BULLETIN OF THE POLISH ACADEMY OF SCIENCES
TECHNICAL SCIENCES, Vol. 73(6), 2025, Article number: e155027
DOI: 10.24425/bpasts.2025.155027

SPECIAL SECTION

Decision tree models for technical due diligence in land development

Marcin WAGA[1]*, **Elżbieta RADZISZEWSKA-ZIELINA**[2], and **Bartłomiej SROKA**[2]

[1] Doctoral School, Cracow University of Technology, Poland
[2] Faculty of Civil Engineering, Cracow University of Technology, Poland

Abstract. In the design of modern urban systems that consider the needs of different resident groups, technical due diligence (TDD) processes play a crucial role. According to current market practice, these processes precede land acquisition and the commencement of construction projects. As part of this process, the feasibility of the planned investment is verified. Already at the preliminary report stage, potential legal, technical, environmental, social, and economic constraints that may prevent the implementation of the project are identified. If no significant barriers are found, a final report is issued. This article presents a methodology for identifying factors that may block the implementation of an investment at the preliminary report stage. It also proposes a supporting model for the investment decision-making process regarding land acquisition, based on decision trees. Based on completed TDD processes, an algorithm was developed that enables the construction of a decision tree, considering various attributes describing the analyzed building plot. The use of decision trees allows for the early identification of key attributes requiring detailed analysis in the initial phase of TDD. This facilitates more efficient preparation of preliminary reports, considering the interests of different resident groups. In the final report stage, decision tree models can serve as a crucial tool to support investors in making decisions regarding the potential land acquisition.

Keywords: technical due diligence; building plot; decision trees.

1. INTRODUCTION

In the process of designing modern urban systems that consider the needs of various resident groups [1], technical due diligence (TDD) procedures play a key role. The term due diligence [2] originates from the 1930s in the United States, where it referred to the obligation of financial instrument sellers to provide the necessary data required by local legislation. Today, according to the American legal terminology dictionary [3], due diligence refers to an analysis conducted by businesses before making strategic decisions in areas such as corporate mergers/acquisitions or the purchase/sale of major assets. According to [4], the purpose of TDD analysis is to minimize risk, i.e., to protect the buyer from unexpected costs resulting from facts disclosed after finalizing the transaction, when its reversal is no longer possible. According to market practice, the purchase of a building plot and the commencement of a construction project are preceded by the preparation of a TDD report.

The scientific literature describes various methods for conducting the TDD process, such as AHP (Analytic Hierarchy Process), machine learning, expert interviews, document analysis, and site inspections [5]. However, the authors have not found any prior use of decision trees to support the preparation of TDD reports, which is the focus of this article. Furthermore, this article attempts to define a consistent methodology for preparing such reports. It is worth mentioning that the use of decision trees has already been discussed in the literature concerning certain aspects of urban planning, such as managing reclamation works [6] and investigating urban construction land [7].

The development of this report involves solving a classification problem [8,9], which consists of confirming that the planned building can be constructed on a given plot in compliance with the currently applicable regulations [10] and the investor's requirements [11, 12]. Figure 1 presents the main stages of the TDD process.

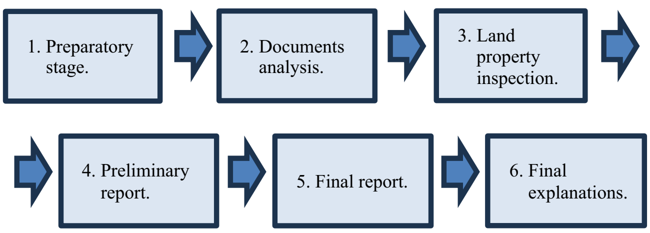

Fig. 1. Stages in the implementation of the TDD process for a land property [13]

At the preliminary report stage, legal, technical, environmental, social, and economic constraints that may become an investment barrier are verified. In such cases, the TDD process concludes with the issuance of the preliminary report. If no such constraints are identified, a final report is issued, containing any reservations identified throughout the TDD process.

The TDD process discussed in this article focuses primarily on technical aspects related to land, but it also examines legal,

*e-mail: marcin.waga@doktorant.admin.pk.edu.pl

Manuscript submitted 2025-03-29, revised 2025-06-01, initially accepted for publication 2025-06-02, published in November 2025.

environmental, social, and economic factors [14]. According to the guidelines of RICS (Royal Institution of Chartered Surveyors) [15], TDD aims to identify significant physical defects or noncompliance with local regulations before the sale of a property, which may affect its value on the commercial market. At the buyer's request, an inspection of the building plot is conducted, all administrative decisions issued for the property in question are reviewed, and all documents provided by the seller are verified.

The preparation of the TDD report can be framed as a binary classification problem [16], where the input consists of plot attributes, which are independent variables, while the output is a recommendation regarding the potential purchase of the property, which is the dependent variable.

