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The Backstage of the Doing Business Index and the Logistic Performance Index: A Machine Learning Analysis

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ABSTRACT

Globalization has significantly boosted foreign commerce, enhancing the flow of capital, information, goods, and services between nations, thereby influencing countries' positions in the industrial market and offering growth opportunities. Concurrently, the mobility of investment capital and entrepreneurs has increased, prompting countries to innovate to attract investors. Investors, aiming to sustain their global market presence and profitability, often establish businesses in various countries. The Doing Business Index (DBI) and the Logistics Performance Index (LPI) are two crucial tools for assessing the investment climate. This study focuses on analyzing the factors affecting DBI and LPI using machine learning algorithms (CatBoost, LightGBM, and XGBoost) on 1478 variables from the World Development Indicators (WDI). The analysis identified the top 20 factors influencing DBI and LPI, highlighting the significance of economic, administrative and legal indicators with technological infrastructure. The findings provide valuable insights for countries aiming to improve their DBI and LPI scores and for investors seeking critical factors beyond these indices, contributing significantly to both the business world and academic literature.

Keywords: Doing Business Index, Logistic Performance Index, CatBoost, LightGBM, XGBoost, Machine Learning.

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INTRODUCTION

Worldwide, trade is growing faster and faster due to globalization. Factors such as the removal of trade barriers, producers' economies of scale targets, increased foreign investments, advances in information and communication technologies, increasing demand in new markets, improved logistics operations and orders exceeding suppliers trigger this growth (Marti et al., 2014).

Countries' positions in the industrial chain and their share of the global trade market are directly impacted by the rise of foreign trade, which is a key driver of economic growth (Feng et al., 2022). Therefore, in today's globalized world, smoother trade between economies is highly important for trade organisations and countries. Excessive document demands, complex customs procedures, inefficient port management and inadequate logistics infrastructure cause additional costs and delays for importers and exporters and limit the potential for trade. For this reason, many countries are realizing various innovations to keep up with increasing competition conditions and attract investors (Yardımcıoğlu, 2015: 292). To put it another way, every nation seeks to draw in foreign capital in order to guarantee economic expansion and advancement and to address the issue of unemployment. Countries where entrepreneurship is encouraged and the business environment is favorable attract foreign investors and enable the establishment of long-term production facilities. This situation positively affects both employment and tax revenues. Therefore, countries must take measures to facilitate the work of investor firms in areas such as taxes, transaction costs and transport (Pala, 2022).

Entrepreneurs and investor firms tend to establish businesses in different countries to increase their profitability and maintain their presence in the global market (Doshi et al., 2019: 615). In this context, investors want to learn how a country's investment climate is shaped and analyze the relationship between the state of the investment climate and its suitability (Acar and Çetinceli, 2020: 892). Therefore, choosing an investor's

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site depends in large part on objectively assessing the performance of the current investment environments in nations or basing them on objective data (Kumar and Kumar, 2020: 589; Yalçın and Yalçın, 2021: 9).

Adding the uncertainty of countries to global competition conditions makes it difficult for investors to have full information about investment opportunities in countries, and extensive research is needed. Therefore, there is a need for a systematic approach that can be utilized by those who invest abroad (Cavusgil et al., 2004). In this framework, indices calculated by some international organisations are taken as references before making investment decisions in foreign countries (Koç et al., 2017). Some of these indices can be listed as Gross Domestic Product (GDP), World Economic Freedom Index, DBI, Purchasing Power Parity, LPI, and International Country Risk Guide (Önalmış, 2017). However, in addition to GDP, the traditional growth indicator, more specific indices such as the DBI have an important place among the factors shaping investors' decisions. Published by the World Bank, the DBI has become a frequently used tool to assess the investment attractiveness of countries by providing quantitative data on regulations affecting the business world (Koç et al., 2017; Acar and Çetinceli, 2020). A comparative evaluation is conducted in the yearly DBI reports based on a number of indicators that could impact a country's investment climate, including ease of starting a business, ease of paying taxes, convenience of registering property, protection of minority investors, and ease of cross-border commerce (Yardımcıoğlu, 2015: 292).

The second most crucial factor in luring investors is logistical performance, which can be at least as successful as ease of doing business. Countries are known to place a high value on the LPI, which gauges the caliber of logistics services, because investment enterprises need to be able to swiftly and reliably make their goods and services available to the market (Kara et al., 2009: 72). The LPI, which is considered as an important indicator in evaluating the efficiency of trade and transport sectors, is updated regularly by the World Bank. LPI is used to comparatively analyse the performance of countries in various factors such as logistics infrastructure, customs processes and the quality of logistics services (Marti et al., 2014: 2984).

As a result, investors prefer countries where business processes are easier, faster and less costly, and a high DBI score provides an attractive business environment for investment. Similarly, investors favor countries where goods and services can be moved efficiently and on time. A high LPI score indicates that the country has an effective logistics infrastructure. Both indices are important tools used by investors to assess a country's business and investment climate and influence investment decisions. Therefore, it is critical to conduct more research on the two indices and to fully understand their scope, which is the starting point of this study. According to an analysis of the literature, there are studies (Ojala and Queiroz, 2002; Burmaoglu and Sesen, 2011; Martí et al., 2014; Ani, 2015; Başar and Bozma, 2017; Bozma et al., 2017; Garcia and Hinayon, 2018; Ofluoğlu et al., 2018; Acar and Çetinceli, 2020; Rençber and Yücekaya, 2021) investigating the relationships between DBI and LPI and various factors. But it's obvious that in order to fully comprehend the extent and influence of two significant indices that show how suitable the business and investment climate is, it's necessary to look at how the two indices relate to one another as well as a wide range of other elements. Machine learning approaches such as the CatBoost, LightGBM, and XGBoost boosting algorithms were used to examine the effects of 1478 components from the World Bank's WDI on DBI and LPI in order to identify the background elements influencing the study. The 20 most significant parameters influencing DBI and LPI were ranked as a consequence of the research. At the end of the study, determining the most critical factors that countries that want to improve their scores for both indices should focus on and determining the most important factors that investors should focus on other than these indices is an important contribution to the business world and the literature.

