Simulation of Discovering Market Opportunities Using AI Methods

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Abstract: Due to the strong turbulence that exists in the business environment, the view is sometimes articulated that the time horizon of decisions is no longer a hallmark of strategic management. Opposing views argue that a turbulent environment changes the trajectory of reaching future objectives determined by strategic decisions. Such trajectories require the company to be agile, which is manifested by seizing opportunities. Opportunities arise because the environment is volatile. An example of market opportunity is the unsatisfied demand for products. Buyers are driven by different motives when choosing between products that are alternative to them. From the producer's point of view, the purchase is therefore random. As a consequence, the alignment of the offered product portfolio with the actual purchasing decisions of customers is undetermined. In this article, we address the problem of determining the product portfolio structure expected by customers, i.e. one that is consistent with their future purchasing decisions. We hypothesise that this problem can be represented by a model of flows between alternative resources. Problems of this type are solved using Markov Chain Monte Carlo (MCMC) methods. In order to discover the expected demand (opportunity), we simulated the flow model we developed using the Metropolis-Hastings algorithm, which is a special case of the MCMC method used in AI. Due to operating on numerical data, such simulations fall under quantitative research. In the article, we present a model of customer flows between alternative products and then the simulation result, which is the expected value of these flows (stationary point). We convert this value into the structure of the product portfolio using a model of customer purchasing decisions that we have developed. The obtained results confirm the effectiveness of our method and have significant practical value, especially for SMEs. It also enables the assessment of the company's product strategy based on real sales data. The application of our methodology is limited to discovering opportunities in situations where purchasing decisions are influenced by variable environmental factors, causing irregular purchases by individual customers. It is useful, for example, in discovering opportunities in markets such as Household Articles, Furniture, Vehicles, Equipment Repairs, Construction, and many others.

Keywords: Opportunity Discovery, Artificial Intelligence, Markov Chain Monte Carlo Method, Metropolis-Hastings Method, Alternative Products Portfolio

1. Introduction

Within contemporary decision support systems (DSS), several IT technologies are starting to clearly dominate due to the rapid increase in access to large amounts of data and the techniques for processing them with the help of artificial intelligence (Provost & Fawcett, 2013). Among these are commonly used tools such as Business Intelligence, Big Data Analytics, and Data Mining, which aim to conduct in-depth analysis of previously collected or real-time data. These are usually employed for forecasting based on historical data, with further analysis conducted using established techniques such as regression analysis, time series analysis, data flow, or qualitative modelling.

Simultaneously, in many areas of economic activity, research is being conducted on prediction in the absence or insufficient amount of data. The approaches used in such studies include data imputation technologies, bootstrap techniques, Bayesian techniques, and generative learning (Jha et al, 2022). They supplement the dataset with artificial data and rely on meta-learning focused on improving the efficiency of learning (Arulkumaran et al, 2017), on the principle of trial and error based on random events, where the search for the optimal decision can be achieved, for example, by sampling the model using the Monte Carlo simulation method (Vodopivec et al, 2017).

The detailed aim of this paper is to describe a decision system related to variable demand for selected goods under random information about possible customer choices (their purchasing preferences). This problem can be framed in terms of resource flow with a specific probability of changing the decision on the selection of a product group. Resource flow research is successfully described by System Dynamics models (Gary et al, 2008), which allow iterative determination of resource changes over time, where an essential condition for describing the model system is the explicit knowledge of differential-integral equations determining the system's dynamics, i.e., the flows between resources. Unfortunately, the analysed problem of variable demand for selected product groups does not adhere to strict analytical records. The issue studied in the work is non-deterministic and an effective way to solve it is the stochastic approach. Here we will limit ourselves to probabilistic techniques based on Bayesian inference (Box and Tiao, 2011), the essence of which is to take into account uncertainty and assign probabilities to various decision hypotheses or parameter values based on available data. The practical implementation of the above idea is Markov chains (Baum and Petrie, 1966), which describe the evolution of a system in which future events depend only on the current state of the system, and not on the entire history. It is assumed that the state of the system is determined by a set of current parameters, which are a sufficient basis for making a decision (via a flow matrix defining the probabilities of change) in order to create a space of solutions in successive steps. Usually, Markov chains converge to a so-called stationary state—a specific expected value (Kurtz, 1981). However, it should be noted that there are particular cases where, for example, the system behaves periodically and exhibits several stationary states (cyclically following each other) for the same set of input data and exceptional situations where a Markov chain does not become stationary in finite time (Cappé et al, 2005).

2. Literature Review

The modelling of sales and demand creation has been the subject of numerous analyses, considering product characteristics, customer preferences, financial conditions, economic indicators, and market conditions. Methods and techniques used in this area include classical time series models (Rippe et al., 1976), analysis of non-deterministic business cycles and turning points (Hamilton, 1990), the application of dynamic programming to study demand cycles (Briffaut and Lallement, 2010), monitoring changes in demand using the Monte Carlo method (Klug, 2011), and forecasting macroeconomic variables on the stock market using hidden Markov chains (Nguyen and Nguyen, 2015).

