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THE USE OF ARTIFICIAL INTELLIGENCE IN AIDING THE STRATEGIC DECISIONS OF BUSINESS LEADERS IN A VUCA ENVIRONMENT

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Abstract: *The ability to make decisions in crisis situations has always been an extremely important quality for leadership. Moreover, the ability to make good decisions is the element that makes the difference between a company that thrives and one that fails. For a long time, it has been assumed that this decision-making ability is exclusively human orientated, and it relies on available data and intuition. The purpose of this article is to show how, in the years ahead, artificial intelligence can be used to make informed and predictive decisions.*

Design thinking programmes and agile working methods are already being used to improve decision-making processes, but given the VUCA environment we live in, proper decisions require a much more complex information base, which can be provided by artificial intelligence. This article will show how specific predictors can be combined to create predefined sets that help determine key information for management decisions, but more importantly, what kind of predictors can and should be considered. Too many predictors complicate the analysis process and can sabotage the result, while a small number of predictors can exclude the most important factors in the area under study. Therefore, the proper selection of predictors is very important and depends on the macroeconomic and microeconomic knowledge of the analyst processing the data. Predictor analysis is performed using artificial intelligence programs so that the decisions generated take into account a much larger number of factors than the human brain can process. The analysis is based on scenarios that span a longer period of time and takes into account the interdependence between the causative factors. Business decisions are already made based on various predictors or parameters, but the use of artificial intelligence can significantly improve the accuracy and reliability of decisions. However, artificial intelligence alone does not *guarantee high prediction accuracy; the business knowledge and skills of the programmer are a key factor in achieving high accuracy. To reduce the risk of poor accuracy even though artificial intelligence is used for prediction, we have developed a scheme for selecting the right parameters. In addition, the use of artificial intelligence in this area will enhance business managers' understanding of the impact of various predictive factors on their business.*

JEL classification: C32, C53, M21

Key words: artificial intelligence, forecasting, machine learning, business decision making

1. INTRODUCTION

Throughout history, people have experienced sudden events, crises, revolutions, and inventions that have greatly impacted their lives. However, the term VUCA was only coined after the Cold War and has become even more relevant following recent global events. It is important to note that current events are not necessarily more severe or revolutionary than those of the past. What makes VUCA a crucial concept is the frequency, diversity, duration, and interconnectedness of these events. Nowadays, it is harder to determine the cause and effect of various events and their combined effects can lead to unexpected outcomes. This makes forecasting for businesses and industries less reliable, and multiple scenarios must be considered.

Companies need to go beyond traditional evaluation methods to effectively manage Big Data. The solution lies in utilizing data-based decision-making systems, reacting in real-time to stimuli, analyzing market responses to actions, and considering a global perspective. Artificial intelligence is capable of analyzing vast amounts of data and identifying connections that may not be obvious to humans. This allows for more precise management decisions and reduces the risk of failure.

With the help of artificial intelligence, huge amounts of data can be analyzed and unexpected connections can be discovered. This analysis can lead to more reliable management decisions that are closer to reality, with less risk and a higher chance of success.

Even though machines handle data analysis, collecting and interpreting data, evaluating results and training, AI platforms require specialized human input. An algorithm based solely on artificial intelligence does not guarantee good outcomes. This study investigates the process of selecting appropriate predictors in the VUCA context to achieve successful results with AI.

2. LITERATURE REVIEW

The acronym VUCA originated from the U.S. Army War College in the 1990s, following the aftermath of the Cold War (Kingsinger & Walch, 2012). It stands for "volatility," "uncertainty," "complexity," and "ambiguity," which are all aspects that have increased in frequency and intensity in recent years. With the advent of digitalization, connectivity, trade liberalization, health crises, and political events, VUCA has taken on new meanings and has become a more prominent topic in literature (Reeves, 2012).

The current world is governed by the VUCA phenomenon, which means that businesses and individuals are constantly exposed to change at an accelerated rate. This has become the new norm in the capitalist world, and coping mechanisms have been developed to deal with it (Cliss, 2020). Even during times of economic and political crises, natural disasters, or power shifts, patterns of routine, seasonality, and cyclicity have been identified. As a result, people and businesses have become more tolerant of uncertainty and have learned to accept it as a routine in the midst of chaos (Codreanu, 2016).

