refined solutions (Google Gemini)	*Loan acquisition & structure* *Marketing initiatives* *Skill enhancement & recruitment*	*Partner profile* *Structure & contribution* *Governance & profit/loss sharing* *Partner responsibilities* *Exit strategy*	*Operational cost cutting* *Workforce reduction* *Asset management* *Maintaining core capabilities* *Triggers for resumption*	

The proposals from the AI LLM system are mostly in the form of details and clarifications of the original ideas resulting from engaging with the companies. There are certain redundancies that need to be cleared up (e.g., governance vs. responsibilities), as well as some interconnections that should be observed in a real production environment (e.g., morale depends on workload and job security), while other elements have not been expanded at all (e.g., marketing initiatives). Taking into account these corrections, we proceeded to the next step, performing the MCDM calculation using the HELDA software v1.0 and choosing the weighted sum ranking method, as the most direct one of those available in this product (Figure 2). This step has been performed manually, but it should be noted that LLMs have the capability to implement some of these analysis methods too, with less insights and visual representations.

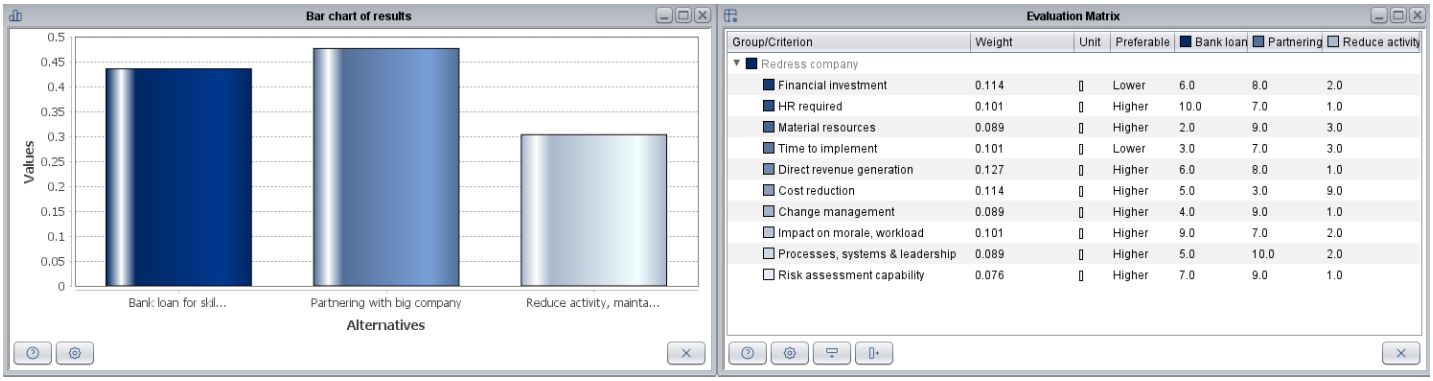

Figure 2. MDCM analysis using HELDA v1.0 reveals "Partnering with a big company" as a preferrable alternative

The final insight was generated with Jeda.ai which can create visual elements for business management (Figure 3). The AI model selected was Claude 3.5 Sonnet from Anthropic and the results are grouped into 4 phases that complete the MCDM analysis, referring to the most common planning tasks: resource allocation, performance monitoring, change management and risk assessment. The system selected the most relevant elements for each category and prepared a visual dashboard for the company redressing project. Also, using the analysis data, it calculated and proposed adequate metrics that can be used to ensure success. It can be noticed that the acumen is high, but human creativity and experience could elevate the results considerably, together with social engagement of stakeholders in the process.

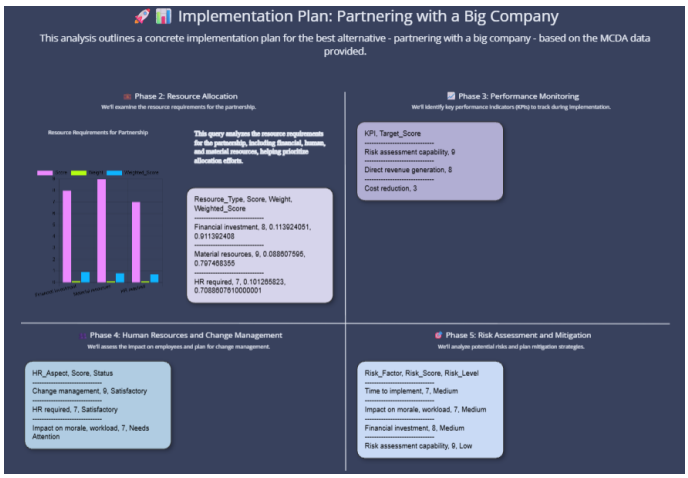

Figure 3. Implementation plan generated with Jeda.ai

4. CONCLUSIONS

The research demarche proposed in this paper aims to combine in a harmonious way the strengths of AI instruments and MCDM analyses in supporting the delicate work of start-up managers in resolving crises. The approach and the case study undertaken to test it display signs of viability, as the complex issues that entrepreneurs are faced with can be broached:

- in a more comprehensive and detailed way, taking into account ramifications, redundancies and incomplete information about the difficulties faced;
- faster and nimbler, with more confidence that the large amount of training data of the AI instruments constitute a knowledge base that is freely and easily available;
- in a scientifically sound manner that makes use of multi-criterial ranking methodologies, without requiring specialized know-how for the company representative;
- using visual monitoring capabilities that enable the decision-makers to engage with the data.

Further investigation is required to test the methodology on a large scale, including not only the process of making decisions but also the tracking of the impact and results stemming from these decisions.

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