One of the most popular methods for solving classification problems is the use of decision trees [17], which aim to divide the data into the most homogeneous groups possible concerning the dependent variable [18]. The method can be presented in a clear graphical form and allows for identifying which attributes have the greatest impact on the outcome.

This paper aims to apply the classifier, which, at the preliminary report stage, will identify attributes that have a decisive impact on the feasibility of the investment, and at the final report stage, will support investment decisions regarding the potential purchase of a building plot.

2. CONSTRUCTION OF A DECISION TREE

2.1. Decision tree based on five attributes

All factors affecting the implementation of an investment can be grouped into five categories: technical, environmental, legal, economic, and social. During the TDD process, factors belonging to these categories are verified in relation to the specific location of the building plot.

Table 1 presents twelve real projects for which TDD reports were prepared between 2005 and 2025 and described using five example attributes corresponding to the five different groups of independent factors. These cases will serve as training and testing data in our analysis. Training data from cases 1 to 10 were used to build the decision trees presented in Figs. 2 and 3. The detailed description of the five attributes is presented in Table 2.

The decision tree required to build the classifier was constructed based on the ID3 algorithm (Iterative Dichotomizer 3) [22] following the principles outlined below:

1. The best attribute is determined (according to the information gain measure test), which is placed at the next node (the root node during the first iteration) of the tree.
2. For each value of the selected attribute, a branch is created with the next tree node.
3. The training set is divided into subsets for each value of the selected attribute to be considered at each newly created node.
4. If all examples have the same decision, a leaf is created, terminating the process. Otherwise, the tree construction starts again from the first step.

The information gain (1) measure test is a statistical test used to evaluate attributes based on their ability to split the training data into subsets. This test measures how much the entropy is reduced after splitting the training set [22].

$$P(A,B) = E(A) - E(A/B), \tag{1}$$

where $P(A,B)$ – information gain – the expected reduction in entropy, $E(A)$ – the entropy calculated for the training set A, $E(A/B)$ – the entropy calculated for the subsets created after splitting the training set A based on the value of attribute B. Set A is divided into two subsets: the first subset contains the

Table 1

A list of ten sample building plots, training data, described by five attributes (F – favorable, U – unfavorable)

	Technical factors (Soil conditions)	Environmental factors (Tree inventory)	Legal factors (Planning decisions)	Economic factors (Purchase price of the plot)	Social factors (Neighbors' attitude towards the investment)	The decision made by the investors
1	F	F	F	F	F	Yes
2	F	F	U	F	U	No
3	U	F	F	F	F	Yes
4	U	F	F	U	F	No
5	F	U	F	U	F	No
6	F	U	F	F	F	Yes
7	F	U	F	U	F	No
8	F	F	F	F	U	Yes
9	F	F	U	F	F	No
10	U	U	F	F	U	Yes
11	U	U	U	F	F	No
12	U	F	F	F	U	Yes

Table 2
Detailed description of five attributes

	Group of factors	Description of attributes
1	Technical factors (soil conditions) [19]	Favorable – the building foundation can be classified as a geotechnical category I or II.
		Unfavorable – the building foundation can be classified as a geotechnical category III.
2	Environmental factors (Tree inventory) [20]	Favorable – the study was found not to include any trees that could be considered natural monuments.
		Unfavorable – the inventory includes trees that the authorities may consider natural monuments and may refuse permission for their removal, which could limit the building area of the future investment.
3	Legal – planning decisions (e.g., zoning decisions, extracts from the Local Spatial Development Plan)	Favorable – planning decisions that allow the construction of the planned building.
		Unfavorable – planning decisions that do not allow the construction of the planned building.
4	Economic factors (purchase price of the plot)	Favorable – the price of the plot is acceptable to the investor.
		Unfavorable – the price of the plot is not acceptable to the investor.
5	Social factors (neighbors' attitude towards the investment)	Favorable – the positive attitude of direct neighbors towards the planned investment [21].
		Unfavorable – the negative attitude of direct neighbors towards the planned investment. In such a case, one can expect them to block, in accordance with applicable law, all formal decisions and approvals issued for the subject plot.

"favorable" values of attribute B, while the second subset contains the "unfavorable" values.

Within the framework of information theory, entropy [23] is defined as the average amount of information per symbol representing the occurrence of an event from a given set [24]. The events in this set are assigned probabilities of occurrence. The formula for entropy for our training data (2)

$$E(x) = \sum_{i=1}^{2} p(i) \cdot \log_2 \frac{1}{p(i)} = -\sum_{i=1}^{2} p(i) \cdot \log_2 p(i), \tag{2}$$

where $p(i)$ – the probability of occurrence of event i, x – the dataset for which entropy is calculated.

The entropy for the training set (A – cases 1–10, see Table 1) amounts to $E(A) = -0.5 \cdot \log_2(5/10) - 0.5\log_2(5/10) = 1$. In Table 3, the information gain was calculated for the subsets of the training set obtained by splitting based on the described attribute.