The BREXIT referendum of 2016 marked the beginning of a period of instability and uncertainty. It triggered a chain of events, including the election of Donald Trump, global economic growth, climate change, North Korea's nuclear testing (Lindsay, 2017), the US-China trade war, devastating wildfires in the Amazon and Australia, the COVID-19 pandemic, fluctuating oil prices, the death of George Floyd and subsequent racism protests (Lindsay, 2020), Joe Biden's election, migration crises, Iran's nuclear program, the Taliban's return to power, supply chain disruptions, Russia's invasion of Ukraine (Lindsay, 2021), US-China tensions, rising inflation, the easing of COVID-19 restrictions, humanitarian crises, political turmoil, natural disasters, and a looming economic crisis (Lindsay, 2022).

The events mentioned earlier had a profound impact on every aspect of life. We often try to identify the causes of specific effects or justify trends. However, the VUCA world is too complex for the human brain to comprehend fully. Even those with a global perspective cannot keep track of all the connections, interdependencies, effects, and consequences. Even if this were possible, it would not be practical to predict the next VUCA episode in time (Nikseresht, *et al.,* 2022). To make better management decisions, analyzing and evaluating the events that influence a business quickly is possible with artificial intelligence.

The impact of global events on businesses is widely recognized and can be significant in today's complex and unpredictable world. The factors affecting businesses are diverse and constantly evolving, as noted by Murugan et al. (2020). These events span various industries, including technology and tourism.

The COVID-19 pandemic has brought dramatic changes to the world economy. The tourism industry has been particularly hard hit, with states of emergency, travel restrictions, and home isolation orders having immediate and direct consequences. The pandemic has affected 320 million people worldwide who earn their livelihood from tourism. The effects on the industry's workforce have been especially severe, with 24% of workers being contractors and unable to claim unemployment benefits when activity levels decline. Moreover, tourism companies employ a high proportion of people from vulnerable groups, such as women (59%) and young people (13% of those aged 15-24), with limited access to alternative employment opportunities (Eurostat, 2021). The COVID-19 pandemic has made tourism forecasts unrealistic.

During the pandemic, many people in the tourism sector turned to vocational retraining to support themselves. However, it's unclear where they migrated to and what effects this had on other sectors. Additionally, personnel crises in tourism and high transportation costs discouraged travel after the pandemic. It is difficult to determine to what extent these factors contributed to a decrease in travel, as there were also other factors such as the Russian-Ukrainian war and medical concerns. Finally, the effects of various events on technology companies on the sector are unclear, as there are many intertwined factors that cannot be easily measured or delimited.

One example of the impact of COVID-19 is the increase in home-based work. This shift to online work was mainly possible for companies in the technology field, and it had various effects on different industries. For instance, it reduced workspaces, impacted the fashion, luxury, and automobile industries, and increased focus on mental health, self-care, and sports. The real estate market for living spaces and interior design or renovations was also affected (Flanagen, 2019). Working from home led to some jobs being given up, while some technologies advanced quickly, leading to workforce replacement with applications. However, remote work teams sometimes experienced communication problems that generated bugs and technical issues, which were costly for businesses (Brueckner, *et al.,* 2021). The sudden surge in demand attracted labor from other fields, which led to an increase in wages. However, relaxing COVID measures and returning to the original lifestyle caused a salary boom crisis, leading to a high percentage of employed people getting fired. Business decisions taken during this period also affected the chip market, which, in turn, had an impact on the automobile and IT components market and every other field of activity. When combined with other global events, it becomes challenging to connect the causes with the effects and find proper solutions.

At this point, the assistance of artificial intelligence comes into play. With the help of AI, large quantities of data can be analyzed quickly. AI can recognize connections between seemingly unrelated factors and determine how certain events affect different aspects of a business. Artificial intelligence can continuously adjust to changes, learn, and select the most accurate results possible (O'Leary, 2013). This allows for effective managerial decisions to be made even in a VUCA environment.

