КОМП'ЮТЕРНІ НАУКИ

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Method and Technological Solution of an AI-Based Adaptive Investor Survey Service for Determining an Individual Risk Profile

An adaptive investor survey model employing advanced machine learning is presented to generate a continuous risk profile. Using conditional logic, weighting coefficients, and a continuous risk scale, it overcomes traditional questionnaire limitations to enhance accuracy and personalization. The system built on React, Node.js/NestJS, and Python/FastAPI efficiently processes responses and delivers tailored investment recommendations. The research also includes the results of a comparative analysis, a description of the data transformation methodology, and a secure data transfer scheme, confirming the practical effectiveness of the proposed solutions. The developed method, model, and technological solution of the AI-driven adaptive survey service enhance the accuracy and personalization of risk profiling.

digital transformation, machine learning, adaptive polling, investor risk profile, conditional logic, continuous risk scale, personalized recommendations

Problem Statement and its Relevance. The modern financial market is characterized by high volatility, significant uncertainty, and a diverse array of financial instruments. These conditions pose a critical challenge for investors who must accurately assess their risk tolerance to develop effective and reliable investment strategies. This issue is particularly relevant in today's complex market environment and is further compounded by the low level of financial literacy observed in regions such as Ukraine.

Analysis of Recent Research and Existing Approaches. Traditional risk assessment methods – typically based on standardized questionnaires and discrete risk scales – have been widely used by financial advisors and institutions. However, extensive research has demonstrated that these approaches often fail to capture the nuanced and individualized risk profiles of investors. Limitations such as inflexibility, redundant questioning, and the inability to address psychological and behavioral factors have led to suboptimal investment recommendations.

Objective of the Research. This study aims to develop an adaptive investor survey model that leverages advanced machine learning techniques to generate a detailed, continuous risk profile. By incorporating conditional logic, expert-determined weighting coefficients, and a continuous risk scale, the proposed model seeks to enhance both the accuracy and personalization of investment recommendations.

Presentation of the Main Material. The contemporary financial market is characterized by high volatility, significant uncertainty, and a diverse array of financial instruments [1]. In such an environment, a critical challenge for investors is the accurate assessment of their risk tolerance - a fundamental prerequisite for developing effective and reliable investment reliable investment strategies [2]. Traditional methods for determining risk profiles typically rely on static questionnaires and simple categorical scales (e.g., conservative, balanced, aggressive), which often fail to capture the unique characteristics of individual investors and therefore provide imprecise estimates of their true risk capacity [3]. As a result, particularly for those without specialized financial expertise, selecting an optimal portfolio can be challenging, sometimes leading to losses or suboptimal investment outcomes. This problem is further exacerbated by the generally low level of financial literacy in Ukraine; research indicates that many Ukrainian citizens lack the necessary skills and knowledge for effective personal financial management, diminishing their ability to make sound financial decisions [4]. Consequently, there is a pressing need for accessible, comprehensible, and adaptive solutions that allow novice investors to accurately assess their risk profiles and obtain high-quality portfolio recommendations. The aim of this study is to develop an adaptive investor survey model using machine learning techniques to generate a detailed, continuous risk profile for users. Such a model is expected to improve both the level of accuracy and personalization of investment recommendations, making the investment process clearer and more accessible to a wider segment of the Ukrainian population.