DOING BUSINESS INDEX (DBI)

The World Bank established and introduced the term "doing business" to refer to both the favorable circumstances that support the robust growth of the business environment in any nation's economy and the unfavorable circumstances that impede it. The important point at this point is to minimize the negative situations and maximize the positive situations. The World Bank also focuses on these aspects, announces the rankings of countries on a yearly basis and recognizes the business environments of countries globally. At this point, the general opinion is that top-ranked countries are preferred by global investors (Kumar and Kumar, 2020).

With developments in the concept of doing business, this concept has been evaluated in different ways. One of these evaluations is the DBI. Despite various attempts to provide quantitative measures of conducting business, the World Bank's DBI has remained the most extensively used metric to this day. In this context, the

DBI is recognized as one of the important types of data provided by the World Bank. Since 2004, the World Bank has released the DBI, a hierarchical country index that provides information on the business climate in about 200 nations. The index consists of a main indicator (doing business) and ten subindicators (enforcing contracts, resolving insolvency, getting electricity, etc.). These factors are combined to create a single primary dimension that shows how simple it is to conduct business in one nation as opposed to another. Every DBI component has a ranking in relation to other nations. After that, these elements are integrated to provide a single overall DBI ranking (Holden and Pekmezovic, 2020). The DBI measures various aspects of business regulation in a multifaceted manner. As a result, the World Bank established the DBI for countries' economic development because it recognizes the importance of ease of doing business (Maričić et al., 2019).

When the literature is examined, some studies are within the scope of DBI. In his study, Aghion (2004) tried to highlight the significance of governance by analyzing it in relation to ease of doing business. In his study, he emphasizes that governments are effective in ensuring a favorable environment for doing business, which is determined by regulatory and legal frameworks based on the power given by general political stability. The European Union's 2021 studies with nations including the Netherlands, Belgium, and Austria as well as the European Commission's 2017 Ease of Doing Business Report both support this. Aghion (2004) also emphasized that governments are responsible for operational issues such as the issuance of business licenses access to electricity, safety and health of customers, adequate transport infrastructure, and transparent tendering processes. As a result, it is mentioned that a favorable business environment increases the attractiveness of investment and makes it easier to do business. Dougherty (2007) emphasized that a successful and qualified business environment in countries is the main factor in the development of entrepreneurship, which is closely related to the ease of doing business. Bruhn (2011), in his study to determine the state of doing business, emphasized that the reform of market entry regulation in Mexico has produced positive results throughout the country and that the number of registered businesses in the country has increased. Finally, Ani (2015) investigated the effects of business accessibility and ease of doing business on economic development in 29 countries in South, Southeast, and East Asia using multiple regression analysis. In this study, GDP was used as an indicator of economic growth, and the World Bank ten DBI dimensions were used as indicators of ease of doing business. The study concluded that while international trade and property registration have a beneficial influence on GDP, obtaining financing and managing building permits have a negative effect.

LOGISTIC PERFORMANCE INDEX (LPI)

The concept of logistics, which initially appeared as a military term, entered the economic literature in the 1960s. In the 21st century business world, logistics refers to a systematic and very large network that connects production and trade centers scattered all over the world in a global sense (Bayraktutan and Özbilgin, 2015). Wood et al. (1995) define logistics as a managerial system that provides strategic storage and transport of materials, semi-finished and finished products to maximize the profits of businesses.

With globalization, countries are moving closer to each other, and the volume of product flows is increasing dramatically. The volume of trade in the world has developed between countries with efficient infrastructures for global logistics networks (Çitil, 2022). As a result, in order to get a greater portion of global trade and boost their competitiveness, nations must now build their logistics infrastructure (Mete, 2020).

With the "Trade Facilitation Agreement" approved by the World Trade Organization (WTO) in 2013, countries have had the opportunity to carry out the delivery and customs procedures of logistics activities, including transit trade, more easily and quickly (Aynagöz Çakmak, 2016). In this framework, it is now required to assess and analyze the logistical performance of nations with international indices, even if the Customs Union's procedures have been greatly standardized (Kaya Somut, 2023). In fact, logistics performance is seen as an indicator and determinant of economic development and countries, regions and cities are now ranked according to their logistics infrastructure development. The existence of an adequate and qualified logistics infrastructure has an impact on socioeconomic development, and investors prefer countries with developed infrastructure and qualified manpower advantages when making investment decisions (Bayraktutan and Özbilgin, 2015). In 2007, the World Bank made the necessary move in this area. Every two years, the World Bank typically evaluates a nation's logistics performance. Under the LPI, nations performance is determined by a set of criteria, including customs (i), infrastructure (ii), tracking and tracing (iii), logistics competence (iv), international shipments (v), and timeliness (vi). The results are ranked into a single value (World Bank, 2023).

The LPI is a useful metric that allows nations to evaluate how well they do in logistics compared to other countries, making it easier to identify possibilities and problems in their own logistics industries (Meşin and Cura, 2022). Modern machine learning techniques, however, can be paired with the LPI, a vital measure of a country's logistics effectiveness, to open up new research directions. Shepherd and Sriklay (2023) used data from the WDI, a worldwide dataset that includes the socioeconomic features of nations, to anticipate LPI values using machine learning techniques. Their research yielded a comprehensive analysis of countries' logistics performance trajectories over time.

In order to forecast LPI scores, Babayigit et al. (2023) investigated the predictive power of the Multi-Gene Genetic Programming (MGGP) algorithm, a well-known machine learning method that can produce both linear and non-linear prediction models. According to simulation data, the MGGP approach is effective at properly forecasting LPI values. Researchers and policymakers working in the logistics field may find the prediction equation developed from the MGGP model used in this study to be a useful tool for creating efficient logistics plans.

METHODOLOGY

Using the machine learning approach, this study seeks to identify the variables influencing the DBI and the LPI, which are crucial for assessing a nation's business and investment climate.