Decision models are the subject of numerous theoretical studies (Fülöp, 2005). Depending on the form and functional description of the optimisation problem, traditional optimisation techniques, linear programming, non-linear programming, or discrete optimisation can be used (Nemhauser et al., 1989). For studying supply and demand issues, so-called Multiple Criteria Decision Making methods (MCDM) are used. These methods involve examining a decision matrix in which the set of all admissible decisions is a discrete set containing a finite, predetermined number of possible solution variants.

Since 2015, there has been a rapid increase in the use of AI in financial analysis, marketing, and business (Ellefsen et al., 2019; Bahoo et al., 2024; Stone et al., 2020). AI is now widely used in the field of analysing customer decision processes, although the problem is posed more broadly and concerns the comprehensive analysis of customer behaviours. The result is targeting customers to tailor offers to target customers, including policies of setting individual prices (discounts) to maximise profit per unit (Marinchak et al., 2018). Methods used to determine potential customer decisions and influence them include quantitative research (surveys, interviews), focus groups (studying feelings about products, services, brands), customer observations, and online behaviour analysis (A/B testing). Using AI tools, individualised relationships with customers are built, paying close attention to factors such as trust, satisfaction, commitment, engagement, and loyalty (Yau et al., 2021).

Another approach that supports decision-making processes is computer simulations. They are used, for example, to estimate the probability of achieving different levels of return on investment, considering various factors such as market conditions, costs, and technological uncertainty (Platon and Constantinescu, 2014). Decision modelling using the Monte Carlo (MC) method allows comparing different options in terms of their expected value and risk, such as comparing different investment strategies related to asset allocation (Cesari et al., 2003). The use of multi-attribute decision-making methods supported by computer simulations enables the identification of potential threats to a project or decision, identification of specific negative factors and determining how they will impact the project's outcome (Mojtahed et al., 2010). In the case of reinforcement learning (Sutton & Barto, 2018), the simulation scenario models a range of decision sequences, which is currently one of the most dynamic areas of artificial intelligence development.

MC modelling can also be applied more broadly within so-called probabilistic programming, which has now become one of the main branches of machine learning and an important element of data analysis (Ghahramani, 2015). Learning from data involves transforming previously defined probability distributions—by observing real data—into posterior distributions generated artificially after observing the data (this is called the application of probability theory to learning from data). The importance of this method is growing rapidly due to the possibility to train very complex models based on computer simulations to classify and predict events in such systems. In the case studied in this paper, these techniques allow searching for business solution spaces to identify opportunities.

It is also worth noting that the use of simulations in learning processes will soon enable the implementation of so-called embodied artificial intelligence, which is a step towards realising the idea of artificial general intelligence (AGI) (Duan et al., 2022).

3. Research

3.1 Materials and Methods

We present the discovery of opportunities using AI methods on the example of global production of jackets made of alternative materials, which are cotton, leather, cashmere and agave fibres. The necessary data on the production volume and demand flows between market fractions corresponding to these products, as well as demographic characteristics of buyers, were obtained using Chat 4.0. We used this technology due to its capabilities of searching and analysing distributed and fragmented databases.

We simulate the states of the system, which is created by customer flows and thus purchase streams between market fractions. The expected result is the proportion between these streams. In order to represent the full characteristics of the studied system, simulation modelling is employed using the Monte Carlo method (Kroese and Rubinstein, 2012). Data collected in this process allows for obtaining higher-level statistics - they are the basis for cluster analysis, multiple regression or correlation (Newbold et al, 2013), which in turn leads to the use of AI technology.

The most popular simulation method with wide application, and appropriate for solving the problem presented in this work, is the Markov Chain Monte Carlo (MCMC) algorithm (Chib, 2001). Monte Carlo Methods are numerical techniques used to approximate solutions to problems that may be difficult to solve analytically, using random samples. Markov Chains is a subset of stochastic models used in Monte Carlo methods. They describe systems transitioning between different states where the probability of transitioning to a given state depends only on the current state. The Metropolis Algorithm is a specific case of Markov Chains (Metropolis and Ulam, 1949; Hastings, 1970. It is a technique used to generate samples from a difficult-to-sample probability distribution by iteratively proposing new states and accepting or rejecting them with a certain probability. The transition from the current state A to a new state B satisfies a proposed symmetric transition function, meaning that the probability of transitioning from A to B is the same as transitioning from B to A. The Metropolis-Hastings Algorithm (M-H) is an extension of the Metropolis algorithm that allows the use of any proposal function, not just a symmetric one. This means that the probability of transitioning from A to B can be different from transitioning from B to A. By allowing asymmetric transition functions, the Metropolis-Hastings algorithm is more flexible and can be more efficient in sampling from complex probability distributions. The state space determined in this way forms the basis for the mathematical analysis of the system, allowing for the creation of higher-order statistics. Modelling the studied system using variable output parameters ultimately allows for the construction of a state diagram.

