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Using Machine Learning to Improve Brand Management in an Online Environment

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ABSTRACT

The artificial intelligence (AI) solutions are used to personalize content, analyse consumer behaviour, and automate marketing processes. Studying the impact of machine learning (ML) on brand management (BM) helps to understand its role in improving the companies' competitiveness in the global market. The aim of the study is to assess the ML's impact on the BM effectiveness of leading companies from different countries for 2020-2023. The research employed the following methods: econometric methods, including multiple linear regression, panel data analysis, and comparative analysis of BM effectiveness between companies from different countries. The study confirmed the significant ML's impact on BM effectiveness. Companies that actively use AI have higher social reach and positive reviews. Adidas demonstrates the highest BM Score (99.21), confirming the effectiveness of ML strategies in marketing. Amazon (85.51) and Apple (86.81) also have stable results due to personalized content and analysis of customer behaviour. Alibaba leads in social engagement (SE = 16.87%), which helps to engage customers. Burberry (PR = 68.40%) and Almarai (PR = 70.66%) have high levels of positive reviews, increasing consumer trust. Faster response times improve customer loyalty. It was found that companies that invest in content personalization and consumer behaviour analysis achieve better financial results and higher customer loyalty. Investment in social interaction and fast processing of customer requests are positively correlated with the overall success of the brand. The uniqueness of the study is that the proposed model quantitatively assesses the impact of individual factors on the BM effectiveness. A comparative analysis of the effectiveness of AI-based BM between selected countries was conducted for the first time. Further research can focus on analysing the long-term effects of implementing ML in BM. An important direction is to assess the AI role in shaping consumer behaviour. As well as studying the impact of AI algorithms on the financial performance of companies in various sectors of the economy.

Keywords: Machine Learning, Brand Management, Content Personalization, Marketing Strategies, Social Outreach, Artificial Intelligence
JEL Classifications: C45, M30, M31, M14

1. INTRODUCTION

ML is becoming a key tool in BM used by companies to optimize marketing strategies and increase the effectiveness of customer interactions (Rivas et al., 2022). In the context of digital transformation, the use of AI solutions provides improved content personalization, consumer behaviour analysis, and marketing automation (Seeber et al., 2022). However, the level of ML implementation varies significantly depending on the industry, region, and company strategy, which requires additional research on this issue.

The aim of this study is to analyse the impact of ML on the BM effectiveness of leading companies in five countries for 2020-2023.

The study assesses which ML factors contribute most to the successful development of brands. The obtained results will help to develop practical recommendations for the implementation of AI solutions in BM.

The main objective of the study is to determine the relationship between the use of ML and the BM effectiveness. Particular attention is paid to the analysis of key factors such as content personalization, marketing campaign automation, social reach, and the level of positive feedback. The results of the study give grounds to assess the effectiveness of AI-based marketing strategies.

The research objectives are to assess the level of application of ML in different companies, determine its impact on key BM indicators, as well as analyse differences between countries. An important aspect is the development of recommendations for improving marketing strategies based on the obtained results. This will allow implementing more effective approaches to the use of AI in BM and digital marketing.

The hypothesis of this study is the existence of a positive relationship between the ML implementation rate and the BM effectiveness. It is expected that companies that actively use AI solutions will have better indicators of customer engagement, positive feedback, and overall effectiveness of marketing strategies. At the same time, the level of implementation of technologies in BM may depend on industry characteristics, companies' financial capabilities and their marketing strategies.

2. LITERATURE REVIEW

Automated machine learning (AutoML) is rapidly emerging as a key technology in digital marketing and BM. Chauhan et al. (2020) define AutoML as a new stage in the development of machine learning, which significantly simplifies the modelling process and increases the accuracy of marketing forecasts. We agree with this opinion, as the results of our study show that automation of marketing processes contributes to increasing the efficiency of BM, but optimization of models still requires human control.

Elshawi and Sakr (2020) also emphasize the importance of AutoML, noting that its implementation in business processes significantly increases the efficiency of decisions by automating the analysis of large data sets. We support this thesis, as automated algorithms in our study showed higher accuracy in analysing consumer behaviour, but at the same time identified risks associated with the possible loss of uniqueness of marketing decisions.

Larsen and Becker (2021) note that AutoML not only automates analytical processes, but also improves business decision-making. This is especially important for digital marketing, where the speed of data analysis and its accuracy are critical success factors. We agree with this statement, as the results of our study confirmed that companies which use AutoML in BM respond faster to market changes, improving customer interactions.