If a VUCA event, such as the COVID-19 pandemic, is entirely new to a business context, even AI cannot accurately predict its impact or correlate its factors on the spot. However, AI is built on adaptive intelligence, which means that if the algorithm detects a significant change, it will adjust to the new circumstances and create new algorithms based on the new data it considers more relevant and essential than past history (Zhou, 2021). If a similar VUCA event occurs in the future, the AI algorithm will recognize the similarities and adapt much faster to the new context, making decisions based on past experiences. For example, if there were to be a new pandemic, the AI would use the COVID-19 pandemic as a basis for adapting to the new trend. Similarly, when the Russian-Ukrainian war broke out, AI relied on previous data about conflicts between the two states until it recalibrated to the new situation.

To run an artificial intelligence program, one needs technological knowledge as well as knowledge of economics, management, psychology, and extensive research to prepare and interpret data. The accuracy of the results increases with the amount of data entered into the AI algorithm. The input data can be divided into two categories:

- Firstly, the data received from the company for analysis, such as sales, revenues, employees, customers, marketing campaigns, promotions, demand, supply chain, P&L, etc. The more historical data is available, the better it is (at least two and a half years, but longer is preferred). The data must be complete, and anomalies and outliers should be justified (Narayan & Tan, 2019).
- Secondly, the introduced predictors, increase the possibility of finding correlations between events and provide more data about the forecast. There is no limit to the number of predictors that can be introduced. However, an excessive number of predictors can increase the data processing period, require more powerful processors, and create random correlations, which can negatively impact management decisions (Stock & Watson, 2006). Therefore, it is necessary to choose enough predictors, but not more than necessary for the chosen domain, the macroeconomic context, and VUCA. Qualitative and quantitative studies identify the predictors specific to the business field, along with macroeconomic and VUCA factors that must be considered (Mincer & Zarnowitz, 1969) (Bai & Ng, 2008).

With complete and relevant company data covering an extended period, and well-chosen predictors that consider various scenarios, artificial intelligence-powered programs can generate scenarios. Entrepreneurs can utilize these programs to identify and evaluate the potential consequences of their business decisions, enabling them to take necessary steps in advance. This helps them consider important factors that may be overlooked without the assistance of such technology.

3. METHODOLOGY

In the world of technology, artificial intelligence comes in various forms and serves different purposes. But what does it mean in the context of forecasting? How is it developed and how does it operate? In the proposed forecasting platform program, the author has combined and adapted various algorithms that have already proven useful in other fields. The uniqueness of this algorithm lies in its ability to choose the most suitable forecast method for a given business situation. Like pieces of a puzzle, the algorithm combines different methods to achieve the most accurate results.

Business leaders face various decisions that vary based on their company's nature and market size. Our study examines explicitly medium to large companies and one crucial decision that leaders must make: the supply chain.

The supply chain plays a crucial role in a company's success, and any disruptions at this level can lead to financial losses, decreased trust in the company, misallocation of resources, and additional costs. Having an excessive amount of inventory can also result in increased storage costs, overcrowding of spaces, damage to goods, and logistical and financial challenges. It's important to maintain a balanced supply chain to avoid these potential issues.

Business leaders traditionally use simple Excel formulas, similar programs, or expert experience to find the supply chain balance line.

Due to the volatile, uncertain, complex, and ambiguous (VUCA) events, traditional predictions are no longer reliable. As a result, companies may end up with excess inventory or run out of stock. To avoid such extreme situations, many companies choose to order a larger inventory, which leads to additional costs and potential supply chain disruptions, creating a new set of problems to solve.

We suggest utilizing AI programs to enhance forecasting accuracy and optimize stock levels. Our AI-based algorithm has been implemented in a Romanian distribution company to test our proposal. In the subsequent section, we will elaborate on our findings.

To gather information about the decision-making process in the construction materials distribution company, we conducted a thorough interview with their CEO. Through this interview, we discovered that the most significant challenge is optimizing stock decisions. Storing construction materials is costly due to the need for ample space and the expiration dates of many materials. Additionally, the volatile market makes predictions difficult, resulting in either an excess of stock or an inability to fulfill larger orders. The second issue identified was the long lead time, which requires planning for future resources.