Boosting algorithms were used within the scope of machine learning. Boosting algorithms are known for their high performance in both classification and regression problems in machine learning. Boosting algorithms achieve high accuracy rates by successively combining weak learners, and each new model corrects the errors of previous models. These algorithms prevent overlearning, create more generalizable models and provide flexibility in regression and classification problems. In addition, boosting algorithms provide transparency by identifying the most effective features in the predictions of the model and are widely used in various fields, such as marketing, finance and health (Friedman, 2001).

In this study, the LightGBM, XGBoost and CatBoost methods, which are the most commonly used methods among the boosting algorithms, were used because they use a dataset consisting of data with different structures and the advantages of boosting algorithms, as explained previously. In this section, the details of the boosting algorithms and information about the dataset are given, and the analysis is carried out.

LightGBM

The machine learning method called LightGBM (Light Gradient Boosting Machine), developed by Microsoft, works best as a gradient boosting structure. This method works faster and uses less memory while working with large datasets and high-dimensional data (Ke et al., 2017).

Unlike traditional decision trees, LightGBM uses a histogram-based approach for data partitioning. This method reduces the processing load and increases the computational speed by dividing the data values into certain intervals. In this way, it enables fast model training even in large datasets (Ke et al., 2017). A leaf-based approach is used by the LightGBM to develop decision trees. This method splits the leaf with the most loss at each iteration, hence expanding the trees. Because leaf-based development enables the trees to become deeper and more strong, the model's overall accuracy rises. However, as this method may increase the risk of overlearning, it should be controlled by pruning techniques and regularization parameters where necessary (Chen and Guestrin, 2016).

To further enhance the dataset, the LightGBM employs the Gradient-Based One-Side Sampling (GOSS) technique. It minimizes the dataset by selecting samples with high gradient values, thus increasing the training time and improving model performance. The algorithm also reduces the number of features and optimizes memory usage by combining features that are rarely active together with the Exclusive Feature Bundling (EFB) method. With these features, LightGBM stands out as an important tool in large-scale data analyses and rapid training and deployment of machine learning models (Natekin and Knoll, 2013).

XGBoost

XGBoost, or Extreme Gradient Boosting, is a well-liked machine learning method that works especially well for supervised learning problems. This algorithm, which is an enhanced variant of the gradient boosting technique, is notable for its excellent speed, versatility, and performance (Brownlee, 2016).

XGBoost is a machine learning method that improves decision tree prediction accuracy by utilizing ensemble learning approaches. This algorithm is based on the gradient boosting method proposed by Friedman (2001) and adds new decision trees sequentially to reduce the error. The goal of every new tree is to fix the mistakes in the current model so that it can gradually get more accurate (Chen and Guestrin, 2016).

One of the main features of XGBoost is its speed and efficiency. The algorithm avoids overlearning by using regularization techniques and thus produces more generalizable models. It can also run quickly on large datasets owing to advanced techniques such as parallel processing and memory optimization (Friedman, 2001; Chen and Guestrin, 2016).

CatBoost

The machine learning algorithm CatBoost (Categorical Boosting) was developed by Yandex in 2017. The gradient boosting technique CatBoost effectively manages categorical features and reaps the advantages of handling them during training rather than preprocessing (Dorogush et al., 2018).

CatBoost is a gradient boosting strategy that aims to reduce prediction drift during training. This distribution shift shows that, when xi is regarded as a training sample, F(xi) represents the output of the function F(x) for a test sample x. This change happens as a result of gradient boosting during training, which estimates gradients and models that minimize them using the same samples. CatBoost proposes a method to estimate the gradient using a set of base models that exclude this sample from the training set (Prokhorenkova et al., 2018).

With every boosting iteration, the CatBoost algorithm expands from i=1 to N base models. This approach predicts the gradient of sample i+1 for the (m+1)th increment iteration after training model i of the mth iteration using the first samples of the permutation. This process is repeated with different random permutations to be independent of the onset of the random permutations. The implementation of CatBoost is optimized to process all permutations and models as a single model in each iteration. The base models are symmetric trees that are grown via levelwise expansion of all the leaf nodes using the same splitting conditions. This method allows a high prediction rate to be obtained without creating very deep trees and avoids overlearning. If overlearning occurs, the algorithm stops learning before reaching the specifications (e.g., number of trees) specified in certain parameters (Altınok, 2022). The CatBoost algorithm can be expressed by the following equation:

$$z = H(x_i) = \sum J_j = 1 c_j 1\{x \in R_j\}$$

In this context, x_i refers to the decision tree associated with the explanatory variable x_i, whereas R_j represents the discrete region corresponding to the leaf nodes of the tree (Prokhorenkova et al., 2018).

According to the literature, the CatBoost algorithm is used in many fields. For example, Sanjeetha et al. (2021) used the Catboost algorithm to detect and mitigate cyber attacks called DDos, Tekin and Sarı (2022) for store demand forecasting.

Data

Both high-income and upper-middle-income nations were included in the study based on income levels. The DBI and LPI were used in the study. The LPI was announced every two years between 2007 and 2010-2022. The DBI data from 2009-2019 were analyzed. The data used in this study were obtained from the World Bank's official data platform, DataBank. The study employed the 1478 variables that were published in the DataBank and included in the WDI, and it examined how these factors affected the DBI and LPI.

Four datasets about DBI and LPI were developed for upper-middle-income countries (UMCs) and high-income countries (HCs). Accordingly, the dataset in which the factors affecting DBI for HCs are analyzed is named HC_DBI, and the dataset in which the factors affecting DBI for UMCs are analyzed is named UMC_DBI. Similarly, the dataset in which the factors affecting LPI for HCs were investigated was named HC_LPI, and the dataset in which the factors affecting LPI for UMCs were investigated was named UMC_LPI.