3.2 Modelling Purchase Flow Streams

In this article we will focus on the example of jackets made from four types of materials: cotton, leather, cashmere, and agave. Purchase decisions are influenced by a range of factors, which can be grouped into the following categories:

1. Economic Factors
   - Price: Cotton jackets are usually cheaper, making them more accessible to a wider range of consumers. Leather jackets are more expensive, limiting their purchase to those with higher incomes. Cashmere jackets are among the most expensive, classifying them as a luxury product. The price of agave fibre jackets varies, but due to the rarity of the material, they can be more expensive.
   - Buyer's Income: Buyers with higher incomes are more likely to purchase more expensive materials, such as leather and cashmere.
2. Demographic Factors
   - Age: Younger consumers may prefer cheaper and more common materials like cotton. Older consumers may be more inclined to purchase durable materials like leather and cashmere.
     - Gender: Men may more frequently choose leather jackets, whereas women might prefer cashmere due to its softness and elegance.

3. Cultural Factors

    - Fashion and Trends: Fashion plays a significant role in material choice. Fashion trends may promote a specific material in a given season. Marketing campaigns greatly influence the perception of a material as fashionable or luxurious.
    - Lifestyle: People leading active lifestyles may prefer cotton for its comfort and ease of care. Conversely, buyers who value elegance and prestige may choose leather or cashmere.

4. Ecological Factors. Environmental Awareness: Growing ecological awareness may prompt buyers to choose more environmentally friendly materials, such as organic cotton or agave fibres. Additionally, they may avoid leather due to concerns about animal welfare.

Taking into account the partial overlap of the characteristics of the above-mentioned groups with the characteristics of such buyer types as Fashion Enthusiasts, Tech-Savvy Consumers, Professional and Business Executives, Health-Conscious Consumers, Luxury Lifestyle Seekers Kotler and Armstrong (2010), Rogers (1983) and Euromonitor (2021), Chat GPT 4.0 estimated the share of these four groups in the global market as follows: Pragmatists - 36%; Extravagant - 17%; Prestige Seekers - 34%; Eco-conscious - 13%.

People enjoy variety, so although they have preferences, they also buy substitutes to meet their diverse expectations. For instance, when purchasing jackets or clothing more broadly, the shift from cotton may occur as more buyers seek ecological alternatives. In the case of leather, growing ethical awareness encourages buyers to avoid products made from this material. Additionally, the high price of leather may drive people to seek cheaper alternatives. The move away from cashmere to alternative materials may be due to its high price and fashion trends. Although agave fabric is ecological, its relatively small supply might prompt buyers to purchase alternative products.

Taking into account the above trends influencing the change of purchasing decisions, Chat GPT 4.0 estimated the potential redistribution of preferences and the flow of the customers stream between the market fractions, which is the result of random purchase decisions (Figure 1). The share of each fraction is 100%. Such data can be obtained from sales reports as well as through market condition surveys in individual market fractions. It is important to note that we are dealing with percentage shares rather than absolute values.

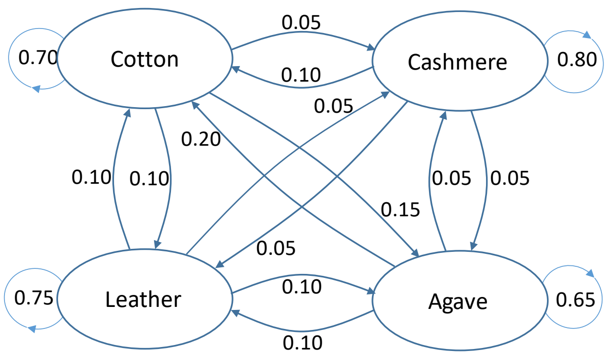

Figure 1: Model of potential flow of the purchase streams of jackets between market fractions

3.3 Modelling Buyers' Purchase Decisions

When making a purchase, customers take into account a number of functional, economic, and social features of these products, assigning different ranks to these features (Table 1).

Due to the preference for the highest-ranking features, four groups of buyers can be distinguished:

1. Pragmatist – These buyers choose cotton for its softness and breathability, making it comfortable to wear, especially in warm conditions. Cotton is relatively easy to wash and iron, and its versatility allows it to be used in various styles, from casual to more formal.

2. Extravagant – These buyers prefer leather jackets because of their elegant and luxurious look, which is highly valued in fashion. Leather is very durable and can last many years with proper care. Each leather product has a unique appearance due to natural variations in the leather, adding to its uniqueness.

Table 1: Ranks of features of four types of materials

Material	Breathability	Comfort	Durability	Warmth	Ease of Care	Affordability	Sustainability	Style/Aesthetic	Status Symbol
Cotton	5	5	3	2	5	5	4	4	2
Leather	3	4	5	4	3	2	3	5	5
Cashmere	4	5	3	5	4	1	2	5	5
Agave	2	3	4	2	3	4	5	3	3

The individual ranks mean: (1) Very Low, (2) Low, (3) Moderate, (4) High, (5) Very High.

Source: Own study based on: Peterman (2024), Sewport Support Team (2024a), Leather Naturally (2024), Endorfeen (2024), Sewport Support Team (2024b), Hulle, Kadole, and Katkar (2015).

