Knowledge in the Discovery of Market Opportunities

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Abstract: An opportunity is a relationship between a company's objectives, the resources at its disposal, and the situation in the environment, such that it favours the achievement of the objectives with the available resources. Opportunities arise in a changing environment. The dynamics of change causes the life cycle of an opportunity to shorten and companies that discover the opportunity and can exploit it gain a competitive advantage. Opportunity discovery means that opportunities exist but the company does not know about them. Opportunity discovery is the subject of several scientific disciplines. They are dealt with by strategic management using the methods of strategic analysis. They are also of interest to agility theory, which focuses on reacting quickly to market opportunities. In addition, entrepreneurship theory deals with them, which addresses the issue of cognitive traits in their discovery. New possibilities in discovering opportunities are created by artificial intelligence. The article aims to present the opportunity discovery model understood as the relationship between three vectors: the company's goals, its resources, and the external environment in which it operates. The discovery of the opportunity consists in finding such a value of the environment vector at which the desired value of the vector of goals is achieved at a given value of the resource vector. The article answers the question of how the knowledge necessary to find such a relationship between these vectors must be structured so that this relationship reflects the opportunity. It was hypothesized that this structure can be modelled using a network of cause-and-effect relationships leading to the determination of the relationship between demand and supply. This hypothesis was verified using artificial intelligence with the Monte Carlo algorithm, Markov chain, and the Metropolis-Hastings algorithm. The results obtained confirmed the validity of the model structuring the knowledge. The article presents the result of a pilot study. The results concerning knowledge structuring are useful for opportunity discovery both in the case of traditional approaches i.e. using the achievements of strategic management theory, corporate agility and entrepreneurship theory, and in the case of using artificial intelligence. In the first case, the target audience for these results is business executives while in the second case, the research community working on this problem and IT companies.

Keywords: Opportunity discovery, Strategic analysis, Cognitive traits, Artificial intelligence

1. Introduction

The turbulent and unpredictable environment of modern business generates not only threats but also opportunities. Their use gives enterprises a competitive advantage. To take advantage of an opportunity, it must first be created or discovered. Creating opportunities requires creativity and innovation. The development of these features requires knowledge, especially about the technological segment of the macro-environment. Knowledge about new technologies allows entrepreneurs to see their use in areas that have not been explored before. This leads to the creation of new industries and products that later imitators and buyers were unaware of. Google, SpaceX, and Netflix are examples of this.

Opportunities can also be discovered. This means that they exist but entrepreneurs do not know about them. Searching for existing opportunities, companies conduct strategic analyses of the macro-environment and industry environment, as well as conduct marketing research. In this way, they acquire knowledge that helps to identify underserved market segments, market gaps, and sources of low efficiency of their activities. This knowledge lays the groundwork for opportunity recognition. It is very useful, but even when the needs of the market are known, it does not mean that the opportunity exists. Identification of opportunities requires confronting these needs, or more broadly - the situation that exists in the macro-environment and in the industrial environment with the goals that the company wants to achieve and with the resources at its disposal. If the existing or anticipated situation in the environment is conducive to achieving the company's goals with the use of available resources, then the recognized situation creates an opportunity. However, determining whether the relationship between objectives, resources and the situation in the environment creates an opportunity is not a simple matter, especially in small and medium-sized enterprises (SMEs). These companies have limited knowledge about conducting such analyses and limited analytical potential. As a result, the information they have about the macro-environment segments (political, regulatory, economic, socio-demographic, natural, and technological environment) and about the segments of the industry environment (customers, suppliers, companies interested in entering the sector, competitors, substitute products) is modest. It is general and fragmentary. It is even more difficult to transform this information into knowledge. This requires a methodologically and intellectually advanced analytical potential, thanks to which events taking place in the environment are associated with situations conducive to achieving goals with the use of available resources, i.e.

opportunities. Therefore, the fact that some companies see opportunities and others do not, depends, among other things, on the cognitive characteristics of entrepreneurs, their experience, intuition, stubbornness and not being discouraged in the event of failure. As a result, SMEs discovery of opportunities is often associated with art rather than scientific management. This applies mainly to the theory of entrepreneurship.