Analysis

Separate analyses were performed on each dataset. The analyses are shown in Figure 1. The LightGBM, XGBoost and CatBoost algorithms were analyzed via the R programming language. To achieve better accuracy in modeling, the data were divided 80% by 20% for training and testing. Hyperparameter changes were applied to the boosting techniques in order to improve the model's process accuracy. Cross-validation was carried out to assess the model's stability and avoid overlearning following hyperparameter adjustment.

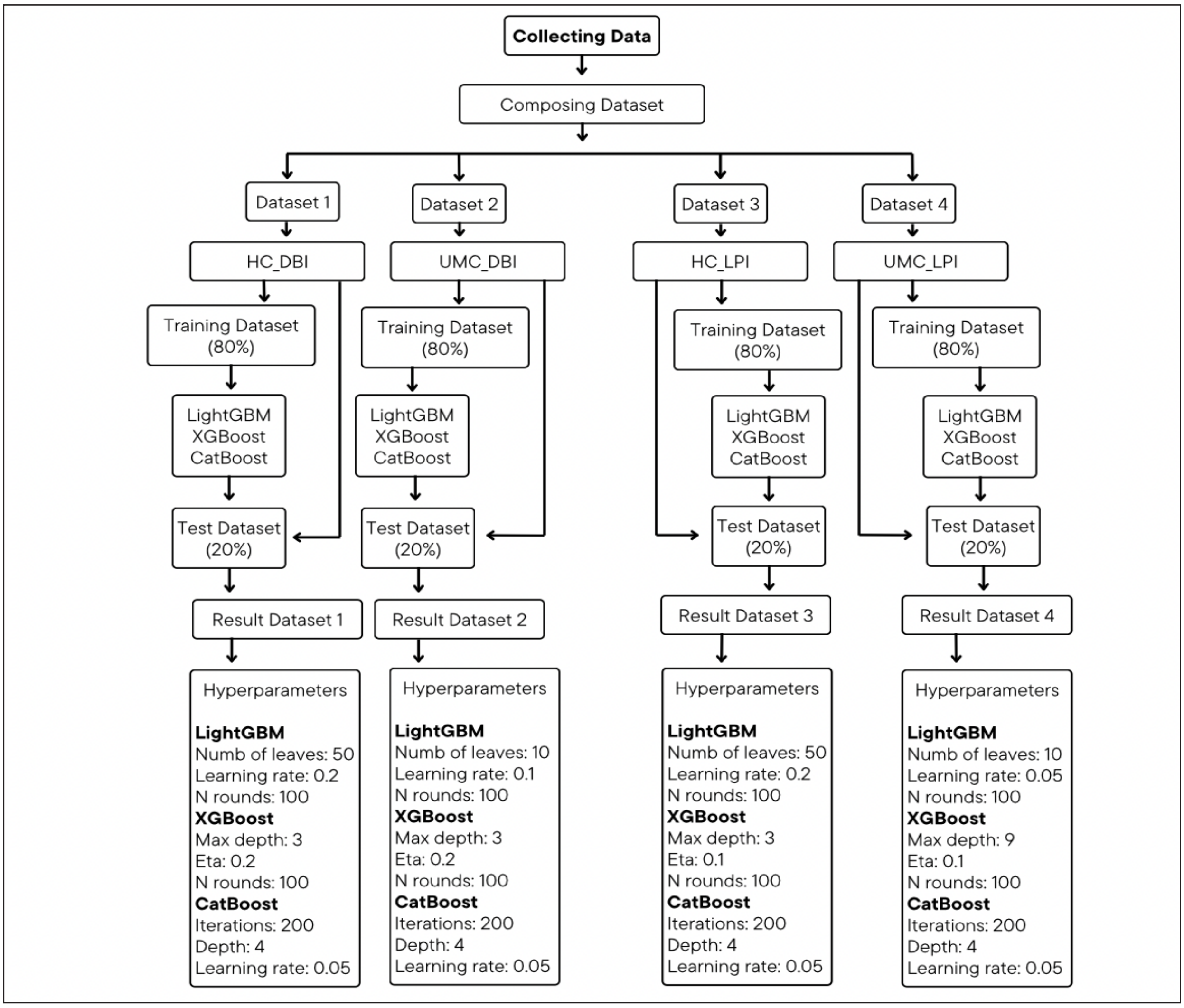

Figure 1. Data Analysis

Table 1: Hyperparameter Optimization of the Algorithms

Algorithm	Hyperparameter	HC_DBI	UMC_DBI	HC_LPI	UMC_LPI
LightGBM	Number of leaves	50	10	50	10
	Learning rate	0.2	0.1	0.2	0.05
	N rounds	100	100	100	100
XGBoost	Maxiumum depth	3	3	3	9
	Eta	0.2	0.2	0.1	0.1
	N rounds	100	100	100	100
CatBoost	Iterations	200	200	200	200
	Depth	4	4	4	4
	Learning rate	0.05	0.05	0.05	0.05

Table 1 displays the hyperparameter optimizations of the methods used in the investigation. The hyperparameters indicated in Table 1 were chosen in order to enhance the model's functionality and generalizability. Specifically, maintaining a modest learning rate made the learning process more accurate, while balancing the number of iterations and tree depth kept the model from growing unduly complicated.

RESULTS and DISCUSSION

To obtain the factors (features) that are effective on DBI and LPI for both HCs and UMCs, it was first desirable to determine the machine learning algorithm that provides the highest rate of correct prediction success on each dataset. For this purpose, analyses were conducted with the CatBoost, LightGBM and XGBoost algorithms. The performance metrics showing the correct prediction success of each algorithm for each dataset are presented in Table 2.