3. Prestige Seeker – These buyers opt for cashmere as it is a symbol of high status. Cashmere is exceptionally soft and pleasant to the touch, making it one of the most luxurious materials. It is also lightweight and warm, which is especially valuable in colder months, and ensures good breathability.
4. Eco-conscious – These buyers choose agave because it is a fast-growing plant, making it a more sustainable material option. Agave fibres are very strong and durable, although less commonly used in clothing compared to other materials.

Taking into account the partial overlap of the characteristics of the above-mentioned groups with the characteristics of such buyer types as Fashion Enthusiasts, Tech-Savvy Consumers, Professional and Business Executives, Health-Conscious Consumers, Luxury Lifestyle Seekers Kotler and Armstrong (2010), Rogers (1983) and Euromonitor (2021), Chat GPT 4.0 estimated the share of these four groups in the global market as follows: Pragmatists - 36%; Extravagants - 17%; Prestige Seekers - 34%; Eco-conscious - 13%.

Despite preferring certain products, people also buy alternative products that meet their diverse needs. For jacket buyers, and more broadly clothing, the following external factors influence changes in purchase preferences: shifts in fashion trends, seasonal changes, effective marketing campaigns, economic downturn, income level, increasing ecological awareness, and corporate social responsibility initiatives. Under the influence of these factors, buyers make purchase decisions based on the following criteria:

1. Value for Money – 0.16 (Nielsen Global Survey, 2024)
2. Functionality and Maintenance – 0.14 (McKinsey & Company, 2024)
3. Comfort and Reliability – 0.14 (Cotton Incorporated, 2024)
4. Budget Sensitivity – 0.10 (Sheehan, 2023)
5. Luxury and Exclusivity – 0.09 (Bain & Company, 2023)
6. Statement and Uniqueness – 0.09 (Euromonitor International, 2021)
7. Status and Sophistication – 0.09 (Avery and Gupta, 2022)
8. Material Quality and Craftsmanship – 0.09 (MarketResearch.com, 2024)
9. Sustainability and Eco-friendliness – 0.04 (Nielsen, 2024)
10. Ethical Production and Sourcing – 0.04 (Ethical Consumer, 2024)
11. Natural and Organic Materials – 0.04 (Busalim, Fox, Lynn, 2022)

The weights of these criteria were proposed by Chat GPT 4.0 considering the importance of features of the four products for the types of buyers: Pragmatist, Extravagant, Prestige Seekers, and Eco-conscious. Using these weights and the impact of these criteria on purchase decisions, the weighted average purchase decisions for each buyer type were determined (Table 2).

Both the criteria and their weights as well as the impact on purchasing decisions can be determined by examining buyers' preferences and their tendency to purchase alternative products. The data in Table 2 corresponds to the following buyer profiles:

- PRAGmatist – Middle-income earners who prioritize practicality and cost-effectiveness. Often found in professions that require durability and comfort in clothing, such as teachers, office workers, and manual laborers. Generally middle-aged adults, around 30-50 years old equally distributed between male and female. They are typically from regions with moderate to warm climates, such as parts of North America, Europe, and Asia. They represent a significant portion of the population, likely around 30-40% of the market.

Table 2: Weight matrix of purchase decision of jacket buyers

Type of customer	Fabric	Fabric			
		Cotton	Leather	Cashmere	Agave
Pragmatist	Cotton	0,65	0,10	0,05	0,20
Extravagant	Leather	0,10	0,60	0,25	0,05
Prestige Seekers	Cashmere	0,05	0,20	0,70	0,05
Eco-conscious	Eco-conscious	0,30	0,05	0,10	0,55

- EXTRAvagant – Higher-income individuals who can afford luxury and statement pieces. Typically involved in high-paying jobs such as executives, artists, and celebrities. Younger to middle-aged adults, around 25-45 years old with a small predominance of men who often purchase leather jackets. They live in urban areas and regions with a strong fashion culture, such as major cities in the United States, Europe, and Asia. They represent smaller niche market, possibly around 10-15% of the market.
- PRESTige Seeker – Wealthy individuals who seek high-status and premium quality products. Common among high-ranking professionals like executives, lawyers, and entrepreneurs. They are older adults, typically 35-60 years old with predominance females, as cashmere is often associated with luxury women's fashion. They presumably live in affluent areas worldwide, such as upscale neighbourhoods in North America, Europe, and Asia. They represent a very niche market, likely around 5-10% of the market.
- ECO-conscious – Middle to upper-middle-income individuals who can afford to prioritize sustainability. They can be found among a variety of professions but with a higher representation among educators, healthcare professionals, and those in the environmental sector. They are younger to middle-aged adults, around 25-45 years old with small predominance of females who are often more active in sustainability efforts. They live in urban and suburban areas with a strong focus on sustainability, often found in parts of North America, Europe, and Oceania. They represent the growing segment, potentially around 15-20% of the market.

3.4 Simulation

Using the data on the flow of purchase streams (Figure 1) the potential demand for jackets made of cotton, leather, cashmere and agave was generated. The demand was determined using a method developed by us, based on the Markov Chain Monte Carlo (MCMC) and the Metropolis-Hastings (M-H) algorithm in 1000 steps of simulation (Figure 2). Each step can be interpreted, for example, as one day. Then this figure shows the fluctuation of the purchase stream of each product on subsequent days.