A methodical approach to this problem consists in determining the system of factors influencing the emergence of a market opportunity, which may be expressed by a situation when demand is higher than supply. This means that there is a gap in meeting the needs and thus an opportunity for the producer. In this case, the systemic approach consists in determining the cause-and-effect linkage chains between these factors, affecting demand on the one hand and supply on the other. Such a model can be called the feedback network of opportunity drivers model. It structures the knowledge that is the basis for discovering opportunities in a traditional - analytical way. Such an analytical approach is characteristic of strategic management.

It seems that the use of artificial intelligence (AI) methods creates new opportunities for discovering opportunities in conditions of limited knowledge and poor data. In particular, it is about Monte Carlo methods, MCMC algorithms, and the Metropolis-Hastings algorithm that play essential roles in AI by enabling probabilistic modelling, uncertainty quantification, and inference in complex systems. These techniques help AI systems handle uncertainty, approximate solutions and make informed decisions based on available information. We hypothetically assumed that the feedback network of opportunity drivers model, in which the relationships between the factors shaping the opportunity are not explicitly defined, may be the basis for discovering the opportunity using the above-mentioned techniques. To verify this hypothesis, we conducted a simulation experiment, the results of which confirmed our belief that the developed model is promising and that research on the use of AI should be continued.

2. Literature Review

Discovering opportunities is the domain of various scientific disciplines. In strategic management, opportunities and chances are sought in the environment of the organization and then, by confronting them with the strengths and weaknesses of this organization, a strategy is developed to use the opportunities and avoid threats. This process is supported by methods that are dedicated to the analysis of the macro-environment, industrial environment, and the inside of the organization (Trzcielinski et al, 2023).

In agile enterprise theory, an opportunity is viewed as an advantageous situation that requires a quick response. In today's fast-paced and rapidly changing business environment, organizations that are able to quickly identify and respond to new opportunities are more likely to succeed and remain competitive. An agile enterprise is well-suited to identifying and exploiting new opportunities because it is designed to be bright, flexible, intelligent and shrewd, and responsive to change (Trzcielinski, 2007; Trzcielinski, 2021).

In the theory of entrepreneurship, opportunity is a central element of entrepreneurial activity. This theory suggests that successful entrepreneurs are those who are able to identify and exploit opportunities that others have overlooked or failed to capitalize on. A lot of cognitive traits have been identified as important for effective opportunity recognition. Among them are:

- Creative thinking that helps entrepreneurs think outside the box and thus identify unique opportunities (Baron, 2006),
- Cognitive flexibility that refers to the ability to adapt thinking and approach problems from different perspectives. It enables entrepreneurs to recognize opportunities in diverse contexts (Sarasvathy et al, 2003),
- Perceptual acuity that involves the ability to notice and interpret subtle cues and signals in the external environment. It helps entrepreneurs identify emerging trends and opportunities (Shane and Venkataraman, 2000),
- Efficient information processing skills, such as pattern recognition and information synthesis, are crucial for recognizing and evaluating opportunities (Ardichvili et al, 2003),
- Prior knowledge and expertise in the relevant domain that equips entrepreneurs with tools to recognize opportunities within their field and leverage their existing knowledge (Shane, 2003).

Based on her research, Trzcielinska (2021) found that among the 17 entrepreneurial traits, the following have the greatest impact on discovering opportunities: courage in decision-making, dedication and hard work, risk propensity, and assertiveness.

In the traditional approach to discovering opportunities using these theories, knowledge is a key factor. Through domain expertise, market intelligence, technological awareness, networking, continuous learning, and adaptive thinking, entrepreneurs can effectively identify and capitalize on opportunities. However, it is always to some extent an art dependent on human intelligence, creativity, intuition, and the ability to process information.

New possibilities are created by the development of artificial intelligence (AI), which increasingly supports business activities and this process is at the stage of intensive growth. This also applies to discovering opportunities.

AI technologies, such as machine learning, natural language processing, and computer vision, can analyse large volumes of data to identify patterns and trends that may indicate opportunities for innovation and growth (Priporas et al, 2020).