The information gain measure test yielded the best result for the economic attribute, which is why this attribute was placed at the root of the tree. After applying the procedure twice, we obtained the final version of the decision tree. Attributes that do not have a decisive impact on investment implementation were omitted from the model.

Table 3
Information gain calculated for the five attributes using training data (cases 1–10, see Table 1)

	Attribute: technical conditions	Attribute: environmental conditions	Legal attribute	Economic attribute	Social attribute
Favorable E_F	$E_F[4,3] = -4/7\log_2(4/7) - 3/7\log_2(3/7) = \mathbf{0.98}$	$E_F[3,3] = -3/6\log_2(3/6) - 3/6\log_2(3/6) = \mathbf{1}$	$E_F[5,3] = -5/8\log_2(5/8) - 3/8\log_2(3/8) = \mathbf{0.954}$	$E_F[5,2] = -5/7\log_2(5/7) - 2/7\log_2(2/7) = \mathbf{0.86}$	$E_F[5,2] = -5/7\log_2(5/7) - 2/7\log_2(2/7) = \mathbf{0.86}$
Unfavorable E_U	$E_U[2,1] = -2/3\log_2(2/3) - 1/3\log_2(1/3) = \mathbf{0.907}$	$E_U[2,2] = -2/4\log_2(2/4) - 2/4\log_2(2/4) = 1$	$E_U[2,0] = -1\log_2(1) - 0\log_2(0) = \mathbf{0}$	$E_U[3,0] = -1\log_2(1) - 0\log_2(0) = \mathbf{0}$	$E_U[2,1] = -1/3\log_2(1/3) - 2/3\log_2(2/3) = \mathbf{0.92}$
The amount of information per attribute $E(A/B)$	$7/10 \cdot 0.98 + 3/10 \cdot 0.907 = \mathbf{0.958}$	$6/10 \cdot 1 + 4/10 \cdot 1 = \mathbf{1}$	$8/10 \cdot 0.954 + 2/10 \cdot 0 = \mathbf{0.7632}$	$7/10 \cdot 0.86 + 2/10 \cdot 0 = \mathbf{0.602}$	$7/10 \cdot 0.86 + 3/10 \cdot 0.92 = \mathbf{0.878}$
Information gain $E(A) - E(A/B)$	$1 - 0.958 = \mathbf{0.042}$	$1 - 1 = \mathbf{0}$	$1 - 0.7632 = \mathbf{0.2368}$	$1 - 0.602 = \mathbf{0.398}$	$1 - 0.878 = \mathbf{0.12}$

Figures 2 and 3 show a graphical representation of the decision tree based on the training data (cases 1–10, see Table 1).

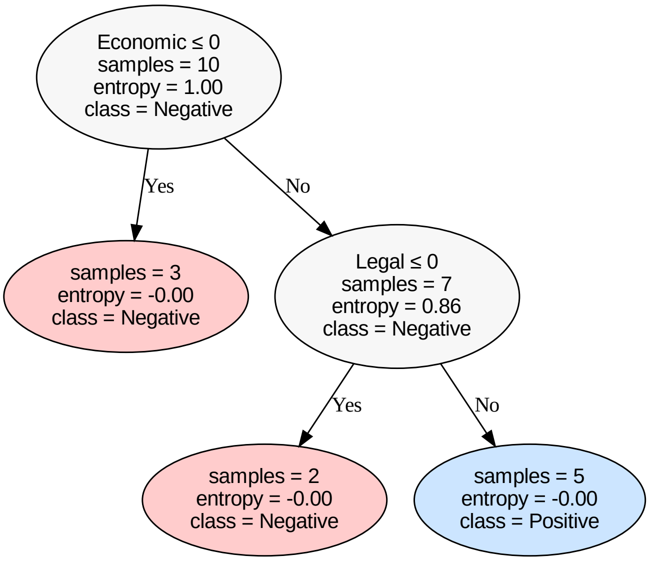

Fig. 2. Diagram of a decision tree based on five attributes. It is constructed using the ID3 algorithm. Blue leaves indicate a positive decision, pink ones a negative decision

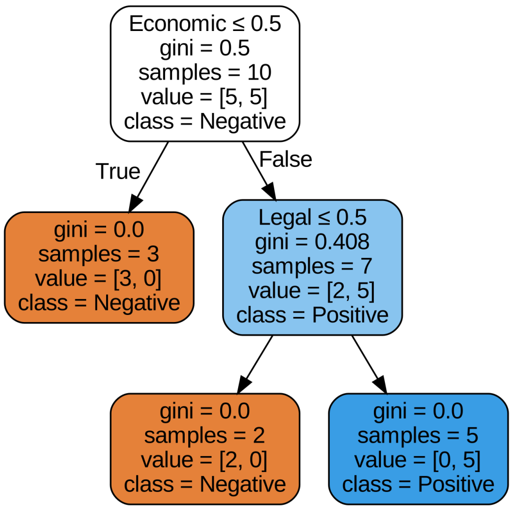

Fig. 3. Diagram of a decision tree based on five attributes. It is built using the CART algorithm. Blue leaves indicate a positive decision, orange ones a negative decision