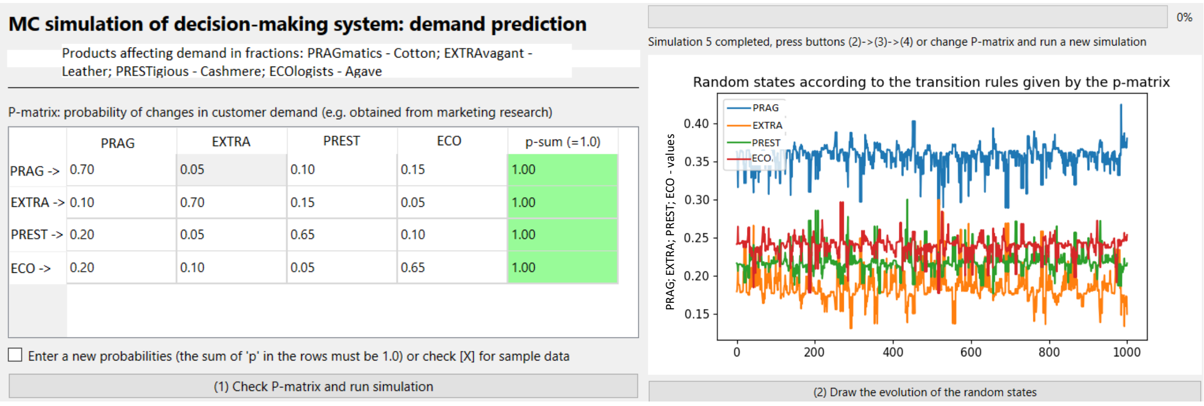

Figure 2: Probability of the flow of the purchase stream and the random distribution of this stream

Figure 3 shows simulated random states of the purchase stream of the four products under consideration. Each point on the horizontal axis of Figure 2 corresponds to one point in Figure 3. The coordinates of these points determine the proportions between the purchase streams of the products under consideration in the individual market fractions. Since the figure is made in 3D, one fraction (PREST) has been omitted. Despite this, the density of points in this figure shows well how the system is approaching the state represented by the stationary point, which is the expected state (averaged from 1000 iterations). This point corresponds to the proportion of purchases, amounting to 36%, 18%, 21% and 24%, respectively for the Pragmatist, Extravagant, Prestige Seeker, and Eco-conscious fractions. It is worth noting that there can be an infinite number of distributions (Figure 2), but for each of them the stationary point of the system will be the same.

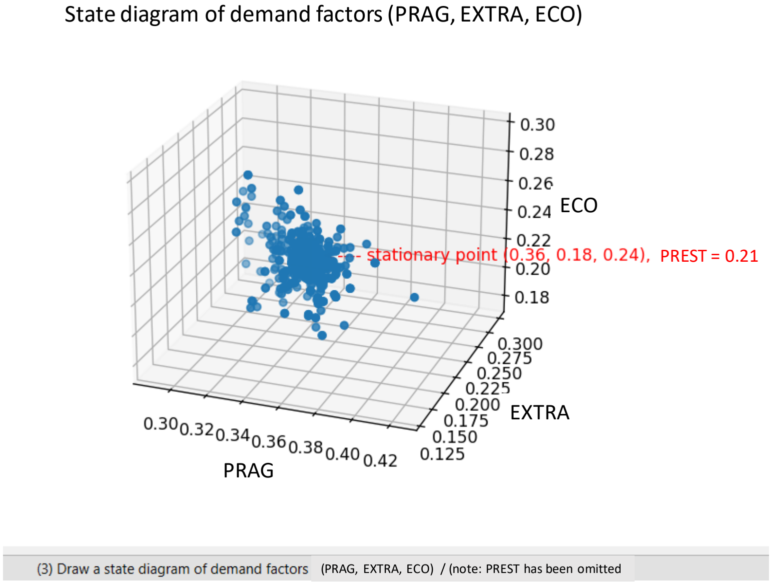

Figure 3: System state diagram in 1000 simulation steps

The stationary point shown in Figure 3 abstracts from the profile of buyers making purchases in the different market fractions. In each fraction, purchases are made by various buyers, not just those who prefer the product specific to that fraction. This is why there are flows between fractions, which in our case are shown in Figure 1 and also in the table in Figure 2. However, this does not mean that there is no buyer profile behind the stationary point. In our case, we identified this profile based on the purchasing criteria, their weights, and their impact on purchasing decisions, as presented in Section 3. 3, particularly in Table 2 and the table in Figure 4. Taking into account the profiles of Pragmatist, Extravagant, Prestige Seeker, and Eco-conscious buyers, the proportion between the purchase flows of the four considered types of products is 40%, 14%, 20%, and 26% respectively.