One area where AI is being used to discover business opportunities is market research. By analysing social media data, customer feedback, and other sources of information, AI can help businesses identify new market trends, customer preferences, and areas where there is unmet demand. Among others, AI algorithms can support understanding sentiment, opinions, and trends. This information helps businesses gain insights into customer preferences, brand perception, and public sentiment. Also they automate the analysis of survey data, extracting key insights and identifying patterns in responses (Hossain et al, 2018).

Another area where AI is being used is in product development. By analysing customer feedback and user behaviour data, AI can help businesses identify opportunities to improve existing products or create new products that better meet the needs of customers. AI algorithms and machine learning techniques are used to optimize product designs, automate design iterations, and simulate product performance. This helps identify optimal design configurations and reduces time-to-market. The algorithms analyse market data, customer insights, and historical trends to predict demand for new products. AI-powered natural language processing techniques analyse customer feedback, reviews, and social media data to understand customer needs, preferences, and sentiment. These insights help inform product development decisions (Thies et al, 2018). AI is used also to automate quality control processes, such as visual inspection and defect detection. Computer vision and machine learning algorithms identify defects, improve accuracy, and enhance product quality (Deng et al, 2020).

AI is also being used in supply chain management to identify opportunities for cost savings and efficiency improvements. By analysing data on inventory levels, transportation routes, and supplier performance, AI can help businesses identify areas where they can reduce costs and improve operations. They are used to demand forecasting and inventory optimization. This enables better inventory management, reduces stockouts, and minimizes excess inventory. Another functionality is predictive maintenance and equipment optimization. This helps minimize downtime, optimize maintenance schedules, and improve equipment efficiency (Deng et al, 2019). AI-based analytics and decision support systems assist in supplier selection, procurement negotiations, and contract management. This streamlines the procurement process, improves supplier performance, and reduces costs (Wu & Tang, 2019). They optimize transportation routes, considering various factors such as distance, traffic, and delivery constraints. This reduces transportation costs, improves delivery efficiency, and enhances customer satisfaction (Vahdani & Tavakkoli-Moghaddam, 2019).

Authors dealing with the problem of discovering opportunities with the use of AI more often point to the potential implementation of this technology than to the actual cases of its use. The probable reason for this is that the significant increase in the efficiency of business ventures supported by AI means that many solutions are not made publicly available. However, it is known that, for example, consulting firms such as Deloitte and McKinsey have already developed some intelligent tools that offer monitoring and sensing of an organization's external environment, enabling semi-automated strategy articulation (Jarrahi, 2018).

The potential or actual applications of AI for opportunity discovery mentioned in the literature require Big Data processing, which significantly limits the use of these technologies by small and medium-sized enterprises (SMEs). On the one hand, these companies usually do not have large data sets, on the other hand, they do not have staff with methodological preparation and the potential to conduct analyses of the macro-environment and the industrial environment in a traditional way, i.e. by human teams supported by creative thinking techniques.

The problem we have undertaken fits into the gap between the traditional approach to discovering opportunities and the use of AI based on Big Data processing. We described the knowledge needed to recognize opportunities using the model of feedback network of opportunity drivers and business model matrix, while the AI algorithms we use neither require a large sample of input data nor an explicit mathematical formula describing the relationships between the data.

3. Model of the Research Problem

We define an opportunity as a relationship between the goals that the company wants to achieve, the resources it has at its disposal, and the situation in the environment such that it is conducive to achieving these goals with the help of the available resources (Trzcieliński and Trzcielińska, 2011). Consequently, recognizing an opportunity is either creating such a situation or discovering it. Opportunity creation is a creative and innovative activity, while discovery is an analytical activity.

Figure 1 presents a model of the opportunity discovery problem. The symbol S (Figure 1a) denotes the current situation of the enterprise being the result of the vector of the goal achieved Gc, available resources Rc and the vector of the recognized situation in the external environment Ec. The sizes of these vectors are denoted by /Gc/, /Rc/, and /Ec/, respectively. The vector Gc can move in the space of satisfying goals SG, the resource vector - in the space of available resources SR and the vector Ec in the space of states of the environment SE. Vector Gc may be outside the space SG or its value (Gc) may not be satisfactory. In this case, expected goals are set, described by the Ge vector (Figure 1b). The opportunity discovery problem consists in finding such a situation in the SE environment that the resultant "O" of the vector Ge, the environment vector Ee and the resource vector Re will be an opportunity for the enterprise. In other words, it is about identifying such states /Ee/ in the SE space that will be conducive to achieving the defined goals /Ge/ using the available resources from the SR space. This may require the transformation of the Rc vector into the Re vector, i.e. the use of resources with a new configuration.