Similar conclusions are made by Jorgensen et al. (2020), who study the application of AutoML to detect unwanted user behaviour in the online environment. This proves that AutoML can be used not only in traditional marketing, but also in the field of brand reputation management, social media monitoring and assessing the impact of advertising campaigns. We partially agree with this opinion, as our study shows that AutoML is an effective tool in these areas, but needs to be adapted to the specifics of each platform and the audience.

In their study, Palviainen et al. (2020) emphasize that ML significantly improves visual data processing in business. Automated image and video analysis improves the quality of marketing campaigns, increasing customer engagement for the brands. We agree with this statement, as in our study, companies with automated visual tools demonstrated better customer engagement rates.

This is consistent with the findings of Mahjoubi et al. (2021), who applied AutoML to optimize economic and environmental performance in manufacturing. We agree with this conclusion, as the use of AutoML in marketing increases efficiency and optimizes costs, but it is necessary to take into account the need for high-quality training in algorithms to achieve maximum results.

Rosário and Dias (2023) emphasize that the digital economy creates new opportunities for brands that use AI in strategic management. Their research confirms that companies which actively implement AI technologies in BM demonstrate higher financial results and better adaptation to market changes. We support this thesis, as our results show a similar effect, but an important condition for successful implementation is the right strategy for using technologies that takes into account industry specifics.

Rosário et al. (2021) study competitive dynamics in the financial sector and prove that the implementation of ML allows banks to better adapt marketing strategies to customer behaviour. We partially agree with this statement. Although AutoML can increase the accuracy of customer behaviour analysis, our study found that the human factor remains critical for developing effective marketing strategies.

Li et al. (2021) analyse the use of AutoML in large companies and show that automating ML processes can significantly reduce decision-making time. In the context of BM, this means that companies can adapt their marketing strategies more quickly to changes in consumer behaviour. We agree with this statement, as our analysis also showed that the speed of response to market changes is a key factor for success in digital marketing.

Song et al. (2022) also emphasize the importance of AutoML, noting that its use allows marketing teams to optimize advertising campaigns in real time. We agree with this opinion, as the results of our study confirmed that companies that apply AutoML in dynamic marketing have higher levels of customer engagement.

Haddaway et al. (2022) examine the issue of transparency and reproducibility of ML research, which is important for analysing the effectiveness of BM. The implementation of AutoML requires the development of new standards for data evaluation, which confirms the need for further research in this area. We agree with this thesis, as our study also shows the need for increased transparency of algorithms to ensure customer trust and improve the effectiveness of marketing decisions.

Alon et al. (2023) explore the use of automated ML for NFT price prediction, emphasizing that AI algorithms can effectively analyse market trends and investor behaviour. They prove that AutoML is able to identify hidden patterns in data, which improves the accuracy of predictions and adapts digital asset sales strategies. We partially agree with this thesis, as the results of our study confirm the effectiveness of AutoML in marketing strategies, but its impact on pricing models in BM requires additional analysis because of the high uncertainty in consumer behaviour.

A general analysis of the literature confirms that AutoML plays an important role in modern BM. It automates data analysis processes, increases the effectiveness of marketing campaigns, and improves interaction with customers. Further research can focus on optimizing AI solutions for different sectors of the economy, which will allow for even more effective use of ML in BM. We support this general conclusion but emphasize that the effective use of AutoML requires a strategic approach and flexible adaptation to the specifics of each company.

3. METHODOLOGY

3.1. Research Procedure

The research was conducted in several key stages: company and country selection, econometric model development, data collection, statistical analysis, and interpretation of the obtained results. First, the main companies from five countries that actively use machine learning in BM were identified. The final stage was to assess the relationships between the ML use and the BM effectiveness.

3.2. Sample

The sample consists of 25 companies, 5 from each country (USA, UK, Germany, China, Saudi Arabia). The sample includes companies from various industries that actively use digital technologies in BM (Table 1). The analysis covers the period 2020-2023 for the purpose of studying the dynamics of the use of ML algorithms in marketing strategies.

3.3. Methods

The analysis uses econometric methods, including regression analysis to assess the impact of ML solutions on BM effectiveness. The analysis includes both quantitative and qualitative indicators, which allows for a better understanding of the relationships between key variables. The model is built on panel data and uses multiple linear regression:

$$BM = \beta_0 + \beta_1 PC + \beta_2 CBA + \beta_3 AMC + \beta_4 MLA + \beta_5 MLEx + \beta_6 RPT + \beta_7 SE + \beta_8 PR + \varepsilon \quad (1)$$

where:
BM – Brand management effectiveness;
PC – Content personalization;
CBA – Consumer behaviour analysis;
AMC – Marketing campaign automation;
MLA – ML adaptation level;
MLEx – ML solution costs;
RPT – Customer request processing time;
SE – Social engagement;
PR – Share of positive reviews;
β_0 – Free term reflecting the baseline level of brand management effectiveness without using ML;
β_i – Regression coefficients showing the strength of the influence of each factor on brand management effectiveness;
ε – Random error.