Table 2: Algorithm Performance Results

	UMC_LPI			HC_LPI			UMC_DBI			HC_DBI		
	RMSE	*R^2*	*MAE*	*RMSE*	*R^2*	*MAE*	*RMSE*	*R^2*	*MAE*	*RMSE*	*R^2*	*MAE*
CatBoost	0,182	0,773	0,144	0.163	0,868	0.126	0.816	0,962	1,348	1,320	0,972	0,955
LightGBM	0.204	0,622	0,158	0,174	0,843	0,132	1,585	0,974	0,126	1,385	0,975	0,923
XGBoost	0,177	0,715	0,136	0,174	0,843	0,137	1,905	0,962	1,332	1,247	0,979	0,909

When Table 2 is analyzed, the most successful prediction is achieved with the CatBoost method for almost all the datasets. In general, all methods are more successful on DBI. Although the prediction accuracy for LPI is not as high as that for DBI, the prediction accuracy is sufficient to explain which variables are more important. However, it is seen that especially the CatBoost method is much more successful for LPI than the other methods are. Therefore, the study was conducted via the CatBoost method, and the factors (features) affecting DBI and LPI were obtained for both HCs and UMCs. The 20 most important variables for each country category and index are presented as outputs with their degrees of influence.

As shown in Figure 2, the most effective factor (feature) affecting the DBI values of HCs is machinery and transport equipment (% of value added in manufacturing). Accordingly, the greater share of machinery and transport equipment in the manufacturing industry in HCs increases the DBI. Similarly, Bakmaz et al. (2024) emphasized that the purchase and maintenance of new machinery is important in making business decisions. Regulation quality is one of the most important aspects of DBI, reflecting views on the government's ability to develop and implement reasonable laws and regulations that allow and encourage the expansion of the private sector (in two forms) (World Bank, 2024a). In this context, it is possible to say that as the rate of regularity increases, the DBI score also increases. The World Bank (2015) highlights in its book "*Doing Business 2016: Measuring Regulatory Quality and Efficiency*" that economies with high DBI scores and effective regulatory procedures have higher regulatory quality. The time required to build a warehouse was the other most important variable. Since warehouse construction is a part of infrastructure projects, a short duration (r=-0.36) is an important factor that increases DBI. Another factor that has a major impact on the DBI value is the disclosure index (World Bank, 2024b), which gauges how well investors are safeguarded by the disclosure of financial and real estate information. With this variable, it is understood that the degree of financial transparency and information openness in the country increases the DBI. Important variables have been found for a country's economic indicators, including GDP, unemployment, total mineral reserves, and gold, in addition to elements that reveal information about a nation's legal and political conditions, such as the voice and accountability, rule of law, political stability the absence of violence or terrorism. In addition, research and development expenditures are one of the 20 variables affecting DBI. Spending more on research and development in a nation is likely to make conducting business easier by fostering the growth of a more inventive and dynamic commercial environment. Apart from these, it is noteworthy that variables that provide statistics on women are also among the important variables.

Rençber and Yücekaya (2021) found similar results in their study; they concluded that judicial efficiency, property rights and business freedom variables are the most important indicators in terms of DBI. Similar to these findings, Bayraktar (2015) reported that foreign direct investment (FDI) inflows increase significantly when formalities are less, take less time and property registration costs are lower. Olival (2012) emphasized the importance of property rights and reported that the existence of institutions that protect property rights in a country increases FDI inflows. Akame et al. (2016) reached a similar conclusion on property rights. Doshi et al. (2019) emphasized that countries can increase their DBI score through domestic-political, transnational and

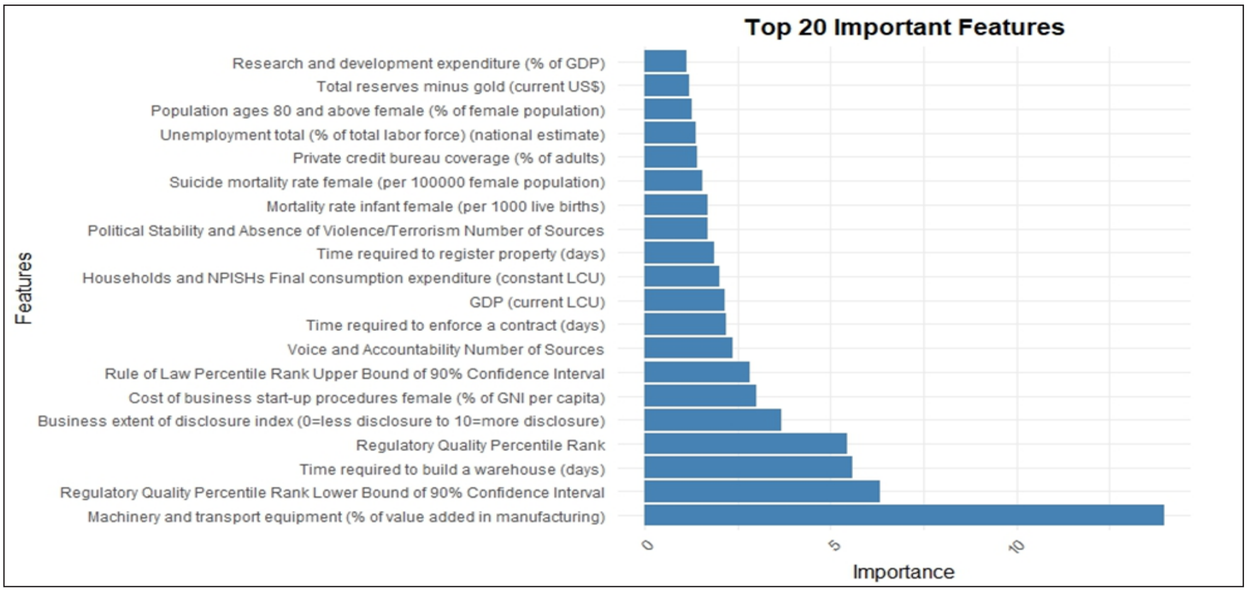

Figure 2. The 20 Most Important Features Influencing DBI for HCs

bureaucratic channels. Mengistu (2016) highlighted that greater DBI is a result of a number of factors, including political stability, government effectiveness the rule of law, lack of corruption and the efficient regulations.