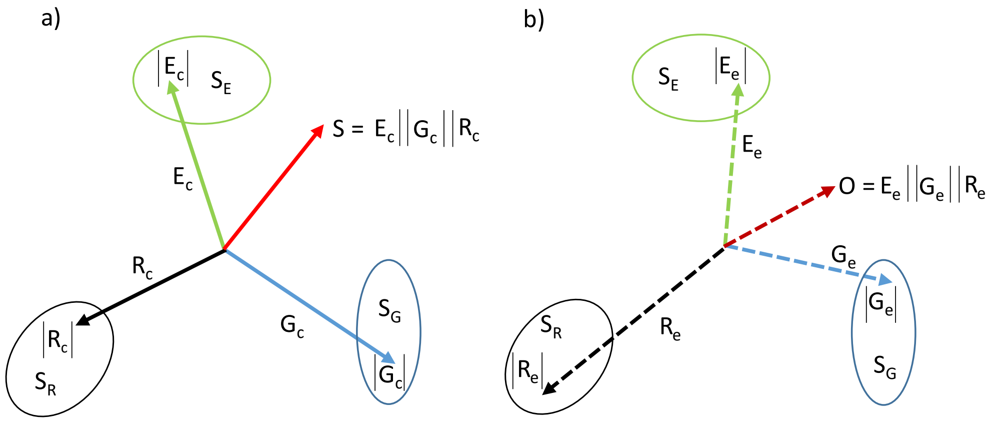

Figure 1: Model of the Opportunity Discovery Problem

4. The Experiment

4.1 Methodology

To answer the research question, an experiment was conducted in which the problem described above was adapted to the refrigeration industry. The opportunity model is presented in Figure 2. It takes into account the situation that existed in the market of producers and buyers in the refrigeration industry in 2020. It shows in a systemic way the cause and effect relationships leading to the creation of an opportunity for the producer (demand is greater than supply). These dependencies structure the areas of knowledge that must be acquired in the process of discovering opportunities. This type of structuring is a good basis for verifying whether the discovery of opportunities can be assisted by artificial intelligence (AI).