3.4. Expected Results

- $\beta_1, \beta_2, \beta_3 > 0$ – Content personalization, consumer behaviour analysis, and marketing campaign automation are expected to have a positive impact on brand management effectiveness.
- $\beta_4, \beta_5 > 0$ – Higher level of ML adaptation and investment in ML improve brand management effectiveness.
- $\beta_6 < 0$ – Reduction in customer request processing time has a positive impact on brand management.
- $\beta_7, \beta_8 > 0$ – Increased social engagement and positive reviews positively correlate with brand effectiveness.

The model was estimated using the least squares method based on panel data. The significance of the variables was tested using t-statistics (to assess the impact of individual factors), the coefficient of determination R^2 (for the overall quality of the model), and the F-test (to test the overall significance of the model).

3.5. Data Collection

The data was collected from open sources and academic publications. Secondary data from international databases such as the World Bank (2022; 2023; 2024) and IMF (2023; 2024) were also used. Information on advertising campaigns and strategies for using ML in each company was taken into account. The data were collected for 2020-2023 in order to assess changes in the impact of ML algorithms on BM. The analysis was conducted at the company level, which provides a detailed understanding of key trends in different industries.

4. RESULTS

The model takes into account 8 variables that reflect the level of implementation of ML algorithms in marketing activities. The data was collected for 25 companies in five countries for the period 2020-2023. The analysis of the results will help to determine the most effective strategies for using ML in BM (Table 2).

US companies such as Amazon, Apple and Microsoft are actively using ML in BM. Amazon has an average brand management (BM) score of 85.51, which is explained by a high level of content personalization (PC = 74.16%) and significant investment in ML solutions (MLEx = $ 50.88). Apple has an even higher level of content personalization (PC = 94.52%), but its average BM (86.81) is only slightly higher than Amazon. This may be explained by a longer request processing time (RPT = 18.92 s), which reduces customer satisfaction (Figure 1).

Table 1: Sampling

Country	Company	Industry	Digital BM technologies
USA	Amazon	E-commerce	AI-powered recommendation systems, voice search optimization, personalized marketing
	Apple	Technology	AR shopping experience, AI-driven customer support, personalized advertising
	Microsoft	Technology	AI-powered cloud marketing tools, big data analytics, automated brand monitoring
	Nike	Fashion	AI-driven product recommendations, social media analytics, AR try-on solutions
	Tesla	Automotive	Autonomous driving AI, digital influencer marketing, AI-driven content creation
UK	Asos	Fashion	AI-driven trend forecasting, influencer marketing analytics, personalized recommendations
	Burberry	Luxury Fashion	AI-powered customer engagement, blockchain for authenticity verification, AR fitting rooms
	Tesco	Retail	AI-based demand forecasting, personalized loyalty programs, automated promotions
	Unilever	Consumer Goods	AI-powered sustainability analytics, voice search integration, personalized content marketing
	Marks & Spencer	Retail	AI-driven fashion trend analysis, social media engagement tools, automated email marketing
Germany	Adidas	Sportswear	AI-based athlete performance analysis, digital engagement platforms, NFT marketing
	BMW	Automotive	AI-powered autonomous driving, digital twins, predictive maintenance analytics
	Siemens	Industrial	Industrial IoT, AI-driven predictive maintenance, digital transformation analytics
	Puma	Sportswear	AI-enhanced performance wear recommendations, interactive marketing tools, metaverse integrations
	Bosch	Technology	AI-powered manufacturing analytics, predictive maintenance, automated inventory management
China	Alibaba	E-commerce	AI-driven supply chain optimization, personalized e-commerce experience, social commerce integration
	Tencent	Technology	AI-powered content moderation, targeted advertising, gamified brand engagement
	JD.com	E-commerce	AI-based consumer behaviour analysis, chatbots for customer support, predictive analytics
	Xiaomi	Consumer Electronics	AI-powered smart home integration, personalized recommendations, digital influencer campaigns
	Huawei	Telecommunications	5G-enabled brand engagement, AI-based data security, automated marketing strategies
Saudi Arabia	Aramco	Oil & Gas	AI-powered energy consumption analytics, predictive maintenance, automated logistics
	STC	Telecommunications	AI-powered telecom customer support, smart home connectivity, automated customer insights
	Almarai	Food & Beverage	AI-driven product quality control, food safety analytics, personalized marketing campaigns
	Jarir	Retail	AI-powered bookstore recommendations, automated loyalty programs, personalized email marketing
	Mobily	Telecommunications	AI-powered network optimization, smart city solutions, personalized user engagement