Based on these requirements, we formulated the following research inquiries: Is it possible to enhance demand forecasting accuracy by 10% or more with the help of artificial intelligence? Can we decrease stocks by 15% or more to optimize storage and fulfill larger orders? To address these questions, the authors employed a primary research method which includes gathering and analyzing data from primary sources, particularly from the ERP of the building materials distribution firm.

This company is quite large, with an annual turnover of over 40 million euros. It is considered one of the top companies in Romania in terms of its profile and operates in multiple subsidiaries throughout the country. They have given us access to the primary monthly logistics data for approximately 4,000 products from their portfolio, covering the period from 2019 until Q2 of 2023.

With the help of the R programming program, our goal was to develop a more efficient stock forecasting and optimization system than what the company currently uses using traditional forecasting methods. As the distribution company used to rely on a fixed set of Excel formulas to predict their orders to suppliers. These formulas were then modified by an expert with relevant experience. At that time, this combination of Excel formulas and expert input provided an accurate prediction for the company since the business environment was stable.

However, with the emergence of VUCA (volatile, uncertain, complex, ambiguous) events, the accuracy of these predictions began to decline considerably, leading to a surge in stock levels.

4. RESULTS

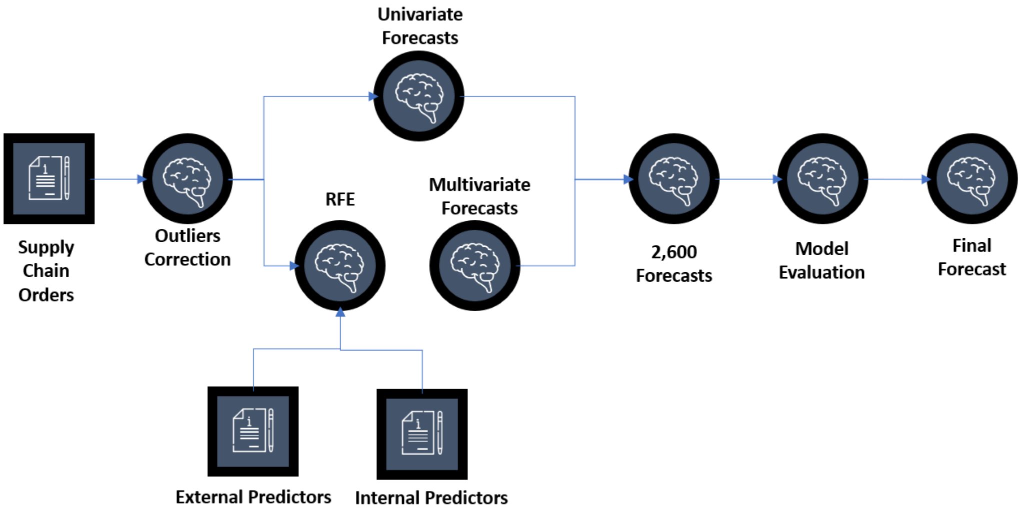
4.1 Description of the forecasting platform

Our forecasting program utilizes over 100 distinct automatic forecasting algorithms to accurately predict product demand. These algorithms range from simple ones like naïve and mean forecast, to advanced ones based on machine learning such as XGBoost, Catboost, and LSTM. By using multiple algorithms, we can account for the unique behaviors of the 4000 products in our portfolio and ensure high accuracy in our predictions.

The forecasting platform comprises three distinct components (refer to Figure 1):

- Data ingestion and data engineering/corrections. This stage refers to the correction of errors and omissions from the data received in raw form from the company.
- Forecasting using a blend of machine learning and statistical techniques (such as ARIMA, Prophet, XGBoost, Lightgbm, etc.). Following this step, the platform produces around 2,600 distinct predicted data points for each time series.
- Selecting the most accurate forecast via a cross-validation method that covers the past two years.

Fig 1. The forecasting platform architecture



Source: The author's contribution.