The graphics in Fig. 2 correspond to the application of the ID3 algorithm as described in this paper, while Fig. 3 represents the CART (classification and regression trees) algorithm, which is a more advanced version of ID3. The CART algorithm [7] uses the G_{ini} index (3) instead of the information gain test to measure how purely the data are split at the nodes.

$$G_{\mathrm{ini}} = 1 - \sum_{i=1}^{2} p_i^2, \tag{3}$$

p_i – the probability that an object belongs to class i.

For the entire training data, the G_{ini} coefficient is 0.5 $[1-(0.5^2+0.5^2)]$. The computation of the G_{ini} coefficient is significantly less time-consuming for enormous data sets than calculating the information gain test, which requires logarithmic operations [24]; however, for our context, it is not a principal issue.

Out of the five attributes used to build the tree, two factors (economic and legal) were identified as decisive for the feasibility of the investment. These factors should be thoroughly verified as early as the preliminary TDD report stage. This provides additional value for the preparation of the preliminary report of the TDD process, outside of the benefits of the decision trees model.

2.2. Model testing – five attributes

The five attributes model was a preliminary proof of concept.

The model was tested using the cross-validation methodology. The data presented in Table 1 were divided into six separate groups presented in Table 4, each consisting of two cases. Six tests with different training and testing sets were conducted. The model consistently produced decisions matching the actual outcomes.

Table 4
Presentation of a cross-validation test

	Training data, number of cases	Testing data number of cases	Results
1	From 1 to 10	11, 12	Correct for all testing data
2	From 3 to 12	1, 2	Correct for all testing data
3	From 5 to 12 and from 1 to 2	3, 4	Correct for all testing data
4	From 7 to 12 and from 1 to 4	5, 6	Correct for all testing data
5	From 9 to 12 and from 1 to 6	7, 8	Correct for all testing data
6	From 11 to 12 and from 1 to 8	9, 10	Correct for all testing data

However, based on the authors' experience, it can be noted that five attributes are not sufficient to satisfactorily reflect reality. For this reason, an attempt was made to expand it into a model based on 15 attributes.

2.3. Decision tree based on fifteen attributes

Below is a decision tree model built based on the training data presented in Table 5, cases from 1 to 20. Each investment is described by 15 attributes assigned to five groups of factors. A detailed description of the 15 attributes is presented in Table 6. Figure 4 shows a graphical representation of the decision tree. The graphic corresponds to the application of the CART algorithm.

Of the fifteen attributes used to build the tree, two main factors (economic – price of the building plot and legal – planning

Table 5
Training data for the decision tree model with 15 attributes (F – favorable, U – unfavorable)

	Technical factors			Environmental factors			Legal factors			Economic factors			Social factors			The decision made by the investors
	Soil conditions	Connection conditions to public roads	Utility connection conditions	Greenery inventory	Soil contamination	Carbon footprint	Planning decisions	Heritage protection of the area	Legal status of neighboring plots	Price of the building plot	Construction market trends	Global economic situation	Direct neighbors' attitude	Social attitude	City authorities' attitude	
1	F	F	F	F	F	F	F	F	F	F	F	F	F	F	F	Yes
2	F	F	U	F	U	F	U	F	F	F	F	F	U	U	F	No
3	U	U	F	F	U	F	F	F	F	F	F	F	U	U	F	Yes
4	U	U	F	F	U	F	F	F	F	U	F	F	F	F	F	No
5	F	F	U	U	F	F	F	U	F	U	F	F	U	U	F	No
6	F	F	F	U	F	F	F	F	F	F	F	F	U	F	F	Yes
7	F	F	U	U	F	F	U	F	F	F	F	F	U	U	U	No
8	F	F	F	F	U	F	F	U	F	F	F	F	U	U	F	Yes
9	F	U	F	F	U	F	F	U	U	F	F	F	F	F	F	Yes
10	U	F	F	U	U	F	F	F	F	F	F	F	U	U	F	Yes
11	F	F	F	F	U	F	F	U	F	U	F	F	F	F	F	No
12	F	U	F	F	U	F	F	F	F	F	F	F	F	F	F	No
13	F	F	U	F	U	F	F	U	F	U	U	U	F	F	F	No
14	F	F	F	F	U	F	F	U	F	F	F	F	U	F	F	No
15	F	F	F	F	F	F	U	U	F	F	F	F	U	F	F	No
16	F	F	F	F	F	F	F	F	F	U	U	F	U	F	F	No
17	U	F	F	U	F	F	F	F	U	F	F	F	F	F	F	Yes
18	U	F	F	F	U	F	F	U	F	F	F	F	U	U	F	Yes
19	F	F	U	F	F	F	F	F	F	F	F	F	U	F	F	Yes
20	F	F	F	U	U	F	F	U	U	F	F	F	F	F	F	Yes
21	F	U	F	F	F	F	U	F	F	F	F	U	U	U	F	No
22	F	F	U	F	F	F	F	F	F	F	U	F	U	U	F	Yes
23	F	F	F	F	U	F	F	F	F	F	U	F	U	U	F	Yes
24	U	F	F	F	U	F	F	F	U	U	F	F	U	F	F	No
25	F	F	U	U	U	U	F	U	F	F	F	U	U	U	F	Yes