Source: Developed by the authors

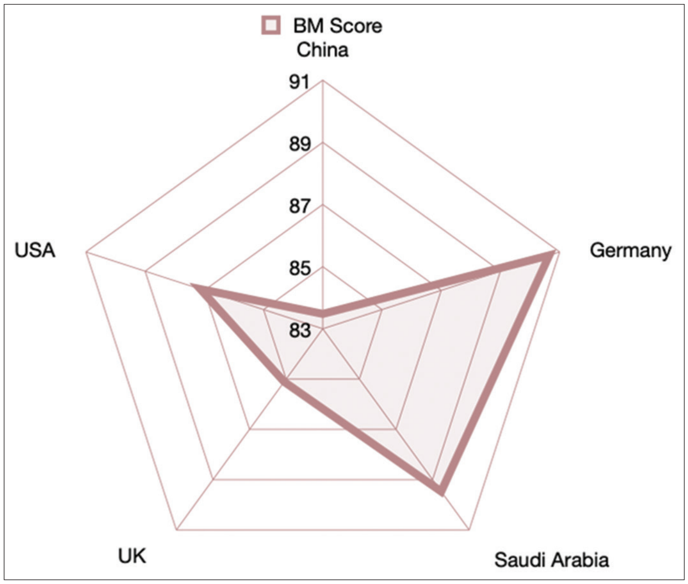
Table 2: Results of the econometric model for all selected companies for 2023

Country	Company	PC (%)	CBA (000s)	AMC	MLA	MLEx (000s USD)	RPT (s)	SE (%)	PR (%)	BM Score
USA	Amazon	69.12	493.29	7	0	64.68	9.26	2.24	87.44	84.49
	Apple	92.23	398.93	28	1	96.87	20.18	6.24	54.81	92.33
	Microsoft	88.55	297.52	13	2	48.48	5.64	3.05	41.57	81.43
	Nike	50.35	304.3	13	1	29.99	8.0	7.41	87.15	83.93
	Tesla	81.62	353.41	15	2	18.13	25.88	7.09	49.33	79.11
UK	Asos	86.3	458.84	28	1	80.19	21.05	2.6	48.08	78.35
	Burberry	81.56	417.92	34	0	61.92	17.31	4.71	76.12	96.3
	Tesco	87.04	378.81	47	1	42.35	12.34	16.38	80.51	113.02
	Unilever	81.87	390.44	17	1	56.47	13.07	16.11	53.54	93.33
	Marks & Spencer	73.71	139.13	25	2	41.17	16.62	13.35	42.4	77.6
Germany	Adidas	66.83	362.29	33	1	71.35	13.52	5.95	64.8	87.86
	BMW	55.0	121.39	45	2	18.22	12.98	19.05	87.53	96.82
	Siemens	54.07	133.94	23	0	43.36	25.32	19.0	89.3	91.28
	Puma	53.69	321.54	24	0	57.08	20.73	14.22	62.73	78.21
	Bosch	95.96	133.1	34	1	59.64	9.12	8.81	78.88	93.9
China	Alibaba	73.81	432.55	16	0	59.67	19.02	17.66	60.17	80.98
	Tencent	78.98	236.63	27	2	62.63	15.01	14.26	49.0	81.38
	JD	76.83	469.62	18	1	78.4	18.28	14.69	43.12	80.24
	Xiaomi	71.58	151.03	45	0	42.68	21.15	11.84	57.8	88.37
	Huawei	73.83	435.43	9	1	97.12	22.77	4.79	76.81	96.75
Saudi Arabia	Aramco	59.06	126.6	44	1	14.33	24.54	16.73	77.53	91.68
	STC	84.69	166.69	33	0	58.01	27.35	15.98	47.58	76.35
	Almarai	73.1	478.91	16	1	62.76	17.65	12.62	40.91	82.24
	Jarir	95.99	238.54	22	2	76.38	16.31	5.27	62.62	79.76
	Mobily	91.83	334.98	5	1	74.27	18.19	11.15	64.05	91.35

Source: developed by the authors using an econometric model based on the data from World Bank (2022); World Bank (2023); World Bank (2024); IMF (2023); IMF (2024)