Analysis of Existing Approaches to Determining Investor Risk Profile. Traditional methods for assessing an investor's risk profile are predominantly based on standardized questionnaires widely employed by financial advisors, investment firms, and banks. Typically, these questionnaires consist of a predetermined set of questions with fixed response options that correspond to specific risk categories (e.g., conservative, balanced, aggressive). Their main advantage lies in their simplicity and ease of use for individuals without specialized training. However, such approaches exhibit several significant limitations that can negatively affect the quality of subsequent investment decisions. One primary shortcoming is the reliance on discrete risk scales, which use clear but limited categories that do not flexibly capture the unique characteristics of each investor. This rigidity can lead to inaccuracies in determining an investor's true risk level, thereby compromising the effectiveness of the recommended investment strategies [5]. Moreover, traditional questionnaires lack adaptability; questions are presented in a fixed sequence regardless of the respondent's previous answers. As a result, the survey may include numerous irrelevant or redundant questions, reducing both its efficiency and the respondent's comfort, ultimately compromising data quality. Such issues can further diminish the quality of the data collected due to fatigue or inattentiveness during lengthy surveys [6]. Additionally, conventional questionnaires often fail to account for the psychological and behavioral dimensions of financial decision-making. Investors may exhibit complex and ambiguous attitudes toward risk that cannot be adequately captured by a few simple categories, leading to imprecise risk assessments and, consequently, inaccurate investment recommendations [7, 8]. Another significant limitation is the lack of personalization in the investment recommendations derived from these surveys. Because traditional questionnaires do not incorporate many individual factors – such as financial literacy, investment experience, or specific economic contexts – the resulting risk profiles are often superficial and offer limited practical value. This issue is particularly pronounced in the Ukrainian market, where many investors, especially novices, struggle with low financial literacy and limited access to quality financial advice. As a result, conventional risk assessment methods, which are generally oriented toward Western markets, may not be well-suited for the Ukrainian context. In light of these limitations, there is a clear need to transition to adaptive risk assessment methods that dynamically tailor the survey process to each respondent. By reducing the number of irrelevant questions and enhancing data quality, such adaptive methods can more accurately capture an investor's risk profile. Modern artificial intelligence and machine learning techniques enable the development of models that simultaneously consider numerous parameters, uncover latent patterns in the responses, and provide a more precise, continuous evaluation of risk. In addition, today there is a trend of digital transformation of business processes in all areas of activity [16, 17]. Thus, an analysis of existing traditional approaches reveals significant shortcomings, underscoring the necessity for contemporary adaptive methods that utilize machine learning to generate individualized investment recommendations.

Theoretical Aspects of the Adaptive Questionnaire for Determining Investor Risk Profile. Adaptive questionnaires represent an innovative approach in the field of survey research, significantly enhancing the quality and relevance of the data compared to traditional methods [10]. The primary advantage of an adaptive survey lies in its ability to modify the questions presented to respondents based on their previous answers, thereby tailoring the process to be more personalized and focused. This dynamic adaptation is implemented using conditional logic, which governs the system whereby subsequent questions are either displayed or skipped according to predefined rules. For instance, if a respondent indicates a low level of financial literacy, the system automatically triggers additional follow-up questions designed to more precisely gauge their financial experience and risk perception. This conditional logic can be structured as an algorithmic decision tree or a sequence of rules, both of which contribute to the flexibility and interactivity of the survey process. Another critical component of adaptive surveys is the use of weighting coefficients. These coefficients assign varying degrees of importance to different questions based on their contribution to the overall risk profile estimation. Consequently, questions that are deemed more critical for the final risk assessment are given higher weights, which in turn allows for a more precise evaluation of the investor's true financial situation. In addition, the proposed system utilizes a continuous risk scale rather than a traditional discrete one. Unlike discrete scales, a continuous risk scale enables a more detailed and nuanced analysis of an investor's risk attitude by expressing their profile as a numerical value within a specified range (for example, between 0 and 1). This continuous approach facilitates a more flexible alignment of investment recommendations with each investor's individual financial needs and risk tolerance. The appropriate determination of weighting coefficients has a significant impact on the accuracy of the risk profile estimation. Proper calibration ensures that the relative importance of various behavioral and experiential factors is accurately reflected in the final assessment. Therefore, incorporating weighting coefficients into the adaptive survey process substantially enhances the precision of the results, thereby enabling more effective and reliable personalization of investment recommendations. In summary, the application of adaptive survey techniques, conditional logic, continuous risk scaling, and weighting coefficients opens new avenues for achieving higher accuracy, deeper personalization, and increased efficiency in the determination of an investor's risk profile.