4.2 **Data ingestion and data engineering/corrections**

To begin forecasting, the first step is to upload the dataset containing historical demand at an article level onto the platform. Once this is done, it is crucial to assess the data and perform the following checks:

- Percentage of outliers: Determine the number of data points in the dataset that are considered outliers, meaning they have values that are either too high or too low compared to the rest of the dataset. In our case, 36% of the data points are outliers, which is a significant percentage.
- Categorization of datapoints: Since we are dealing with supply chain data, it is important to have a clear picture of the current situation of the SKUs. Most companies use the ABC methodology to categorize their SKUs, but we believe that a more comprehensive analysis is necessary. Thus, we have added two dimensions to our assessment: demand and time patterns. Based on these dimensions, we have created four categories for our dataset:
    - volatile demand and regularly sold SKUs;
    - volatile demand and irregularly sold SKUs;
    - stable demand and regularly sold SKUs;
    - stable demand and irregularly sold SKUs;

- In our case, we found that most of the SKUs had stable demand and were sold regularly. Although 36% of the data points were outliers, we could still use an algorithm to correct our dataset.

- Dataset corrections for outliers and missing values: This step corrects the outliers, which is essential in improving the forecasting model's performance.

4.3 Machine Learning forecasting methodologies

Our forecasting platform comprises of two methodologies: univariate and multivariate forecasting (refer to Figure 1). The former only considers historical data and all the relevant information that can be derived from it, such as trends, seasonality, noise, lags, and date engineering. It works well when the data is predictable and stable, and has improved our forecasting accuracy by 5% compared to previously used methods by the company. However, we knew that incorporating multivariate forecasting would yield better results. This method considers past data, as well as various predictors, to determine their impact on the data being forecasted. We have categorized these predictors into two groups to facilitate tracking their influence on the business:

- Internal predictors: Factors that affect the company's supply chain, such as marketing campaigns, strategic business decisions, and new customer acquisitions.
- External predictors: Factors that affect the supply chain outside the company, such as unemployment rates, purchasing power, and GDP.

Collecting external predictors from sources like Moody's is usually straightforward. However, acquiring internal predictors can be difficult as it depends on how each company gathers, manages, and displays its data. While working on our multivariate forecasting, we faced two main challenges with internal predictors. Some critical data was absent, or it needed encoding to work with our AI-based forecasting algorithm.

Regarding the first issue, we were unable to find a short-term solution. However, for the second issue, we have implemented various traditional data encoding techniques such as onehot encoding, label encoding, ordinal encoding, binary encoding, scale and normalization, and feature scaling.

We began using the multivariate forecasting methodology after obtaining the external and internal predictors. Our first step was to normalize and scale all of the predictors. Next, we focused on feature selection, which is a crucial step in using artificial intelligence algorithms. Feature selection involves choosing the most relevant predictors from the original set of predictors to maximize forecast accuracy. There are various methods for feature selection, including filter methods such as Pearson Correlation and Chi-Square Test, as well as wrapper methods such as Forward Selection, Backward Elimination, and Recursive Feature Elimination (RFE).
Our testing has shown that the recursive feature elimination method produced the most favorable outcomes. This algorithm eliminates less significant predictors and generates a subset of predictors that enhances the accuracy of forecasting. It accomplishes this by utilizing a machine learning algorithm to rank the significance of the predictors that are being analyzed.

Besides improving forecast accuracy, RFE identifies key predictors affecting a business. We found that the construction sector and internal decisions impacted the company we analyzed.

4.4 Selection of the best forecast

The platform produces approximately 2,600 distinct forecasts for every time series. Therefore, it is crucial to select the most appropriate forecast for each specific product. To accomplish this, we utilized a cross-validation process spanning the past two years. Since we are analyzing time series data (demand over time), we must account for the temporal nature of the dataset in addition to the standard k-fold cross-validation procedure. As a result, we implemented TSCV (time-series cross-validation), which involves sequential splits of the data instead of random ones.