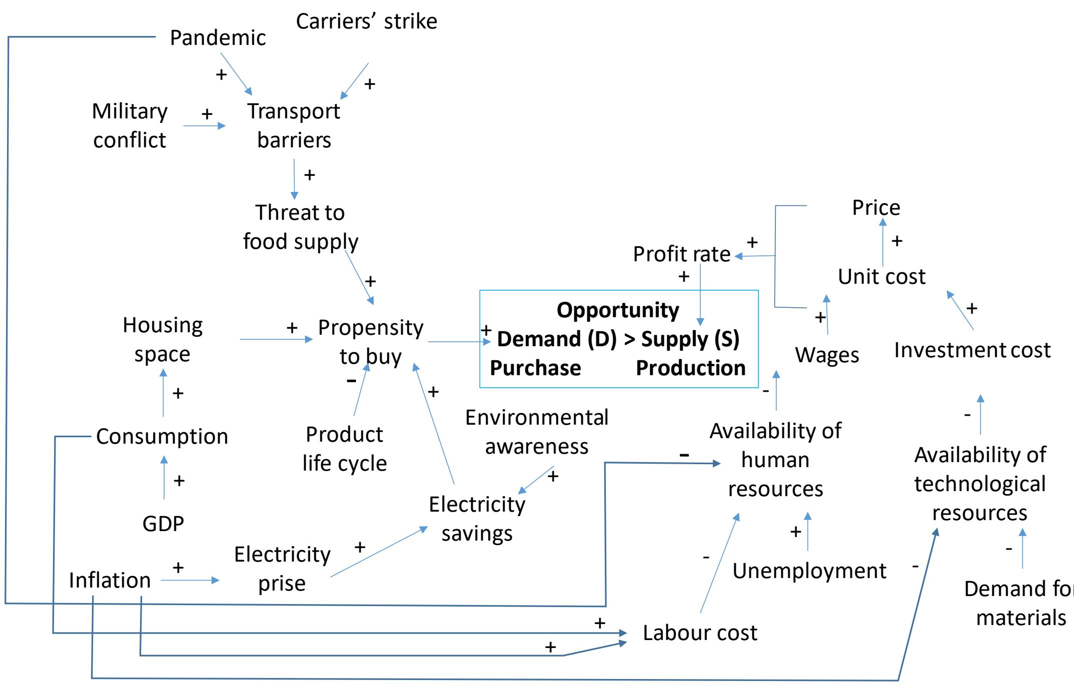

Figure 2: Feedback Network of Opportunity Drivers in the Refrigeration Industry

Due to the high complexity of this model, the experiment testing the use of AI was limited to only four factors directly influencing the propensity to buy, i.e. demand. These are the following factors (Figure 3):

- threat to the food supply - increases the willingness to buy refrigerators in order to stock up on food for fear of interrupting supply chains,
- housing space - increases the willingness to buy a refrigerator with larger dimensions or a second refrigerator by buyers who increase their living space,
- product life cycle - increases the willingness to buy due to the need to replace the refrigerator,
- electricity savings – increases the willingness to buy a newer generation refrigerator that consumes less electricity.

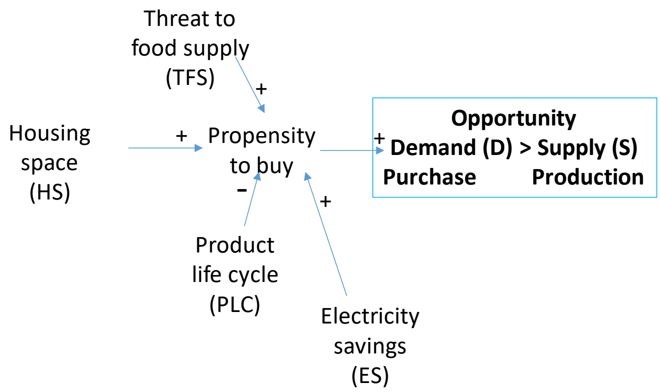

Figure 3: Factors Directly Affecting the Propensity for Buying a Refrigerator

According to these factors, buyers for whom a particular factor is a leading motive for purchase were named: scaremonger (TFS), developer (HS), innovator (PLC), and ecologist (ES). Assuming the existence of these four buyer groups, a business model matrix was developed (Table 1). These four types of buyers form fractions of the "MF" market. The size of these fractions is not known, but each can take values in the range <0, 1>. The probability "p" that a given fraction occurs is also unknown, but the sum of these probabilities is 1.00. This means that the market is formed by at least one fraction of buyers. On the other hand, if a given fraction does occur, then the probability "w" of a given type of buyer purchasing in each market is known. It is worth noting that obtaining knowledge of this probability is relatively easy using marketing research.

Table 1: Business Model Matrix

Type of purchaser MF	Market's fraction MF(TFS,HS,PLC,ES) Sum = 1,00	Probability of market fraction occurrence P(TFS,HS,PLC,ES)				
		p_{TFS} ϵ <0, 1>	p_{HS} ϵ <0, 1>	p_{PLC} ϵ <0, 1>	p_{ES} ϵ <0, 1>	Sum = 1,00
		Probability of a purchase decision W(TFS,HS,PLC,ES)				
		w_{TFS}	w_{HS}	w_{PLC}	w_{ES}	Sum
Scaremonger: TFS	MF_{TFS} ϵ <0, 1>	0,60	0,10	0,10	0,20	1,00
Developer: HS	MF_{HS} ϵ <0, 1>	0,20	0,70	0,00	0,10	1,00
Innovator: PLC	MF_{PLC} ϵ <0, 1>	0,20	0,10	0,60	0,10	1,00
Ecologist: ES	MF_{ES} ϵ <0, 1>	0,30	0,20	0,00	0,50	1,00

The data categories contained in the business model matrix were used in an experiment testing the use of AI to discover opportunities. With the introduced simplifications of the problem, identification of the opportunity consists in finding the structure of the product portfolio, due to the particular types of buyers. With very poor data, as shown in Table 1, it is not possible to solve this problem using optimization methods. Therefore, a simulation approach was used.