Matrix of demand factor preference weights for different types of buyers:

	w_PRAG	w_EXTRA	w_PREST	w_ECO	w-sum (=1.0)	type of buyers
MF_PRAG	0.65	0.10	0.05	0.20	1.00	Pragmatists
MF_EXTRA	0.10	0.60	0.25	0.05	1.00	Extravagant
MF_PREST	0.05	0.20	0.70	0.05	1.00	Prestigious
MF_ECO	0.30	0.05	0.10	0.55	1.00	Ecologists

(4) Draw a diagram of the market fraction (MF_FSR, MF_LS, MF_ES) /note: MF_PLC has been omitted

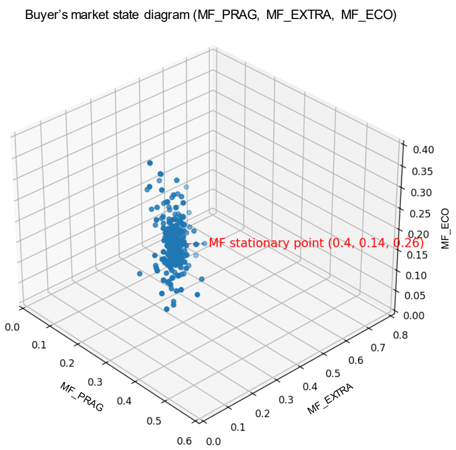

Figure 4: Stationary pint of the jackets buyers' market state

4. Discussion and Conclusions

In the problem that is the subject of this article, the opportunity is the gap between the proportion of products available on the market and the proportion expected by buyers. Taking into account: (1) the global production volume of cotton, leather, cashmere and agave fibre in 2023, (2) the consumption of these raw materials for clothing production, (3) the share of jacket production in clothing production, (4) the material consumption standards for the production of one jacket, it is possible to estimate the number of jackets made of cotton, leather, cashmere and agave produced on a global scale. The share of production of these products is 95.065%, 4.748%, 0.164%, 0.023%, respectively. The summary of the expected and available shares and thus the opportunity constituting the demand gap is presented in Table 3.

Table 3: Demand gap in the jacket segment

Fabric	Expected demand	Estimated current supply	Gap	Opportunity
Cotton	40,00%	95,07%	-55,07%	
Leather	14,00%	4,75%	9,25%	Increase production
Cashmere	20,00%	0,16%	19,84%	Increase production
Agave	26,00%	0,02%	25,98%	Increase production

In order to define the profile of buyers, we have formulated the following criteria: financial status, type of work, education, living conditions, gender, age, and potential population. According to these criteria, based on the following reports: Statista. "Apparel Market Report"; Nielsen, "Consumer Research Report"; U.S. Bureau of Labor Statistics, "Consumer Expenditure Survey"; Urban Institute, "Urban and Suburban Population Reports"; Verified Market Reports, "Formal Wear Market Size, Share and Trends"; Market Research.com, "Trusted market research and industry insights", Chat GPT 4.0 has developed demographic profiles of current and potential jacket buyers. The current supply of jackets is targeted to buyers with middle financial status who perform jobs that require comfortable clothing, like teachers, administrative workers, and service sectors. They live in cities and suburbs and have access to a wide range of clothing stores and shopping centres. These are both men and women with slight predominance of women, who might be more interested in clothing variety all the specified criteria. On the other hand, buyers with expectations consistent with the results of our simulation have a higher financial status and are entrepreneurs, professionals in technology, creative industries, or managers. They have higher education. They are residents of large cities and metropolises with access to stores offering luxury and ecological clothing products. These are people aged 30-45, mostly women, who are more likely to lead in eco-movements and sustainable fashion. This population constitutes 5-10% of buyers of jackets. Promotion should be directed to this group to take advantage of the opportunity of unmet demand.

The methods and AI algorithms we employed yielded results that enable the identification of opportunities for producers of alternative products. This opportunity arises from the existence of unfulfilled demand for certain products. In our case, this applies to jackets made from leather, and especially from cashmere and agave fibres. For these latter two, the differences between the simulated demand and the analytically estimated supply are very significant. Their rational reduction requires market segmentation and identification of segments whose demand is not satisfied. In our case, the basis for segmentation is the demographic profile of buyers. Comparing the buyer profiles for the simulated and actual proportions of purchase flows for each product allows us to identify the customer types whose satisfaction of needs leads to the use of a market opportunity.

Our analysis of the global market case confirmed that the challenge of discovering opportunities arising from unmet demand for alternative products and shaping a product portfolio to balance this demand can be effectively addressed using MCMC methods, particularly the Metropolis-Hastings algorithms. This method can be employed even when data is limited to the probability of purchase flow between market fractions corresponding to these products. Such data can be obtained from sales reports or through conducting marketing research. This characteristic makes the method particularly useful for SMEs, which typically do not employ AI methods based on Big Data. This is possible because the method generates its own dataset based on the previously defined purchase flow matrix. A significant modification we introduced is the consideration of purchase decision weights, which means taking into account the buyer profile. This provides data for market segmentation and thus the basis for identifying segments with unmet demand, creating a market opportunity.

While MCMC and M-H algorithms are fully adequate for identifying opportunities with defined probabilities of purchase flow between market fractions, the reliability of the solutions obtained depends on the accuracy of the data on these flows and the weights of purchase decisions. The data in the purchase flow matrix is relatively easy to obtain, especially for SMEs. However, determining the weights of purchase decisions requires a multi-criteria assessment of the factors influencing buyers. Our experience indicates that these weights are correlated with the purchase flow, but the mechanism of this dependency is not defined. This issue is the subject of our ongoing research because even small changes in weights significantly impact the simulated production portfolio.