The 20 factors that have the most effects on DBI for UMCs are ranked in order of significance in Figure 3. The percentage of information and communication technology (ICT) products to total global commodity exports is thus the most important number. In light of this, countries' DBI scores rise in tandem with their exports of ICT items. The registered new business variable, which indicates economic vitality and the entrepreneurial environment, is also found to be one of the most important variables affecting DBI for UMCs. A large number of new business registrations can be viewed as a major and expected outcome, given that it indicates the business environment's favorability and the economy's vitality. DBI is also impacted by another indicator, the private sector credit to GDP ratio. Improvements in the provision of the necessary financing for the growth and expansion of enterprises are factors that increase the DBI score. The number of ATMs per 100,000 individuals is another noteworthy statistic that is among the most crucial factors in DBI. The predominance of ATMs might be seen as an indication that raises DBI as it is a measure of access to financial services. The variable of the methodological assessment of statistical capacity is also among the five most important variables affecting DBI for UMCs. A good methodological assessment of the country's statistical capacity provides accurate results in data collection and analysis, enabling policy makers and businesses to make better decisions. In addition, variables such as regulatory quality and the business extent of the disclosure index, which are important variables in DBI for HCs, are also found to be important for UMCs. However, they are slightly behind in importance ranking. Apart from these, variables that provide information about the economic, environmental, legal and political situations of countries as important variables have also found a place in the top 20. In particular, the presence of variables in terms of environmental sustainability (adjusted savings carbon dioxide damage and adjusted savings particulate emission damage) is remarkable. Environmentally friendly and sustainable business settings may attract more foreign investors since reduced emission harm is essential for long-term sustainable development and economic progress. Similar results have been reported in the literature. In his study, Eifert (2009) stated that in countries that are relatively well governed in terms of income, the rate of entry to the country for investment and doing business increases in the following year because of the effect of regulatory reforms. According to Haggard and Haggard (2018), cultural differences, legal status, and religious beliefs don't significantly affect the expenses of starting a business and conducting business in a nation. Garcia and Hinayon (2018) find that factors such as standard of living, investment income and economic growth have positive relationships with DBI. They also emphasize that GDP, external debt, political stability, economic freedom and financial literacy also have an impact on DBI. In contrast to these studies, Klapper et al. (2004) emphasized that computer services, telephones and the internet have high regulatory barriers and high entry costs, which hinder entry and doing business. It can be said that the conditions of the day when the study was conducted and the difficulty of access to technology were effective in the emergence of this situation.