Table 6
A detailed description of the 15 attributes

<table>
<tr><th></th><th>Factor group</th><th>Attribute</th><th>Attribute description</th></tr>
<tr><td rowspan="6">1</td><td rowspan="6">Technical</td><td rowspan="2">Ground conditions [19]</td><td>Favorable – the building foundation can be classified as a geotechnical category I or II.</td></tr>
<tr><td>Unfavorable – the building foundation can be classified as a geotechnical category III.</td></tr>
<tr><td rowspan="2">Connection conditions to public roads</td><td>Favorable – the costs associated with the connection to public roads are acceptable to the investor.</td></tr>
<tr><td>Unfavorable – the costs associated with the connection are not acceptable to the investor.</td></tr>
<tr><td rowspan="2">Conditions for connection to utilities</td><td>Favorable – the costs of implementing all utility connections are acceptable to the investor.</td></tr>
<tr><td>Unfavorable – the costs of implementing all utility connections are not acceptable to the investor.</td></tr>
</table>

Table 6 [cont.]

	Factor group	Attribute	Attribute description
2	Environmental	Inventory of greenery [20]	Favorable – the study does not include trees that can be considered natural monuments.
			Unfavorable – the inventory includes trees that the authorities may consider natural monuments and may not grant permission for their removal, which could limit the building area of the future investment.
		Ground contamination [25]	Favorable – there is no soil or groundwater contamination on the building plot.
			Unfavorable – the plot is contaminated, requiring remediation work.
		Carbon footprint	Favorable – the investor is not required to reduce the carbon footprint during the project implementation.
			Unfavorable – the investor imposes a requirement not to exceed the limit of the carbon footprint per square meter of usable floor area of the future building.
3	Legal	Planning decisions	Favorable – planning decisions or an extract from the local zoning plan allow for development in line with the investor's expectations.
			Unfavorable – planning decisions or extracts from the local zoning plan do not allow for development in line with the investor's expectations.
		Heritage protection of the area [26]	Favorable – the building plot is not located in an area under heritage protection.
			Unfavorable – the building plot is in an area under heritage protection.
		Legal status of neighboring plots	Favorable – the legal status of neighboring plots is clear and transparent (e.g., no ongoing inheritance proceedings).
			Unfavorable – the legal status of neighboring plots is unclear, which will result in the inability to establish parties in administrative proceedings.
4	Economical	Price of the building plot	Favorable – the price of the plot is acceptable to the investor.
			Unfavorable – the price of the plot is not acceptable to the investor.
		Construction market trends analyzed in reports by consulting firms, e.g., [27, 28]	Favorable – according to real estate market reports, there is an increasing demand for the planned type of buildings.
			Unfavorable – according to real estate market reports, there is no observed demand for the planned type of buildings.
		Global economic situation	Favorable – the investor has a positive attitude towards the global economic situation (e.g., low inflation, positive economic growth).
			Unfavorable – the investor has a negative attitude towards the global economic situation (e.g., high inflation, negative economic growth).
5	Social	Direct neighbors' attitude	Favorable – the positive attitude of the immediate neighbors towards the planned investment [21].
			Unfavorable – the negative attitude of the immediate neighbors; in this case, one can expect the blocking of all administrative decisions issued for the building plot.
		Social attitude. This attribute has a direct impact on sustainable land use strategies and the development of modern urban systems.	Favorable – social associations (e.g., district councils) do not protest similar investments.
			Unfavorable – social associations (e.g., district councils) are actively protesting similar investments.
		City authorities' attitude. This attribute has a direct impact on sustainable land use strategies and the development of modern urban systems.	Favorable – the city authorities have a positive attitude towards the investment and assure their support.
			Unfavorable – the city authorities have a negative attitude towards the investment.