Selection of Machine Learning Methods for Risk Assessment. Modern machine learning techniques are increasingly applied to risk assessment tasks, resulting in substantial improvements in both accuracy and quality over traditional approaches [11]. Among the most commonly used algorithms for determining an investor's risk profile are neural networks, support vector machines (SVM), decision trees, and random forests. Neural networks are powerful tools capable of modeling complex nonlinear relationships; however, they require extensive datasets for training, are challenging to fine-tune, and demand significant computational resources. In contrast, support vector machines are effective for classification and regression tasks, particularly when dealing with smaller datasets, though they may be less efficient in high-dimensional settings or when interpretability is critical. Decision trees offer the advantages of straightforward interpretability and ease of implementation, but they are susceptible to overfitting and can be unstable in response to minor fluctuations in training data. Random forests, an ensemble learning method, combine the strengths of decision trees with additional mechanisms to enhance predictive accuracy. This approach involves constructing numerous independent decision trees – each trained on random subsets of the data and features – with the final prediction derived from the aggregated outputs of these trees. For this study, the RandomForestRegressor algorithm was chosen [9] due to its robustness to missing values; random forest models can effectively process datasets that include incomplete responses, thereby simplifying the data preprocessing stage. Moreover, considering that the adaptive survey may dynamically omit certain questions based on a respondent's input, random forests offer reliable risk prediction without requiring excessive computational resources. Their high predictive accuracy and ease of integration into modern technology stacks – such as Python (FastAPI) and Node.js (NestJS) – make them ideally suited for rapid deployment in practical applications.

Concept of the Developed Adaptive Survey Model. The proposed adaptive survey model is designed to serve as a flexible and interactive tool that accurately determines an investor's risk profile. Types of Questions:

– Numerical - respondents are required to enter a numeric value (e.g., the percentage of funds they are willing to invest, the investment horizon in years, etc.).

– Scale-Based - these questions ask respondents to evaluate certain aspects on a numerical scale (for example, rating their risk tolerance on a scale from 1 to 5).

– Multiple-Choice Questions **-** respondents select one or more options, which capture distinct behavioral traits or investment experiences.

Adaptive Question Selection Logic. Each question in the survey is accompanied by a condition field that determines whether it should be displayed to the respondent [13]. These conditions are formulated based on the respondent's previous answers. For instance, if a response indicates a low level of financial literacy, the system automatically triggers a subsequent question (identified by a lower question ID) aimed at further detailing the respondent's risk attitude or experience with financial instruments. The underlying algorithm is illustrated in Figure 1.

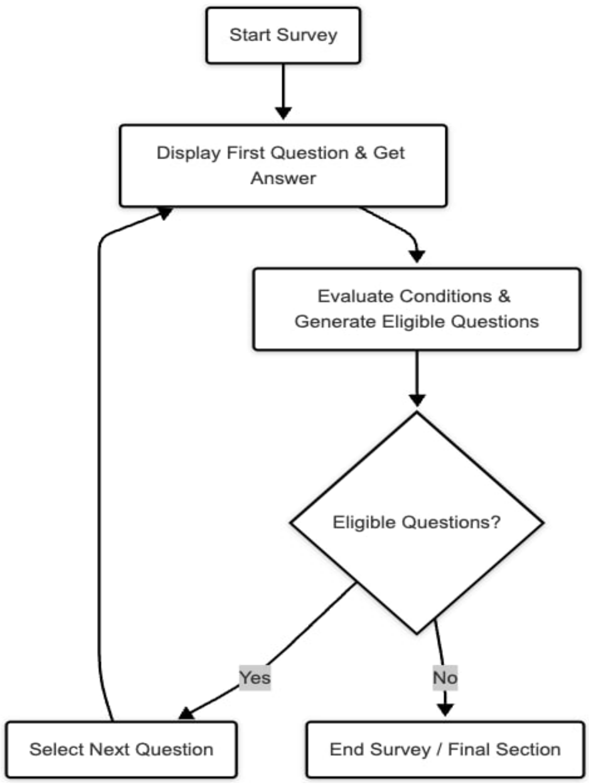

Figure 1 – Flowchart of the algorithm for selecting the next question

Source: developed by the authors.

Table 1 – Example of Precise User Segmentation Based on Multiple Criteria

Question ID	Question	Answer Options	Selection Criteria
1	Do you have any experience investing in the stock market?	- None - Less than 1 year - 1–3 years - More than 3 years	If "None" is selected, trigger a follow-up question to assess basic knowledge (Q2); if any experience is indicated, proceed to further detailed questions (Q3–Q4).
2	What is your level of knowledge regarding financial instruments (stocks, bonds, ETFs)?	- Beginner - Intermediate - Advanced	If "Beginner" is selected, activate a question addressing the need for additional education; otherwise, proceed to subsequent clarifying questions.
3	How would you rate your understanding of the stock market?	- Limited (unfamiliar with key terms) - Moderate (familiar with basic concepts) - Deep (analyzes trends)	If "Limited" is selected, trigger questions related to training and consultation; if "Deep" is selected, activate questions to assess decision-making during market fluctuations.
4	Have you experienced significant financial losses in previous investments?	- Never - Rarely - Often	If "Often" is selected, activate additional questions on risk management strategies; if "Never" or "Rarely" is selected, skip this section and move to the concluding part.