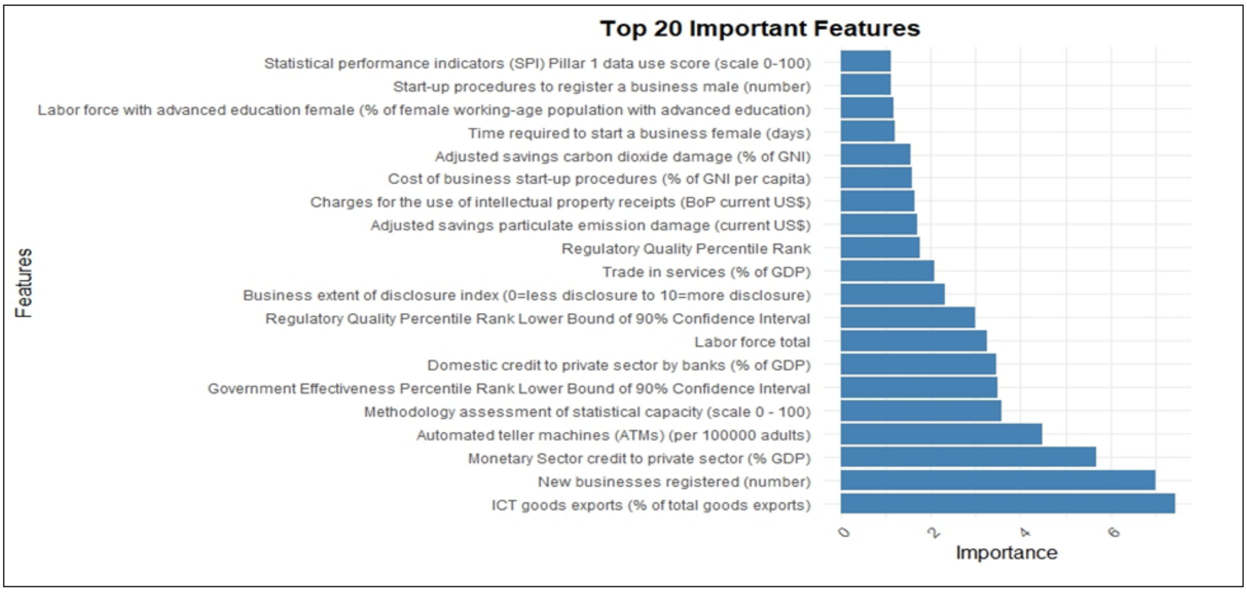

Figure 3. The 20 Most Important Features Influencing DBI for UMCs

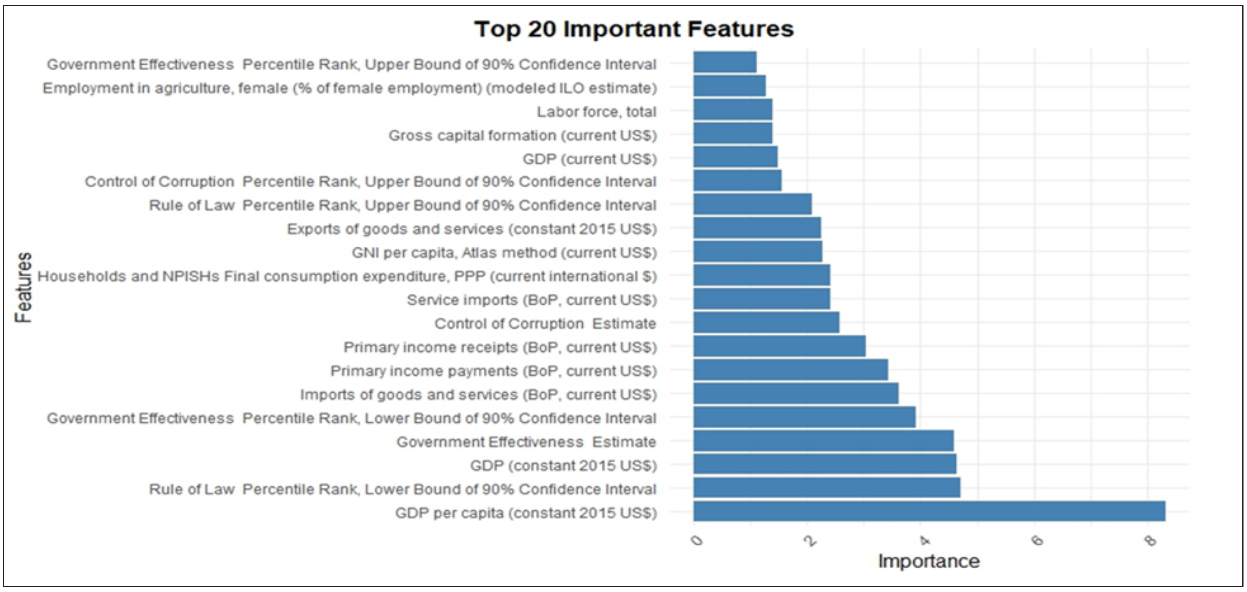

Figure 4. The 20 Most Important Features Influencing LPI for HCs

Figure 4 presents the 20 most important variables affecting the LPI for HCs. When these variables are analyzed, it is noteworthy that similar indicators are included together. For this reason, the important variables will be evaluated on the basis of common points rather than individually. First, the labor force, gross capital formation, household and NPISH (Non-Profit Institutions Serving Households) final consumption expenditures, GDP, GDP per capita, and GNI per capita are all economic and production variables that garner attention. These findings show that the economic size and capital investments of countries have a significant effect on logistics performance. NPISH and household consumer spending, for instance, are crucial indicators of the health and prosperity of an economy, and rising consumption spending is frequently seen as a sign of economic success and expansion. However, increased consumption expenditures mean more demand for goods and services, which can lead to the need to increase the efficiency and capacity of the logistics network. Similar findings are obtained from a review of the literature on the connection between production, logistics performance and economic indices. Economic growth and development are closely linked to logistics performance, according to a number of studies in the literature (Bozma et al., 2017; Ofluoğlu et al., 2018). Second, the impact of main income receipts/payments variables associated with international commerce and the balance of payments, as well as exports and imports of commodities and services, is not surprising. As expected, these variables show that countries' trade volume and foreign trade balances are determinants of logistics performance. Similar strong correlations between foreign trade measures and logistics performance have been reported by other research in the literature (Martí et al., 2014). Finally, among the most important factors are administrative and legal indicators, such as the percentile rank of government performance, the percentile rank of control of corruption, and the percentile rank of rule of law. These metrics show that a country's legal compliance and governance expertise have a big impact on logistical performance. Similarly, Başar and Bozma (2017) concluded in their study that government effectiveness and the quality of regulations increase LPI. The researchers stated that especially in countries with high corruption, transaction times and costs in foreign trade increase, which negatively affects the trade of the foreign trade partner from the country and thus logistics performance. On the other hand, Ojala and Queiroz (2002) concluded in their study that trade and logistics practices can be carried out more easily in a country with a low perception of corruption.

Figure 5 presents the 20 most important variables that have an impact on LPI for UMCs. Here again, the most important 20 variables are discussed on the basis of their common points. In this context, first, fixed broadband subscriptions, mobile cellular subscriptions and ICT service exports are among the most important variables. These variables show the importance of the impact of countries' technology infrastructure and utilization on logistics performance. In their study, Burmaoglu and Sesen (2011) came to the conclusion that the logistics infrastructure, which includes all forms of transportation as well as information and communication technology, is the most useful factor in determining how different nations differ in terms of logistical activities and performance. ICT is crucial for increasing the efficacy and efficiency of logistical infrastructure, according to research. Similar to this, numerous studies have highlighted the significance and requirement of information and communication technology to have a say in international commerce and to deliver top-notch logistical services (Toh et al., 2009; Sofyalıoğlu and Kartal, 2013). Second, indicators related to the economy and financial markets constitute an important variable group for UMCs as well as for HCs. Economic size, financial markets, and credit facilities have a major impact on the LPI, as evidenced by variables like gross fixed capital creation. GDP, market capitalization of listed domestic businesses. Domestic credit to the private sector, stocks traded, and S&P global equity indexes. In particular, having adequate credit facilities can act as a lever to improve logistics performance, as financial resources will greatly support infrastructure investments and operational improvements. Third, as expected, countries trade indicators, such as service exports, commercial service exports and goods imports, have an impact on LPI.

Finally, when a general evaluation is made in terms of the factors affecting DBI and LPI, which provide important information to investors about the business environment and logistics infrastructure of a country, some common points come to the forefront. First, when DBI is analyzed, it is seen that economic, technological/research & development, legal and managerial indicators and financial transparency are important for both HCs and UMCs, and the variables affecting DBI are largely similar. In terms of LPI, it is observed that economic/production and commercial indicators are jointly important for both HCs and UMCs. Apart from this, administrative and legal variables for HCs and variables related to technological infrastructure and its utilization for UMCs are noteworthy. Finally, when evaluated in terms of the variables that affect DBI and LPI in a common way, it is