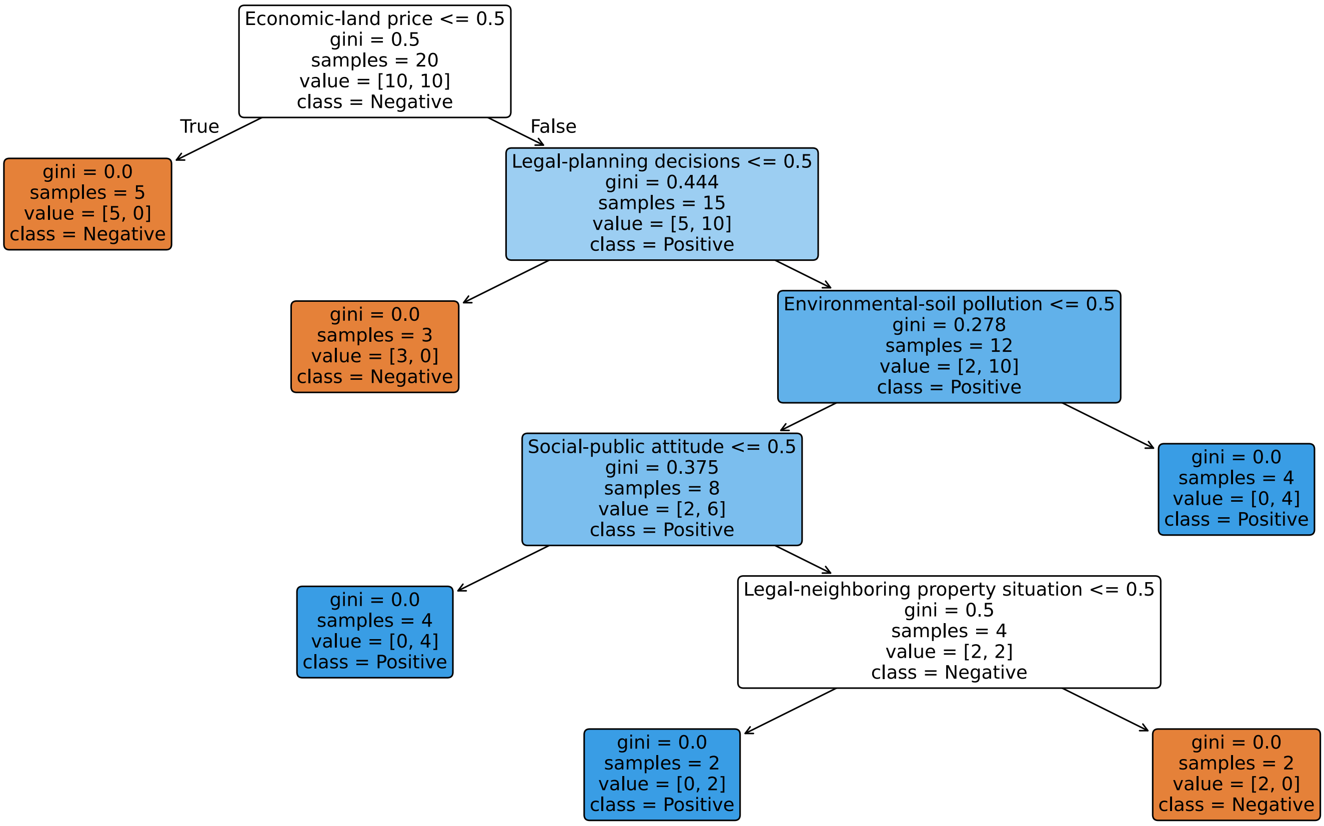

Fig. 4. Diagram of a decision tree based on 15 attributes. The diagram was generated using the CART algorithm. Blue leaves indicate a positive decision, orange ones a negative decision

decisions) were identified as determining the feasibility of the investment. These factors should be verified at the preliminary TDD report stage.

2.4. Model testing – fifteen attributes

The model was tested using the cross-validation methodology. The data presented in Table 5 was divided into five separate groups presented in Table 7, each consisting of five cases. Five tests with different training and testing sets were conducted.

Table 7
Presentation of a cross-validation test

	Training data, number of cases	Testing data, number of cases	Results
1	From 1 to 20	From 21 to 25	Correct results for all cases
2	From 6 to 25	From 1 to 5	Incorrect result for case 3
3	From 11 to 25 and from 1 to 5	From 6 to 10	Correct results for all cases
4	From 16 to 25 and from 1 to 10	From 11 to 15	Incorrect results for cases 12 and 14
5	From 21 to 25 and from 1 to 16	From 16 to 20	Correct results for all cases

The test set achieved an accuracy of 88%, which should be considered a satisfactory result. Bearing in mind the fact that only 25 cases described by 15 attributes were used, the presented decision tree model, following appropriate consultations with the investor regarding their preferences, can be used in a limited capacity to support purchasing decisions.

3. DISCUSSION

In the literature, there are many papers describing decision support systems in various fields (e.g., managing reclamation works [6], economic decisions [29]); however, there is no system specifically addressing the purchase of building plots.