In our study, we found that the most effective techniques for predicting future trends were those that used a combination of machine learning algorithms and statistical methods, known as multivariate methods. This is in line with current industry standards, as these methods have been recognized as the most advanced for time-series forecasting over the past few years.

Our new forecasting algorithm improved accuracy by 20% (refer to Table 1). This improved accuracy also lead to a reduction of the stocks by 32%.

Table 1. Forecasting accuracy for the tested period of 24 months (July 2021 – July-2023)

SKU Category	Traditional Forecasting Accuracy	Machine Learning Forecasting Accuracy	Improvement
A	88%	97%	+9%
B	62%	83%	+21%
C	35%	65%	+30%
Average	**62%**	**82%**	**+20%**

Source: The author's calculations.

Undoubtedly, utilizing an AI-based forecasting platform can enhance the accuracy of supply chain forecasting and decrease excess inventory. However, in reality, it is uncommon to have access to all necessary data. As a result, the input of a subject matter expert is still required to address forecast deviations that predictors do not account for.

5. CONCLUSIONS

After implementing an artificial intelligence program for making business decisions in supply chain stock optimization, we observed the following:

- collecting complete, precise, legible, and constant data remains a challenge for companies, even larger ones when using it as valid input data for more detailed analysis;
- external predictors greatly influence the accuracy of results, but obtaining them online can lead to errors, need for updates, intentional influence, or unavailability, causing errors;

- the person responsible for processing data must have a thorough understanding of the business profile and be capable of assessing the relevance of the predictors used;
- despite gaps in data collection, forecasting programs and machine learning algorithms can adjust, normalize, and complete data;
- if a forecasting module works for one type of business, it does not necessarily mean that it will work equally well for other businesses, even if they are from similar fields;
- within the same company, different products and business lines may require different forecasting methods;
- although a certain product may be accurately forecasted using a specific method for a particular time period, it's important to note that other methods may be more effective during different periods. Therefore, it's necessary to update the program periodically;
- artificial intelligence-based forecasting methods can adapt to unforeseen market events and remain reliable in crises, making them a more viable source for decision-making;
- compared to classical calculation methods, AI programs can offer 20% higher accuracy;
- the new program reduced inventories by 32%, unlocking costs and increasing liquidity;
- however, human reluctance to trust the AI-generated results caused problems, with some business leaders relying on instinct and keeping stocks unnecessarily high.

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REFERENCES

1. Bai, J. & Ng, S., 2008. Forecasting economic time series using targeted predictors. *Journal of Econometrics,* 146(2), pp. 304-317.
2. Batra, R., Ahuvia, A. & Bagozzi, R., 2012. Brand love. *Journal of Marketing,* 76(2), pp. 1-16.
3. Blumberg, K., 2008. Internationalisation in adventure tourism: the mobility of people, products and innovations. In: *International Business and Tourism.* s.l.:Routledge.

4. Brueckner, J., Kahn, M. & Lin, G., 2021. A New Spatial Hedonic Equilibrium in the Emerging Work-from-Home Economy?. *National Bureau of Economic Research.*
5. Carvache-Franco, M. et al., 2022. Motivations and Loyalty of the Demand for Adventure Tourism as Sustainable Travel. *ustainability ,* 14(14).
6. Cliss, T., 2020. Decision-making during VUCA crises: Insights from the 2017 Northern California firestorm. *Journal of Business Continuity & Emergency Planning,* 14(1), pp. 82-94.
7. Codreanu, A., 2016. A VUCA Action Framework for a VUCA Environment. Leadership Challenges and Solutions. *Social Sciences, Economy, Education, Business Economy / Management,* 7(2), pp. 31-38.
8. Damkier, S. & Ozer, S., 2022. Social Identity and Well-being: A Cross-Cultural Examination of Social Identity and Well-being in Light of the Accelerating Cultural Globalisation. *Psychology and Developing Societies,* 34(1).
9. Dickson, T. & Solnicar, S., 2004. No risk, no fun: The role of perceived risk in adventure tourism. *CD Proceedings of the 13th International Research Conference of the Council for Australian University Tourism and Hospitality Education (CAUTHE).*
10. Dumazadie, J., 1974. Sociologie empirique du loisir - Critique ef contre-critique de la civilisation du loisir. pp. 88-134.
11. ETH Zurich, 2022. *2022 KOF GLobalisation Index: Variables description,* s.l.: s.n.
12. Eurostat, 2021. *Tourism statistics,* s.l.: Eurostat.
13. Flanagen, F., 2019. Theorising the gig economy and home-based service work. *Journal of Industrial Relations,* 6(1).
14. Flew, T., 2018. Post-Globalisation. *Journal of the European Institute for Communication and Culture.*
15. Gopinathan, S., 2007. Globalisation, the Singapore developmental state and education policy: a thesis revisited. *Globalisation, Societies and Education ,* 5(1), pp. 53-70.
16. Hoffmann, S. & Akbar, P., 2023. Interindividual Differences. *Consumer Behavior ,* p. 117–129.
17. Hofstede, G., 2009. *Geert Hofstede cultural dimensions.* s.l.:s.n.
18. Hofstede, G., 2011. Dimensionalizing Cultures: he Hofstede Model in Context. *Online Readings in Psychology and Culture,* 2(1).