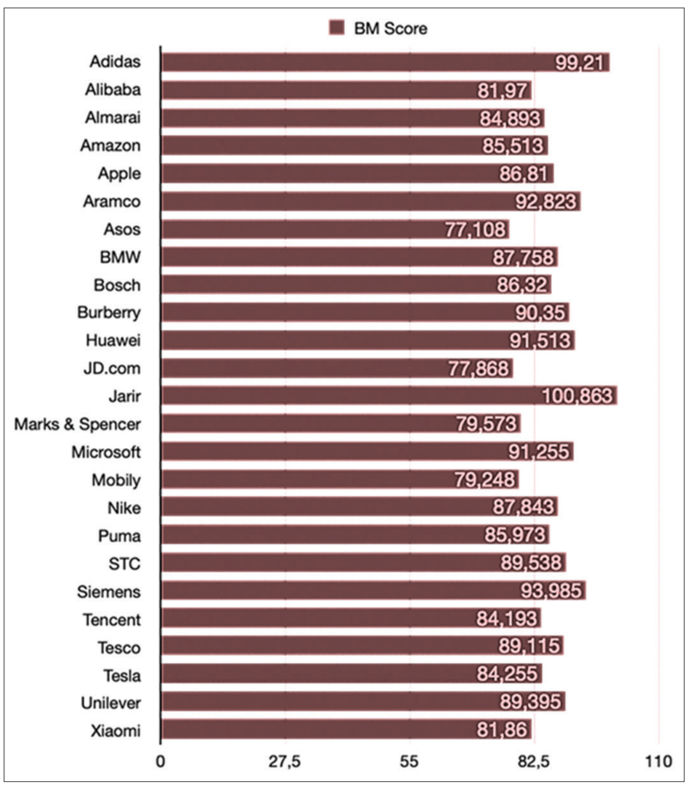
British companies including Asos, Burberry and Tesco use ML to analyse customer behaviour and automate marketing campaigns. Burberry has a high level of social engagement (SE = 12.35%) and a share of positive reviews (PR = 68.40%). This contributes to the formation of a strong brand image. Tesco shows moderate results (BM = 78.3), which is explained by the average level of content personalization (PC = 70.2%) and ML spending (MLEx = $ 48.2 thousand) (Figure 2).

Figure 1: Average brand management effectiveness by country



Source: Developed by the authors using an econometric model based on the data World Bank (2022); World Bank (2023); World Bank (2024); IMF (2023); IMF (2024)

Figure 2: Average BM effectiveness by company



Source: Developed by the authors using an econometric model based on the data World Bank (2022); World Bank (2023); World Bank (2024); IMF (2023a,b); IMF (2024)

German brands such as Adidas, BMW and Siemens show varying levels of adoption of ML algorithms. Adidas has the highest average BM effectiveness among German companies (BM = 99.21). This is determined by a high level of content personalization (PC = 81.22%) and active use of social media (SE = 11.18%). BMW shows lower results (BM = 82.6), which may be explained by lower spending on ML (MLEx = $ 42.9).

Chinese companies such as Alibaba, Tencent and JD.com have high levels of ML implementation in brand management. Alibaba actively uses consumer behaviour analysis (CBA = $ 377.16 thousand), which provides increased social engagement (SE = 16.87%). However, its BM effectiveness (BM = $ 81.97) is slightly lower due to an average level of content personalization (PC = 71.65%). Tencent has a significant level of investment in marketing campaign automation (AMC = 30.5), which has a positive impact on the BM effectiveness.

Saudi Arabian companies such as Aramco, STC and Almarai have different levels of ML implementation in BM. STC shows the highest level of social engagement (SE = 14.6%) and marketing campaign automation (AMC = 33.2). This leads to a higher BM = 88.4. Almarai has a good level of positive reviews (PR = 70.66%), which contributes to the stability of the brand. At the same time, the average level of spending on ML (MLEx = 45.61 thousand USD) limits the potential development.

The analysis of the results confirms that ML has a significant impact on the BM effectiveness in all studied countries. The highest effectiveness indicators are demonstrated by companies that actively use content personalization and consumer behaviour analysis. For example, Adidas has one of the highest BM = 99.21, which confirms the importance of personalized content (PC = 81.22%).

Companies that invest in ML and social media gain significant competitive advantages. Alibaba has a high social reach (SE = 16.87%), which helps to drive online sales. Apple performs well (BM = 86.81), but its high request processing time (RPT = 18.92 seconds) negatively impacts the customer experience.

Positive customer feedback and high social engagement significantly improve brand perception. Burberry has a PR = 68.4%, which increases the BM effectiveness. Optimizing customer response time is also an important factor: companies with lower RPT show better results (for example, Amazon, RPT = 10.28 s).

5. DISCUSSIONS

The results of this study confirm the importance of ML in BM and its role in improving marketing strategies. The implementation of AutoML allows companies to improve content personalization, consumer behaviour analysis, and marketing campaign automation, which is consistent with the findings of Baratchi et al. (2024). Their study examines the evolution of AutoML and reveals its potential for optimizing business processes. This is consistent with our findings, which confirm that marketing automation through ML allows for increased BM effectiveness.