Based on the research, a methodology for constructing an investment decision support system using decision trees was presented. These trees can be built using any number of attributes, considering investors' preferences, such as sustainable land use strategies and modern urban systems, when purchasing building plots for construction projects. For the purposes of this article, decision trees considering 5 and 15 attributes were developed. In both cases, it was possible to identify factors determining the feasibility of a given project. The presented procedure successfully identifies attributes that prevent project implementation at the preliminary TDD phase. This allows for the early termination of land purchase negotiations, helping to avoid additional costs.

It was also demonstrated that at the final report stage, despite the shortage of training data, decision trees could still be used to provide potential purchasing recommendations for specific plots. To enable the model to better reflect real market conditions, an increase in both the number of attributes and the dataset size is necessary, which is planned for subsequent studies. To enhance model accuracy, additional methods based on ensemble or hybrid machine learning techniques (e.g., random forest) will be employed in future research. An additional unresolved issue is the challenge of incorporating all concerns identified in the final TDD report into the planned investment budget. Future research by the authors will focus on applying scientific methods that allow the inclusion of all objections raised in the final TDD report within the planned investment budget. In addition, the TDD process can be accelerated through integration with geospatial or economic datasets, which will also be the subject of further research.

4. CONCLUSIONS

The purchase of a plot, along with the preparation of a TDD report, is the first stage of the investment preparation process, which can determine its success. All technical, environmental, legal, economic, and social constraints affecting the feasibility of the project are analyzed at the preliminary report stage. Other discrepancies identified during the TDD process should be included in the final report.

This study investigates the application of decision trees in the TDD process conducted for the purchase of a building plot intended for construction investment. The training dataset was developed based on TDD processes conducted between 2005 and 2024. The ID3 and CART algorithms were used to build the decision trees. Decision trees can be expanded with additional attributes as needed, allowing customization to the investor's specific requirements. They can also serve as a decision-support tool during the TDD process.

Apart from the direct application of decision trees, our method identifies key attributes that influence purchasing decisions, thereby reducing the workload required to prepare preliminary TDD reports. Moreover, through the careful selection of attributes used in model development, it is possible to contribute to sustainable land use strategies and modern urban systems.

The limitation of the method is the difficulty in building a database containing enough projects described by attributes that align with the investor's expectations. An additional challenge is collecting an adequate number of cases related to the same type of investment (e.g., residential, commercial, or industrial/warehouse developments).

In scientific literature, the authors have not encountered the use of decision trees to support the process of preparing a TDD report.

In line with current market practice, companies prepare TDD reports based on their personal experience, which makes it impossible to establish a standardized format for these documents. This article is an attempt to define a consistent methodology for preparing TDD reports, which will undoubtedly contribute to their standardization, something that will benefit the construction market.

REFERENCES

[1] E. Radziszewska-Zielina, E. Kania, and G. Śladowski, "Problems in carrying out construction projects in large urban agglomerations on the example of the construction of the varso building complex in Warsaw," in *Advances and Trends in Engineering Sciences and Technologies III – Proceedings of the 3rd International Conference on Engineering Sciences and Technologies, ESaT 2018*, 2019, pp. 533–538. doi: 10.1051/matecconf/201711700144.

[2] I. Sanz-Prieto, L. de-la-Fuente-Valentín, and S. Ríos-Aguilar, "Technical due diligence as a methodology for assessing risks in start-up ecosystems: An advanced approach," *Inf. Process. Manag.*, vol. 58, no. 5, p. 102617, 2021, doi: 10.1016/j.ipm.2021.102617.

[3] "Due Diligence Law and Legal Definition," *USLegal, Inc*. [Online]. Available: https://definitions.uslegal.com/d/due-diligence/{#}google_vignette (Accessed: Jan. 27, 2024).

[4] B. Kutera and H. Anysz, "The methodology of technical due diligence report preparation for an office, residential and industrial buildings," in *MATEC Web Conf*, vol. 86, 07009, 2016. doi: 10.1051/matecconf/20168607009.

[5] M. Waga, E. Radziszewska-Zielina, and B. Sroka, "Review of methods for preparing technical due diligence reports for the purchase of commercial real estate," *Przegląd Budowlany*, vol. 96, no. 1, pp. 102–106, 2025, doi: 10.5604/01.3001.0055.0060.

[6] X. Li, S. Yi, A.B. Cundy, and W. Chen, "Sustainable decision-making for contaminated site risk management: A decision tree model using machine learning algorithms," *J. Clean. Prod.*, vol. 371, p. 133612, 2022, doi: 10.1016/j.jclepro.2022.133612.

[7] Y. Yao, J. Li, X. Zhang, P. Duan, S. Li, and Q. Xu, "Investigation on the expansion of urban construction land use based on the CART-CA Model," *ISPRS Int. J. Geo-Inf.*, vol. 6, no. 5, p. 149, 2017, doi: 10.3390/ijgi6050149.

[8] J. Surma, "Hacking Machine Learning: Towards The Comprehensive Taxonomy of Attacks Against Machine Learning Systems," in *ACM Int. Conf. Proc. Ser.*, 2020, pp. 1–4. doi: 10.1145/3390557.3394126.