19. Hofstede, G., 2022. *Hofstede Insights.* [Online] Available at: https://www.hofstede-insights.com/fi/product/compare-countries/ [Accessed 12 02 2022].
20. Holm, M., Lugosi, P., Croes, R. & Torres, E., 2017. Risk-tourism, risk-taking and subjective well-being: A review and synthesi. *Tourism Management,* Volume 63, pp. 115-112.
21. Ismulyati, S. & Ngarbingan, H. G. G., 2022. Modeling of Co-Creation in the Adventure Tourism: Empowering the Role of Customer Participation to Strengthen Behavioral Intention (Best Practice: Tourism Village Nglangeran - Gunung Kidul DIY). *Journal of International Conference Proceedings,* 5(2).
22. Kingsinger, P. & Walch, K., 2012. *Living and leading in a VUCA world.* [Online] Available at: http://knowledgenetwork.thunderbird.edu/research/2012/07/09/kinsinger-walch-vuca/
[Accessed 2023].
23. Krause, K., 2022. Conversion/Change/Transformation of Lifestyle. *International Handbook of Practical Theology,* Volume 301.
24. Lawrence, K., 2013. *Developing Leaders in a VUCA Environment,* s.l.: UNC Kenan-Flagler Business School.
25. Lindsay, J., 2017. *Ten Most Significant World Events in 2017.* [Online] Available at: https://www.cfr.org/blog/ten-most-significant-world-events-2017 [Accessed 05 03 2023].
26. Lindsay, J., 2020. *Ten Most Significant World Events in 2020.* [Online] Available at: https://www.cfr.org/blog/ten-most-significant-world-events-2020 [Accessed 05 03 2023].
27. Lindsay, J., 2021. *Ten Most Significant World Events in 2021.* [Online] Available at: https://www.cfr.org/blog/ten-most-significant-world-events-2021 [Accessed 05 03 2023].
28. Lindsay, J., 2022. *The Water's Edge Ten Most Significant World Events in 2022.* [Online]
Available at: https://www.cfr.org/blog/ten-most-significant-world-events-2022 [Accessed 05 03 2023].