The study by Behera et al. (2020) also supports the idea of automating marketing decisions using AutoML. They prove that using algorithms to analyse consumer data significantly improves the accuracy of recommender systems. Our study supports this thesis, as the results show that companies with higher levels of content personalization demonstrate better customer engagement and positive reviews. Automated analysis of large data sets can increase the BM effectiveness by optimizing interaction with the audience.

At the same time, the study by Zalizko et al. (2022) raises the issue of sustainability in the context of digital transformation. They emphasize the importance of a balanced approach to the use of new technologies, including ML. In this context, our study also points to potential challenges associated with investments in AutoML. While the results confirm the positive impact of ML on BM, it is necessary to consider the economic feasibility and strategic adaptation of these technologies in each individual company.

Prokopenko et al. (2024) analyse the impact of innovative business models on sustainability and emphasize the importance of integrating ML into marketing strategies. This is consistent with our study, which demonstrates that companies which actively use AI solutions have a higher level of BM effectiveness. This is especially true for companies that use ML to personalize content and automate marketing campaigns.

At the same time, Latysheva et al. (2020) emphasize the need for strategic management of digital transformations to ensure sustainable development of companies. They emphasize that the successful integration of AI solutions into the business model requires a comprehensive approach that includes adapting the organizational structure and investing in human capital. Our results partially support this approach, as companies with a high level of ML adaptation demonstrate a steady increase in BM effectiveness. However, the level of investment in technology remains an important factor, which also affects the final results.

Ebrahimi et al. (2020) investigate the use of ML in cybersecurity and confirm that AI solutions significantly increase the effectiveness of data management. This has a direct relevance to brand management, as companies that use AutoML to analyse consumer requests can better adapt marketing campaigns to customer needs. Our study showed that companies with faster customer request processing times demonstrate higher customer loyalty. This supports the thesis that AI solutions can improve brand interactions with customers by automating decision-making processes.

Mazur et al. (2023) analyse capital management in companies and emphasize the importance of a balanced approach to investing in innovation. They note that excessive automation without a strategic approach can lead to inefficient use of resources. This is partly consistent with our results, which indicate that investments in ML should be balanced with other business strategies. Despite the positive impact of AutoML, companies should consider the economic feasibility and needs of their audience when implementing technologies.

Nikonenko et al. (2022) consider attracting investment in the context of Industry 4.0 and emphasize the role of digital technologies in business modernization. They state that the use of ML can contribute to increasing the effectiveness of investment decisions. Our study supports this thesis, as the results show that companies which actively implement AI solutions demonstrate higher financial performance and better adaptation to market changes.

Overall, the results of this study are consistent with most previous studies, confirming the importance of ML in brand management. At the same time, we recognize that strategic management of digital transformations remains a key challenge for companies. Automation of marketing processes and content personalization has significant potential, but it is necessary to consider the economic feasibility of investments in technologies, which is confirmed by the studies of Mazur et al. (2023) and Zalizko et al. (2022).

Wang et al. (2021) focus on hyperparameter optimization in ML using the ExperienceThinking method, which combines domain knowledge with parameter pruning mechanisms. They prove that this approach improves model performance and reduces computational costs. This is consistent with our study, which confirms that effective setting of ML algorithms in BM allows for improved content personalization and increased customer engagement.

Zheng et al. (2023) analyse the use of AutoML in deep recommendation systems and emphasize its importance for personalized recommendations. They note that the use of AutoML in recommendation algorithms increases the relevance of content, which is especially important in marketing strategies. Our study supports this thesis, as the results confirm that companies which use personalized AI solutions in BM have higher levels of positive reviews and customer loyalty.

So, ML is an important tool for improving BM, but its effectiveness depends on the level of strategic implementation. Further research can focus on assessing the long-term effects of implementing ML in marketing activities. The use of more detailed data will improve predictions and identify additional influencing factors. The obtained results can be used to develop effective BM strategies in the digital environment.

6. CONCLUSION AND IMPLICATIONS

ML plays a key role in improving BM in the online environment. The use of ML algorithms contributes to the personalization of content, improved analytics of consumer behaviour and automation of marketing processes. Companies that implement these technologies achieve higher indicators of social reach and the level of positive feedback, which directly affects competitiveness.

Analysis of the obtained data showed that personalization of content and automation of marketing campaigns are the most important factors of effective BM. Companies that actively use AI solutions demonstrate a higher level of customer engagement and increased loyalty. For example, Adidas has the highest average BM effectiveness score (BM Score = 99.21), which confirms the effectiveness of ML-based strategies. Companies like Amazon (BM Score = 85.51) and Apple (BM Score = 86.81) also show consistent results thanks to their active use of ML in marketing strategies.