[9] I. Rojek, R. Burduk, and P. Heda, "Ensemble selection in one-versus-one scheme – case study for cutting tools classification," *Bull. Pol. Acad. Sci. Tech. Sci.*, vol. 69, no. 1, p. e136044, 2021, doi: 10.24425/bpasts.2021.136044.

[10] E. Radziszewska-Zielina, "Analysis of the impact of the level of partnering relations on the selected indexes of success of Polish construction enterprises," *Eng. Econ.*, vol. 21, no. 3, pp. 324–335, 2010.

[11] K. Galjanić, I. Marović, and T. Hanak, "Performance Measurement Framework for Prediction and Management of Construction Investments," *Sustainability (Switzerland)*, vol. 15, no. 18, p. 3617, 2023, doi: 10.3390/su151813617.

[12] E. Radziszewska-Zielina, G. Śladowski, E. Kania, B. Sroka, and B. Szewczyk, "Managing Information Flow in Self-Organising Networks of Communication between Construction Project Participants," *Arch. Civ. Eng.*, vol. 65, no. 2, pp. 133–148, 2019, doi: 10.2478/ace-2019-0024.

[13] M. Waga, E. Radziszewska-Zielina, and B. Sroka, "The role of the technical due diligence process at the stage of land acquisition for construction investment," *Struct Environ.*, vol. 16, pp. 213–221, 2024, doi: 10.30540/sae-2024-020.

[14] S. Reich, "Technical Due Diligence", in *Real Estate Due Diligence*, vol. Part F614, Springer, 2018. doi: 10.1007/978-3-319-62510-2_5.

[15] "New guidance note: Building surveys and technical due diligence of commercial property," *Struct. Surv.*, vol. 29, no. 2, pp. 39–41, May 2011, doi: 10.1108/SS.2011.11029BAE.010.

[16] J. Surma, *Business Intelligence: Making Decisions Through Data Analytics*. Business Express Press, 2011. doi: 10.4128/9781606491867.

[17] L. Breiman, J.H. Friedman, R.A. Olshen, and C.J. Stone, *Classification and regression trees*. Chapman and Hall/CRC, 2017. doi: 10.1201/9781315139470.

[18] A. Fattah, M.M. Fouad, P.S. Yu, and T.F. Gharib, "A Decision Tree Classification Model for University Admission System," *Int. J. Adv. Comput. Sci. Appl.*, vol. 3, no. 10, 2012, doi: 10.14569/ijacsa.2012.031003.

[19] "Regulation of the Minister of Transport, Construction, and Maritime Economy on the determination of geotechnical conditions for the foundation of building structures," *Dz.U. 2012 poz. 463*, Apr. 2012.

[20] "Regulation of the Minister of the Environment of December 4, 2017, on the criteria for recognizing natural formations, both living and non-living, as natural monuments," *Dz.U.2017 poz.2300*, Dec. 2017.

[21] E. Kania, E. Radziszewska-Zielina, and G. Śladowski, "Communication and information flow in polish construction projects," *Sustainability (Switzerland)*, vol. 12, no. 21, 2020, doi: 10.3390/su12219182.

[22] J.R. Quinlan, "Induction of Decision Trees," *Mach Learn*, vol. 1, no. 1, pp. 81–106, 1986, doi: 10.1023/A:1022643204877.

[23] C.E. Shannon, "A Mathematical Theory of Communication," *Bell Syst. Tech. J.*, vol. 27, no. 3, pp. 379–423, 1948, doi: 10.1002/j.1538-7305.1948.tb01338.x.

[24] Y. Wang, Y. Li, Y. Song, X. Rong, and S. Zhang, "Improvement of ID3 algorithm based on simplified information entropy and coordination degree," *Algorithms*, vol. 10, no. 4, p. 124, 2017, doi: 10.3390/a10040124.

[25] "Regulation of the Minister of the Environment of September 1, 2016, on the method of assessing soil contamination," Dz.U. 2016, poz. 1395, 2016.

[26] "Act of July 23, 2003, on the Protection and Care of Monuments," Dz.U. 2003 nr 162 poz. 1568, Jul. 2003.

[27] Knight Frank, "Kraków commercial real estate market – 2025." [Online]. Available: https://www.knightfrank.com.pl/research/krakow-rynek-nieruchomosci-komercyjnych-2025-11977.aspx (Accessed: Apr. 01, 2025).

[28] Jones Lang LaSalle, "CEE Investment Market Perspective – 2024." [Online]. Available: https://www.jll.pl/en/trends-and-insights/research/cee-investment-market (Accessed: Apr. 01, 2025).

[29] B. Liu and Z. Sun, "Global Economic Market Forecast and Decision System for IoT and Machine Learning," *Mob. Inf. Syst.*, vol. 2022, p. 8344791, 2022, doi: 10.1155/2022/8344791.