The simulation was carried out using the Markov chain Monte Carlo method (MCMC) and the Metropolis-Hastings algorithm in 1000 steps. Markov chain algorithms generate a sequence of random variables where each variable depends only on the previous variable in the sequence. The Metropolis-Hastings algorithm generates a Markov chain that converges to the target distribution by accepting or rejecting proposed samples based on specific acceptance criteria. The Metropolis component of this algorithm evaluates the gain or loss in a single step, while the Hastings component evaluates the gain or loss in the entire process of system state changes. The adopted simulation methodology does not require large samples of input data because the method generates its own set of data (non-relational databases of the NOSQL type) that can be analysed using AI methods.

Using the mentioned algorithms, the static point in which the chain reaches a stationary or equilibrium distribution, which represents the desired probability distribution, was determined. The static point refers to the most probable state of the system, i.e. the most probable combination of buyer transitions between market factions (MF). Since the graphical representation of the system state in 4D is not possible, the PLC - Innovator fraction has been omitted.

In order to determine the structure of buyers, and thus the structure of the product portfolio, the state of the system was projected onto the vectors MFTFS, MFHS, MFPLC, and MFES. This required solving in each step of the simulation the matrix equation W(TFS,HS,PLC,ES)*MF(TFS,HS,PLC,ES)=B, where B=P(TFS,HS,PLC,ES), i.e.

MFTFS*0.6 + MFHS*0.2 + MFPLC*0.2 + MFES*0.3 = PTFS

MFTFS*0.1 + MFHS*0.7 + MFPLC*0.1 + MFES*0.2 = PHS

MFTFS*0.1 + MFHS*0.0 + MFPLC*0.6 + MFES*0.0 = PPLC

MFTHS*0.2 + MFHS*0.1 + MFPLC*0.1 + MFES*0.5 = PES

4.2 Results and Discussion

A given type of MF buyers may make purchases with the probability "w" also in other market fractions. Each combination of probabilities of buyers' transitions between market fractions determines the state of the system. A sampling of the system states was carried out randomly using the Monte Carlo method, and the transition of the system from state to state was carried out with the determined probability according to the Markov sequence method. The state of the system was thus a random variable. The most probable state of the system is called the "stationary point". The stationary point was reached using the Metropolis-Hastings algorithm. The simulation gave a stationary point P(TFS, HS, PLC, ES) → 0.3333, 0.25, 0, 0.4166. These are the probabilities of the occurrence of market fractions corresponding to particular types of buyers.

The size of the market fraction was obtained by solving the matrix equation W(TFS,HS,PLC,ES)*MF(TFS,HS,PLC,ES)=P(TFS,HS,PLC,ES) with the "Innovator" (PLC) fraction omitted. It gave the result MF(TFS,HS,ES) → 0.14444444, 0.12407407, 0.73555556, which means that the forecast distribution of the customer fraction is as follows: 14% of customers are "Scaremongers" (TFS), 12% are "Developers" (HS), 0% is "Innovators" and 74% is "Ecologists" (ES) (Figure 4).

Assuming that Scaremonger is interested in large refrigerators, Developer in modular refrigerators that can be expanded, and Ecologist in equipment with the highest energy class, the structure of the product portfolio is as follows: 14% is large-size refrigeration equipment, 12% is modular equipment and 74% of A+++ and A++ energy class refrigerators.