29. Lorentzan, A., 2009. Cities in the Experience Economy. *European Planning Studies,* 17(6), pp. 829-845.
30. McCracken, G., 1986. Culture and Consumption: A Theoretical Account of the Structure and Movement of the Cultural Meaning of Consumer Goods. *Journal of Consumer research,* 13(1), pp. 71-84.
31. McGrew, A. & Held, D., 2002. *Globalization/Anti-globalization.* Cambridge: Polity.
32. Mincer, J. & Zarnowitz, V., 1969. The Evaluation of Economic Forecasts. In: *Economic Forecasts and Expectations: Analysis of Forecasting Behavior and Performance.* s.l.:NBER.
33. Murugan, S., Rajavel, S., Aggarwal, A. & Singh, A., 2020. Volatility, Uncertainty, Complexity and Ambiguity (VUCA) in Context of the COVID-19 Pandemic: Challenges and Way Forward. *International J Health Systems and Implementation Research,* 4(2).
34. Narayan, S. & Tan, H., 2019. ADOPTING BIG DATA TO FORECAST SUCCESS OF CONSTRUCTION PROJECTS: A REVIEW. *MCRJ Special Issue ,* 6(1).
35. Nikseresht, A., Hajipour, B., Pishva, N. & Mohammadi, H., 2022. Using artificial intelligence to make sustainable development decisions considering VUCA: a systematic literature review and bibliometric analysis. *Environmental Science and Pollution Research,* Volume 29, p. 42509–42538.
36. Norton, D. & Pine, B., 2009. Unique experiences: disruptive innovations offer customers more “time well spent”. *Strategy& Leadership,* 37(6), pp. 4-9.
37. O'Leary, D., 2013. Artificial Intelligence and Big Data. *EEE Intelligent Systems,* 28(2).
38. Pop, A. N. et al., 2021. Motivational Factors Enticing Young Travelers to Engage in Adventure Tourism Activities. *Emerging Trends in Marketing and Management.*
39. Pop, A. N., Stancioiu, F. O. L. & Baba, C. N.-A. R., 2022. Exploring the attitude of youth towards adventure tourism as a driver for post-pandemic era tourism experiences. *Current Issues in Tourism,* pp. 1-15.
40. RAMSA Interreg Europe, 2021. *The Use of Natural and Cultural Heritage for Adventure Tourism,* s.l.: CIMMA Comunidade Intermunincipal do Alto Alentejo.

41. Reeves, M. &. L. C., 2012. *The most adaptive companies 2012. Bcg.perspectives.* [Online] Available at: https://www.bcgperspectives.com/content/articles/corporate_strategy_portfolio_management_future_of_strategy_most_adaptive_companies_2012/ [Accessed 2023].
42. Reisinger, Y. & Crotts, J., 2009. Applying Hofstede's National Culture Measures in Tourism Research: Illuminating Issues of Divergence and Convergence. *Journal of Travel Research,* 49(2).
43. Ritpanitchajchaval, N., Ashton, A. & Apollo, M., 2023. Eudaimonic well-being development: Motives driving mountain-based adventure tourism. *Journal of Outdoor Recreation and Tourism,* Volume 42.
44. Rityer, G., 2007. *The Blackwell Companion to Globalization.* Malden, USA: Blackwell Publishing.
45. Roman, M. et al., 2022. Poles' Perceptions of Extreme and Adventure Tourism. *Journal of Tourism & Adventure,* 5(1).
46. Salvatore, D., 2010. Globalisation, International Competitiveness and Growth: Advances and Emerging Markets, Large and Small Countries. *Journal of International Commerce, Economics and Policy,* 1(1), pp. 21-32.
47. Schwarz, N. & Ernst, A., 2009. Agent-based modeling of the diffusion of environmental innovations — An empirical approach. *Technological Forecasting and Social Change,* 76(4), pp. 497-511.
48. SINUS-Institut, 2021. *SINUS.* [Online] Available at: https://www.sinus-institut.de/en/sinus-milieus/sinus-milieus-international [Accessed on 12.02.2022].
49. Stock, J. & Watson, M., 2006. Chapter 10 Forecasting with Many Predictors∗. In: *Handbook of Economic Forecasting.* s.l.:Elsevier, pp. 515-554.
50. Svanberg, J., 2021. International trade-unionism and migration: European integration and the post-war 'Free' movement of labour. *Labor History,* 62(5-6), pp. 671-687.

51. Torres, E., Wei, W. & Ridderstaat, J., 2022. The adventurous tourist amidst a pandemic: Effects of personality, attitudes, and affect. *Journal of Vacation Marketing,* 28(4).
52. Yang, E. & Vikneswaran, N., 2014. Tourism at Risk: A Review of Risk and Perceived Risk in Tourism. *Asia-Pacific Journal of Innovation in Hospitality and Tourism (APJIHT) ,* 3(13).
53. Zhou, Z., 2021. *Machine Learning.* Nanjing: Springer.