Note: This table is provided as a representative example to facilitate precise segmentation of respondents across multiple criteria, thereby ensuring a comprehensive assessment of their profiles.

Source: developed by the authors.

Such an approach optimizes survey duration, enhances the accuracy of the collected data, and ultimately improves the overall user experience.

Conversion of Responses into a Numerical Format. A crucial step in the survey process is the transformation of collected responses into a numerical vector that serves as input for training machine learning models [12]. This process involves normalizing various types of responses so that they are mapped onto a uniform range – for instance, scale-based answers might be normalized to values between 0 and 1, while percentage-based responses are similarly scaled to the [0, 1] interval. In addition, expert-determined weighting coefficients are applied based on the relative importance of each question in determining the overall risk profile. This approach ensures that the final numerical vector maintains a consistent dimensionality, even if certain questions are omitted due to the adaptive logic of the survey; any missing responses are filled in with default values or designated markers.

Data Preparation for Model Training. The data preparation phase involves constructing a cohesive dataset consisting of paired "response vector – risk rating" entries. For initial model training, expert assessments are used to generate a synthetic yet realistic dataset, which facilitates the derivation of reliable risk predictions during the early stages of system deployment. The preprocessed data is then utilized to train a RandomForestRegressor model, which is chosen for its high accuracy and robustness in risk prediction. In subsequent phases, the synthetic dataset may be replaced with a fully expert-curated dataset to further enhance precision and monitor dynamic changes in risk assessments.

Technological Solutions for System Implementation. To realize the adaptive survey system integrated with machine learning, a modern technology stack was selected for its convenience, efficiency, and ease of integration across various system components.

Formalization of the Adaptive Investor Survey Process for Determining an Individual Risk Profile. Training a classifier requires specifying input and output data. For this task, the classifier input should be a vector of normalized scores corresponding to the survey responses, with a length equal to the number of questions in the survey:

$$\overline{v}_i = \{v_0; v_1; v_2; \dots\}.$$

Accordingly, for the training set, the set of risk profile class is determined by expert assessments:

$$C = [c_0; c_1; c_2; \dots].$$

Based on the specified input and output parameters, the task is to find a mapping function:

$$c_i = F(\overline{v}_i).$$

where F is a classifier that maps the vector of normalized response scores to a corresponding safety class; $c_i \in R$ is a continuous (non-discrete) estimate of the risk level.

To account for the optimized survey, where certain questions may be skipped, the classifier replaces missing responses with an "impossible" score (e.g., -1) with probability 1-μ_i. The value -1 is inserted not only during the training but may also appear during real questionnaire completion if certain questions are skipped due to adaptive logic. The coefficient μ_i r epresents an expert-defined importance weight for a specific question, as described above. As a result, the training dataset is transformed according to the following algorithm:

1. A set of responses to the full survey $V = [\overline{v}_i]$ is formed through test surveys or based on expert evaluations.
2. Each response in the set is assigned a corresponding safety class $C = [c_0;\ c_0;\ c_1; c_5; \dots]$. At the same time, the cardinalities of the sets are equal, i.e., $|V| = |C|$, meaning both contain the same number of elements.
3. The set V is expanded to $\{V_e;\ C_e\}$ by applying a process of simulating question omissions to each element. Depending on the total number of questions, each input vector $\overline{v}_i$ serves as a source for multiple modified versions, generated by randomly excluding responses with probabilities 1-μ_i. Each modified input vector retains the safety class originally assigned by experts.
4. The classifier is trained on the dataset $\{V_e;\ C_e\}$, where V_e represents the input data, and C_e contains the corresponding class labels indicating the safety class assigned to each response vector.