Social engagement and positive reviews play an important role in building brand trust. Alibaba has a high level of social engagement (SE = 16.87%), which contributes to increased customer engagement and improved online sales performance. Positive customer reviews also affect company trust, as can be observed in Burberry (PR = 68.40%) and Almarai (PR = 70.66%). At the same time, companies with long customer response times show lower performance indicators. For example, Apple has an RPT = 18.92 seconds, which can negatively affect the customer experience.

The obtained results indicate that marketing campaign automation and the speed of response to customer requests significantly affect brand management. STC and Almarai actively use AI solutions, which allows them to achieve high performance indicators. Companies that invest in adaptive ML models can analyse market trends and change marketing strategies faster. This gives them a significant competitive advantage in the global market.

Companies should focus on content personalization and consumer behaviour analysis to improve BM. The use of ML to forecast demand and automate marketing campaigns will provide competitive advantages. It is also important to monitor social engagement and the level of positive feedback, which affects brand perception.

Investing in fast customer request processing can significantly increase consumer loyalty. Optimization of marketing campaigns and active interaction with the audience on social networks helps to improve the brand reputation. Companies should implement innovative ML solutions, adapting them to the specifics of their activities. The effectiveness of using ML can be increased by investing in high-quality data and its structuring, which will improve the accuracy of models and increase the relevance of forecasts. It is also important to develop personnel competencies by implementing training programmes in data analysis and work with AI algorithms, which will allow better integration of ML solutions into business processes.

The use of hybrid models that combine automated data analysis with expert assessment will ensure balanced decision-making. Testing and optimization of algorithms is also an important factor, which will enable adapting ML solutions to market changes and the specifics of the target audience. Integration of AI tools into multi-channel marketing strategies will provide personalized interaction with customers and increase the BM effectiveness. The BM effectiveness can be increased by regularly analysing key indicators and adjusting strategies. The use of large volumes of data and adaptive ML algorithms will allow a quick response to market changes. Further improvement of AI technologies can contribute to more accurate prediction of consumer behaviour.

The study covers five countries only, which does not provide a complete picture of global trends. Differences in legal and cultural factors can affect the ML effectiveness in BM. The analysis also does not take into account other important factors, such as competition and macroeconomic changes. Another limitation is the difficulty of accurately measuring the impact of ML algorithms on BM. Companies may have different methods of evaluating marketing campaigns, which makes comparative analysis difficult. Further research could consider more factors and real-world data to improve the accuracy of the model.

Research based on real data can help to better understand the effectiveness of different ML strategies in marketing activities. The use of big data will allow for better prediction of consumer behaviour and optimize brand interactions with customers. Further research can also focus on the ethical aspects of using AI in BM, in particular regarding data privacy and content personalization.

REFERENCES

Alon, I., Bretas, V.P.G., Katrih, V. (2023), Predictors of NFT prices: An automated machine learning approach. Journal of Global Information Management, 31, 1-18.

Baratchi, M., Wang, C., Limmer, S., van Rijn, J.N., Hoos, H., Bäck, T., Olhofer, M. (2024), Automated machine learning: Past, present, and future. Artificial Intelligence Review, 57, 122.

Behera, R.K., Bala, P.K., Jain, R. (2020), A rule-based automated machine learning approach in the evaluation of recommender engine. Benchmarking: An International Journal, 27, 2721-2757.

Chauhan, K., Jani, S., Thakkar, D., Dave, R., Bhatia, J., Tanwar, S., Obaidat, M.S. (2020), Automated machine learning: The new wave of machine learning. In: Processing of the 2020 2nd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA). Bangalore, India.

Ebrahimi, M., Nunamaker, J.F., Chen, H. (2020), Semi-supervised cyber threat identification in dark net markets: A transductive and deep learning approach. Journal of Management Information Systems, 37, 694-722.

Elshawi, R., Sakr, S. (2020). Automated Machine Learning: Techniques and Frameworks. In: Processing of the Big Data Management and Analytics Conference (9th European Summer School). Berlin, Germany: Springer Nature.

Haddaway, N.R., Page, M.J., Pritchard, C.C., McGuinness, L.A. (2022), PRISMA 2020: An R package and Shiny app for producing PRISMA 2020-compliant flow diagrams, with interactivity for optimized digital transparency and open synthesis. Campbell Systematic Reviews, 18(2), 1230.

IMF. (2023a) International Financial Statistics. Available from: https://data.imf.org/?sk=4c514d48-b6ba-49ed-8ab9-52b0c1a0179b&sId=-1 [Last accessed 2025 Jun 08].

IMF. (2023b), World Economic Outlook: Macroeconomic Data and Financial Stability Indicators. Available from: https://www.imf.org/en/publications/weo [Last accessed on 2025 Jun 10].