References

Arulkumaran, K., Deisenroth, M. P., Brundage, M., & Bharath, A. A. (2017) „Deep reinforcement learning: A brief survey", *IEEE Signal Processing Magazine*, Vol *34* No.6, pp 26-38.

Avery, J. and Gupta, S. (2022) "Farfetch: Digital Transformation for Luxury Brands." *Harvard Business School Teaching Note 522-061*, https://www.hbs.edu/faculty/Pages/item.aspx?num=61654 (access in May 2024).

Bahoo, S., Cucculelli, M., Goga, X. (2024) „Artificial intelligence in Finance: a comprehensive review through bibliometric and content analysis", *SN Bus Econ* Vol 4, No. 2, p 2-46.

Bain & Company (2023) "Report: Luxury Goods Worldwide Market Study", https://www.bain.com/about/media-center/press-releases/2023/global-luxury-goods-market-accelerated-after-record-2022-and-is-set-for-further-growth--despite-slowing-momentum-on-economic-warning-signs/

Baum L. E., Petrie T., (1966), „Statistical Interference for Probabilistic Functions of Finite State Markov Chains", *The Annals of Mathematical Statistics*, Vol 37, No. 6, pp 1554–1563.

Box, G. E. and Tiao, G. C. (2011) *Bayesian inference in statistical analysis*, John Wiley & Sons, New York.

Briffaut J. P., Lallement P. (2010) „Volatility Forecasting of Market Demand as Aids for Planning Manufacturing Activities", *Service Science & Management*, No. 3, pp 383–389.

Busalim, A., Fox, G., Lynn, T. (2022) "A systematic literature review and future research agenda", [online], International Journal of Customer Studies, 2022, No. 46 pp 1804–1828, file:///C:/Users/Lenovo/Downloads/Consumer_behavior_in_sustainable_fashion_A_systema.pdf

Cappé O., Moulines E., Rydén T., (2005) *Inference in Hidden Markov Models*, Springer, New York.

Cesari, R., and Cremonini, D. (2003) „Benchmarking, portfolio insurance and technical analysis: a Monte Carlo comparison of dynamic strategies of asset allocation", *Journal of Economic Dynamics and Control*, Vol *27*, No. 6, pp 987-1011.

Chib, S. (2001) „Markov chain Monte Carlo methods: computation and inferencje". *Handbook of econometrics*, Vol 5, pp 3569-3649.

Cotton Incorporated (2024) "Cotton Incorporated Consumer Survey", *Cotton Incorporated Lifestyle Monitor*, https://www.cottoninc.com (Access in May 2024).

CyberPublicity (2024), "Fashion Enthusiasts", https://www.cyberpublicity.com/programmatic-advertising/hobbies-passions/fashion-enthusiasts/) (access in May 2024).

Duan, J., Yu, S., Tan, H. L., Zhu, H., & Tan, C. (2022) „A survey of embodied ai: From simulators to research tasks", *IEEE Transactions on Emerging Topics in Computational Intelligence*, Vol 6, No. 2, pp 230-244.

Ellefsen, A. P. T., Oleśków-Szłapka, J., Pawłowski, G., & Toboła, A. (2019) „Striving for excellence in AI implementation: AI maturity model framework and preliminary research results". *LogForum*, Vol 15, No. 3.

Endorfeen (2024) "Cashmere – Understanding The Impact of That Luxury Fabric", https://endorfeen.com/cashmere-understanding (access in May 2024).

Ethical Consumer (2024) "Fashion and Clothing Guide"; https://www.ethicalconsumer.org/fashion-clothing (Access in May 2024)

Euromonitor International (2021) "Global Consumer Types: Who They Are and How They Live", *Euromonitor International*, July 2021, www.euromonitor.com (access in May 2024).

Fülöp, J. (2005)." Introduction to decision making methods", In BDEI-3 workshop, Washington*,* pp. 1-15.

Gary, M. S., Kunc, M., Morecroft, J. D., & Rockart, S. F. (2008) „System dynamics and strategy", *System Dynamics Review: The Journal of the System Dynamics Society*, Vol 24, No. 4, pp 407-429.

Ghahramani, Z. (2015) „Probabilistic machine learning and artificial intelligence", *Nature*, Vol 521, pp 452-459.

Hamilton J. D. (1990) „Analysis of Time Series Subject to Changes in Regime", *Journal of Econometrics*, Vol 45, No. 1–2, pp 39–70.

Hastings, W. K. (1970) „Monte Carlo sampling methods using Markov chains and their applications", *Biometrika* Vol 57, No. 1, p 97-109.

Hulle, A., Kadole, P., and Katkar, P. (2015) "Agave Americana Leaf Fibers", *Fibers*, No. 3, pp 64-75.

Jha, S., Gong, D., Wang, X., Turner, R. E., & Yao, L. (2022) „The neural process family: Survey, applications and perspectives", *arXiv preprint arXiv:2209.00517*.