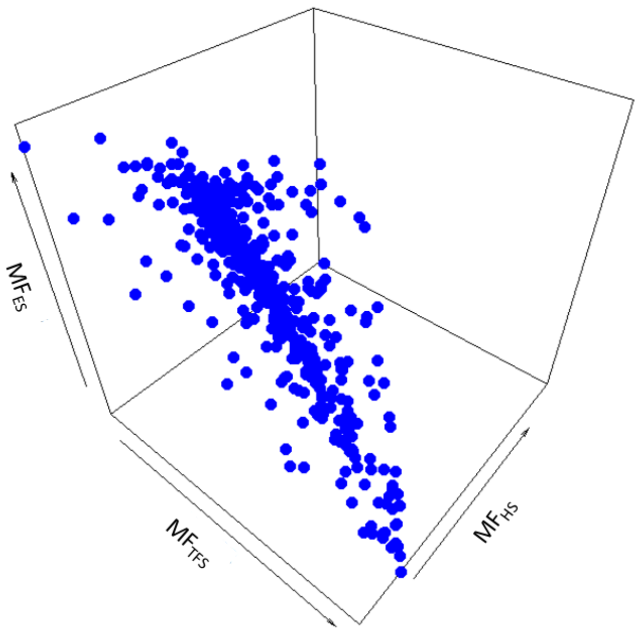

Figure 4: System State Diagram

5. Conclusions

5.1 Applicability

Pilot studies have shown that by using AI, it is possible to discover market opportunities with very little knowledge about the factors shaping the demand for products. However, it is necessary to have a model of knowledge about the mechanisms shaping demand and supply. In our case, this mechanism was described using the feedback network of opportunity drivers. The only "hard" data concerned the probability of buyers switching between market fractions of a given industry. These are easily obtained through an interview questionnaire used in marketing research. Such a situation of very limited knowledge about the mechanisms of the influence of the external environment on the emergence of opportunities occurs mainly in small and medium-sized enterprises. Therefore, the addressee of the results, which are announced by our pilot studies, is the management staff of SMEs. The knowledge structuring model we have verified is useful for discovering opportunities both in the traditional approach and with the use of AI. In the first case, it can rationalize the intuition of entrepreneurs, while in the second, it leads to results that seem impossible to obtain only with the use of human intelligence. Unlike the use of AI involving the processing of huge data sets, the approach we use consists in obtaining data from the business model in mathematical terms, using Monte Carlo simulation procedures. The advantage of this approach is that:

- a large sample of input data is not necessary,
- no specific structure of observable data is necessary - we operate directly with the effective variables of the model (in the sense of Bayesian variables),
- the method generates its own set of data that can be analysed using artificial intelligence methods.

Problems with such characteristics are classified as "Data Imputation" because MCMC techniques generate missing or incomplete data sets that incorporate uncertainty and capture the underlying patterns of the available data. This approach is used in industries such as healthcare (Choi et al, 2017; Ranganath et al, 2016), finance (Breymann et al, 2003; Jia et al, 2018), and social sciences (Nowak et al, 2018). In all these areas, the successful application of MCMC and Metropolis-Hastings methods relies on appropriate modelling choices, understanding the problem domain, and ensuring the generated data accurately represents the desired characteristics for analysis using artificial intelligence methods. We believe that our research is another example that operationalizes these requirements and can be an inspiration for other researchers and IT companies tackling data imputation problems.

5.2 Limitations

While we believe that limited data is not an obstacle for AI to discover opportunities, based on the conducted experiment, we cannot assess whether the product portfolio structure obtained is indeed an opportunity. This is due to:

- including in the feedback network of opportunity drivers model only the factors directly influencing customers' propensity to buy the product,
- the restriction to the demand side of the model only,
- the exemplary definition of market fractions,
- the exemplary nature of the probabilities of buyers moving between market factions.

5.3 Prospective Research

In order to eliminate or at least reduce the listed limitations, it is necessary to use actual data either from the entire refrigeration industry or from an individual manufacturer of these products. This applies to both demand and supply factors. Data on the probability of buyers switching between market fractions is also needed. As a result, we expect to estimate the value of the opportunity.

The results obtained so far are promising and can be the basis for an in-depth analysis using AI tools. We will develop our research in terms of cluster analysis and anomaly discovery. The most interesting seems to be the analysis of clusters in multidimensional space, consisting of the search for separate areas with increased entropy. These are usually areas related to repetitive (in different periods) trends or a longer but one-off, temporary trend, which is undoubtedly interesting from a business point of view. Such clusters are already observed in the preliminary results of the experiment.

Taking into account the complexity of the model, the existence of non-standard solutions should be expected. Anomaly detection can be a useful tool to determine deviations in cyclically repeated experiments. This allows to determine the conditions for obtaining particularly good results from the point of view of the objective function.

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Conflicts of Interest: The authors declare no conflict of interest.

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