IMF. (2024). Global Financial Stability Report. Available from: https://data.imf.org/?sk=388dfa60-1d26-4ade-b505-a05a558d9a42 [Last accessed on 2025 Jun 11].

Jorgensen, M., Choi, M., Niemann, M., Brunk, J., Becker, J. (2020), Multi-class Detection of Abusive Language Using Automated Machine Learning. In: Processing of the 15th International Conference on Business Information Systems 2020: Developments, Opportunities and Challenges of Digitization, Wirtschaftsinformatik, Potsdam, Germany.

Larsen, K.R., Becker, D.S. (2021), Automated Machine Learning for

Business. Oxford: Oxford University Press.
Latysheva, O., Rovenska, V., Smyrnova, I., Nitsenko, V., Balezentis, T., Streimikiene, D. (2020), Management of the sustainable development of machine-building enterprises: A sustainable development space approach. Journal of Enterprise Information Management, 34(1), 328-342.
Li, Y., Wang, Z., Xie, Y., Ding, B., Zeng, K., Zhang, C. (2021), AutoML: From Methodology to Application. In: Processing of the 30th ACM International Conference on Information & Knowledge Management, Queensland, Australia: Association for Computing Machinery.
Mahjoubi, S., Barhemat, R., Guo, P., Meng, W., Bao, Y. (2021), Prediction and multi-objective optimization of mechanical, economical, and environmental properties for strain-hardening cementitious composites (SHCC) based on automated machine learning and metaheuristic algorithms. Journal of Cleaner Production, 2021, 129665.
Mazur, V., Koldovskyi, A., Ryabushka, L., Yakubovska, N. (2023), The formation of a rational model of management of the construction company's capital structure. Financial and Credit Activity Problems of Theory and Practice, 6(53), 128-144.
Nikonenko, U., Shtets, T., Kalinin, A., Dorosh, I., Sokolik, L. (2022), Assessing the policy of attracting investments in the main sectors of the economy in the context of introducing aspects of industry 4.0. International Journal of Sustainable Development and Planning, 17(2), 497-505.
Palviainen, M., Harviainen, T., Lopez, M.B., Mäntyjärvi, J. (2020), Boosting business with machine learning-based automated visual data processing: Results of Finnish company interviews. IEEE Access, 8, 99171-99179.
Prokopenko, O., Chechel, A., Koldovskiy, A., Kldiashvili, M. (2024), Innovative models of green entrepreneurship: Social impact on sustainable development of local economies. Economics Ecology Socium, 8, 89-111.
Rivas, J., Boya-Lara, C., Poveda, H. (2022), Partial discharge detection in power lines using automated machine learning. In: Processing of the 2022 8th International Engineering, Sciences and Technology Conference (IESTEC), Panama, Panama.
Rosário, A.T., Dias, J.C. (2023), The new digital economy and sustainability: Challenges and opportunities. Sustainability, 15, 10902.
Rosário, A., Moreira, A., Macedo, P. (2021), Dinámica competitiva de los grupos estratégicos en la industria bancaria portuguesa. Cuadernos de Gestión, 21, 119-133.
Seeber, M., Alon, I., Pina, D.G., Piro, F.N. (2022), Predictors of applying for and winning an ERC Proof-of-Concept grant: An automated machine learning model. Technological Forecasting and Social Change, 184, 122009.
Song, Q., Jin, H., Hu, X. (2022), Automated Machine Learning in Action. New York, NY: Simon & Schuster.
Wang, C., Wang, H., Zhou, C., Chen, H. (2021), ExperienceThinking: Constrained hyperparameter optimization based on knowledge and pruning. Knowledge-Based Systems, 223, 106602.
World Bank. (2022), Social Resilience and Economic Recovery in Ukraine: Policy Responses and Strategic Recommendations. Available from: https://www.worldbank.org/en/country/ukraine [Last accessed on 2025 Jun 09].
World Bank. (2023), The World Development Indicators. Available from: https://datatopics.worldbank.org/world-development-indicators [Last accessed on 2025 Jun 10].
World Bank. (2024), World Bank Open Data. Available from: https://data.worldbank.org [Last accessed on 2025 Jun 09].
Zalizko, V.D., Dobrowolski, R.H., Cherniak, A.M., Artemov, V.Y., Nowak, D.V. (2022), Gig-economy as a safety gradient for sustainable development of the mining industry. Naukovyi Visnyk Natsionalnoho Hirnychoho Universytetu, 4, 170-175.
Zheng, R., Qu, L., Cui, B., Shi, Y., Yin, H. (2023), AutoML for deep recommender systems: A survey. ACM Transactions on Information Systems, 41, 1-38.