Klug F., (2011), „Automotive Supply Chain Logistics: Container Demand Planning using Monte Carlo Simulation", *International Journal of Automotive Technology and Management*, Vol 11, No. 3, pp 254–268

Kotler, P., Armstrong, G. (2010) *Principles of Marketing*, Prentice Hall, Saddle River.

Kroese, D. P. and Rubinstein, R. Y. (2012) „Monte carlo methods", *Wiley Interdisciplinary Reviews: Computational Statistics*, Vol 4, No. 1, pp 48-58.

Kurtz, T. G. (1981) „The central limit theorem for Markov chains". *The Annals of Probability*, Vol 9, No. 4, pp 557-560.
Leather Naturally (2024) "Benefits of leather", www.leathernaturally.org (access in May 2024).
Marinchak, C., Forrest, E. and Hoanca, B. (2018) "Artificial intelligence: redefining marketing management and the customer experience", *International Journal of E-Entrepreneurship and Innovation*, Vol. 8 No. 2, pp 14-24.
MarketResearch.com (2024) "Report: Understanding Consumer Preferences in Apparel", https://www.marketresearch.com (Access in May 2024)
McKinsey & Company (2024), "Report: The State of Fashion 2024", *McKinsey & Company*, https://www.mckinsey.com/industries/retail/our-insights/state-of-fashion, (Access ib May 2024).
Metropolis N., & Ulam S. (1949) „The Monte Carlo metod*", Journal of the American Statistical Association* Vol 44, pp 335-341
Mojtahedi, S. M. H., Mousavi, S. M., & Makui, A. (2010) „Project risk identification and assessment simultaneously using multi-attribute group decision making technique", *Safety science*, Vol 48, No. 4, 499-507.
Nemhauser, G.L., Rinnoy Kan, A.H.G. and Todd, M.J. (1989), *Handbooks in Operations Research and Management Science: Volume 1 Optimization*, North-Holland, Amsterdam.
Newbold, P., Carlson, W. L., & Thorne, B. M. (2013). *Statistics for business and economics*. Pearson, London.
Nguyen N., Nguyen D. (2015) „Hidden Markov Model for Stock Selection", *Risks*, Vol 3, No. 4, pp 455–473.
Nielsen (2024) "2023 ESG Report", https://microsites.nielsen.com/globalresponsibilityreport (May 2024)
Nielsen Global Survey (2024), **"**Report: Nielsen Global Survey of Consumer Shopping Behavior", https://www.mintel.com/insights/consumer-research/global-consumer-trends (Access in May 2024)
Peterman, W. (2024) "The Advantages of Cotton Clothing", *Livestrong.com*, www.livestrong.com (May 2024).
Platon, V., and Constantinescu, A. (2014) „Monte Carlo Method in risk analysis for investment projects", *Procedia Economics and Finance*, Vol 15, pp 393-400.
Provost, F. & Fawcett, T. (2013) „Data science and its relationship to big data and data-driven decision ma king", *Big data*, Vol 1, No. 1, pp 51-59.
Rippe R., Wilkinson W., Morrison D., (1976) „Industrial Market Forecasting with Anticipations Data", *Management Science*, Vol 22, No. 6, pp 639–651.
Rogers, A.M. (1983) *Diffusion of Innovations,* The Free Press, New York.
Sewport Support Team (2024a) "What is Cotton Fabric: Properties, How its Made and Where", *Sewport*, https://sewport.com/fabrics-directory/cotton-fabric (access in May 2024).
Sewport Support Team (2024b) "What is Cashmere Fabric: Properties, How its Made and Where", *Sewport*, https://sewport.com/fabrics-directory/cotton-fabric (access in May 2024).
Sheehan, E. (2023) "Global Powers of Retailing: Revenue growth and continued focus on sustainability", Deloitte, February 2023, https://www2.deloitte.com/content/dam/Deloitte/at/Documents/presse/at-deloitte-global-powers-of-retailing-2023 (Access in May 2024).
Stone M., Aravopoulou E., Ekinci Y.,Evans G. ,Hobbs M., Labib A., Laughlin P. , Machtynger J., Machtynger L. (2020), „Artificial intelligence (AI) in strategic marketing decision-making: a research agenda", *The Bottom Line*, Vol. 33 No. 2, pp. 183-200 .
Sutton, R. S., & Barto, A. G. (2018), *Reinforcement learning: An introduction*. MIT Press, Cambridge.
Time & Space Media (2024) "Market Segmentation in Fashion: Tailoring Success for Today's Audiences", https://timespacemedia.com/market-segmentation-in-fashion-tailoring-success-for-todays-audiences (access in May 2024).
Vodopivec, T., Samothrakis, S., & Ster, B. (2017) „On monte carlo tree search and reinforcement learning", *Journal of Artificial Intelligence Research*, Vol 60, 881-936.
Yau, K. L. A., Saad, N. M., & Chong, Y. W. (2021) „Artificial intelligence marketing (AIM) for enhancing customer relationships", *Applied Sciences*, Vol 11, No. 18, 8562.