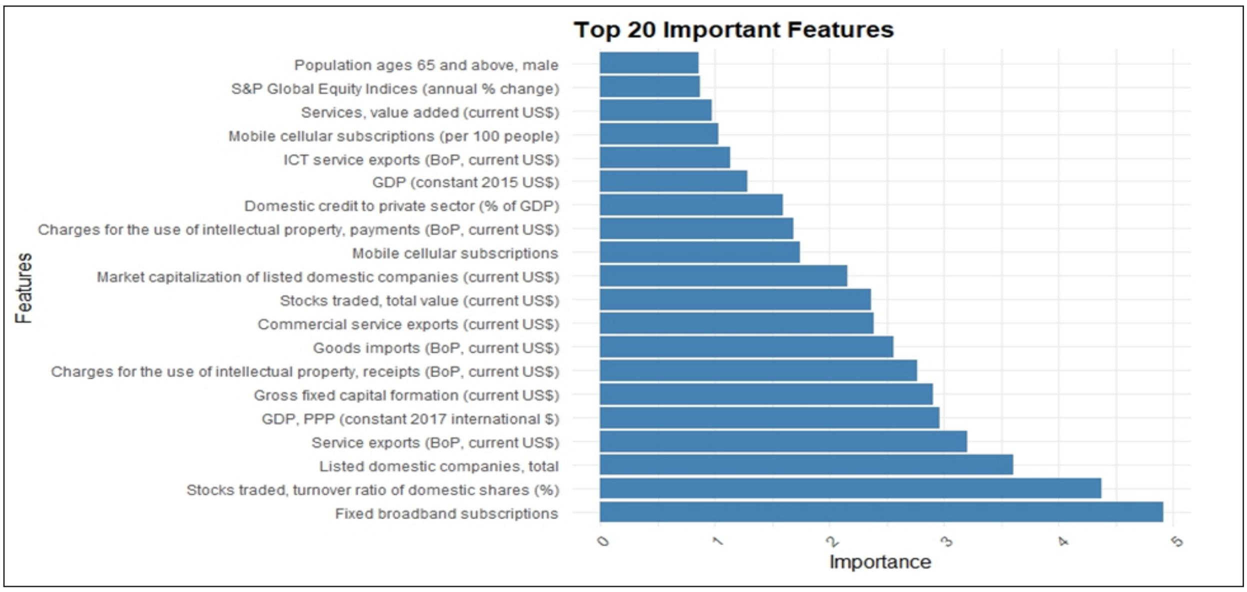

Figure 5. The 20 Most Important Features Influencing LPI for UMCs

seen that economic, administrative, and legal indicators and the technological infrastructure of countries are effective on doing business and logistics performance.

CONCLUSION

These days, foreign investment is crucial to a nation's economic growth (e.g., economic growth, development, employment increase and tax revenues). A favourable business and investment environment stands out as one of the main factors enabling investment flows (Pala, 2022). However, when it is considered from the perspective of investors who aim to establish businesses in different countries to increase their profitability and maintain their presence in the global market, it is seen that the addition of the uncertainty of countries to global competition conditions makes it difficult for investors to have full information about investment opportunities, and the need for comprehensive research emerges (Cavusgil et al., 2004). In this framework, before making investment decisions in foreign countries, indices calculated by some international organisations (GDP, DBI, World Economic Freedom Index, Purchasing Power Parity, LPI, etc.) are taken as references (Koç et al., 2017). At this point, in addition to classical indicators such as GDP, two indices stand out as the most important indices for investors to benefit from in terms of investment; DBI and the LPI.

A thorough analysis of the relationship between the two indices and a variety of other factors is required to gain a better understanding of the scope and impact of two significant indices that show how suitable the business and investment environment is, according to a review of the literature. The study's objective is to determine the background elements that influence the DBI and LPI. To this end, 1478 variables from the World Bank's released data on the WDI were incorporated into the study. In addition, to obtain the factors affecting DBI and LPI for both HCs and UMCs, first of all, the machine learning algorithm that provides the highest rate of correct prediction success on each data set was wanted to be found and accordingly, analyses were carried out with the CatBoost, LightGBM and XGBoost boosting algorithms. Since the most successful prediction for almost all the datasets was achieved with the CatBoost method, the study was conducted via the CatBoost method, and the factors affecting DBI and LPI for both HCs and UMCs were obtained. The 20 most important variables for each country category and index are presented as outputs with their degrees of influence.

First, when the results regarding DBI are evaluated, it is found that economic, technological/research & development, legal and managerial indicators and financial transparency are jointly important for both HCs and UMCs, and the variables affecting DBI are largely similar. In addition to these, for HCs, the variables of the time required to build a warehouse and the variables providing statistics related to women; for UMCs, the variables of the number of ATMs and the environmental variables were noteworthy. In terms of LPI, it is observed that economic/production and commercial indicators are jointly important for both HCs and UMCs. In addition to these, administrative and legal variables for HCs and variables related to technological infrastructure and its utilization for UMCs are noteworthy. Finally, when the variables that jointly affect DBI and LPI are analyzed, it is seen that economic, administrative, and legal indicators and the technological infrastructure of countries are effective on doing business and logistics performance. In other words, it can be said that high DBI and LPI scores are generally associated with advanced economic indicators, effective administrative structures, strong legal systems and sound technological infrastructures. The economic performance and global competitiveness of nations may be better understood and enhanced with the use of these metrics. In particular, the use of information and communication technologies can help UMCs accelerate their economic development processes and achieve more sustainable growth. Therefore, investing in and promoting the use of ICTs should be a strategic priority for UMCs to improve in DBI and LPI.

At the end of the study, it is thought that determining the most critical factors that countries that want to improve their scores for both indices should focus on and determining the most important factors that investors should focus on other than these indices will make a significant contribution to the business world and the literature. However, the study's primary weakness is that it solely uses World Bank data for its purposes. In this regard, data gathered from other universities in subsequent research might enhance the study.

The findings of this study reveal that DBI and LPI indices play a crucial role in assessing the investment environment. However, it should not be overlooked that these indices alone may not be sufficient to guide investment decisions. Factors such as political and social stability, infrastructure investments, workforce quality, and innovation capacity also play a critical role in investors' decision-making processes. Therefore, future research is recommended to expand the scope by incorporating these additional variables to provide a more comprehensive evaluation of investment attractiveness. Furthermore, testing the machine learning models used in this study with different datasets and variables could enhance methodological diversity and strengthen the reliability of the findings.

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