Front-end: React. React is a powerful JavaScript library for building interactive and adaptive user interfaces. It enables rapid development of dynamic applications with effective state management, making it ideally suited for implementing complex adaptive surveys. The front-end is responsible for dynamically generating and adapting survey questions based on user responses, as well as collecting and transmitting the responses to the back-end.

Back-end: Node.js with NestJS. Node.js combined with the NestJS framework provides high performance, scalability, and seamless integration. Thanks to its support for REST APIs and modular architecture, NestJS efficiently handles data validation, normalization, and the conversion of user responses into a numerical vector before transmitting the data to the machine learning service [15].

ML Service: Python with FastAPI. For the machine learning component, Python paired with FastAPI was chosen due to its rapid service deployment capabilities and high performance [14]. FastAPI supports modern data processing libraries such as Pandas and NumPy and integrates well with popular machine learning frameworks like Scikit-learn. The ML service receives the numerical vector from the back-end, processes it using pre-trained models, and returns the risk prediction back to the back-end for further use.

Together, these technological solutions form an integrated system that efficiently converts survey responses into a robust numerical format for accurate risk assessment and personalized investment recommendations.

Data transmission scheme. The data transmission process follows the sequence illustrated in Fig. 2.

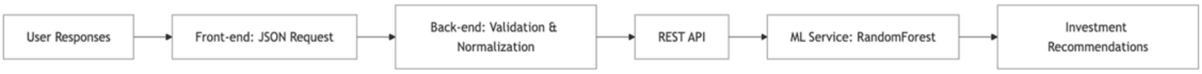

Figure 2 - Data Transmission Flowchart

Source: developed by the authors.

Explanation:

1. User: The respondent completes the adaptive survey.
2. Front-end (JSON): The front-end formats the survey responses into a JSON request and sends it to the back-end.
3. Back-end (Validation & Normalization): The back-end receives the responses, validates them, normalizes the data, and constructs a numerical vector.
4. REST API: The numerical vector is transmitted via a REST API to the machine learning (ML) service.
5. ML Service (RF): The ML service, utilizing a RandomForestRegressor, processes the data and returns a risk prediction.
6. Recommendations: The predicted risk value is then used to generate personalized investment portfolio recommendations.

Conclusions. The proposed adaptive investor survey model effectively addresses the limitations of traditional risk assessment questionnaires. By utilizing a continuous risk scale and advanced machine learning techniques, the model delivers a more precise and personalized risk profile for investors. The integration of conditional logic and weighting coefficients further refines the survey process, ensuring that investment recommendations are tailored to individual financial needs.

Future Research Directions. Future research should involve experimental testing of the proposed model under real-world conditions, followed by iterative refinements based on user feedback. Additionally, the collection of more extensive real data will be essential for further improving model precision and for adapting to the dynamic nature of financial markets.

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Метод і технологічне рішення ШІ-сервісу адаптивного опитування інвестора для визначення індивідуального ризик-профілю

Праця присвячена розробці адаптивної моделі опитування інвесторів, яка використовує сучасні методи машинного навчання для формування детального континуального ризикового профілю. Традиційні анкети з оцінки ризику, які гуртуються на статичних і дискретних шкалах, часто не враховують багатовимірність індивідуальної толерантності до ризику, особливо в умовах низького рівня фінансової грамотності. Це дослідження має на меті подолати зазначені обмеження, підвищити точність і рівень персоналізації інвестиційних рекомендацій.

В роботі представлено інноваційну модель адаптивного опитувальника, яка динамічно коригує послідовність запитань за допомогою умовної логіки. Модель адаптує хід опитування на основі попередніх відповідей респондента, що забезпечує релевантність та цілеспрямованість кожного наступного запитання. Завдяки використанню експертно визначених вагових коефіцієнтів і континуальної шкали ризику, суб'єктивні відповіді перетворюються на надійний числовий вектор, придатний для обробки за допомогою алгоритмів машинного навчання. Технічна реалізація моделі ґрунтується на сучасному технологічному стеку, зокрема використовується React для фронтенду, Node.js з NestJS для бекенду, а також Python з FastAPI для сервісу машинного навчання, який застосовує RandomForestRegressor для обробки відповідей і прогнозування рівня ризику. У статті також представлені результати порівняльного аналізу, опису методик трансформації даних та схему безпечної передачі інформації, що підтверджує практичну ефективність запропонованого підходу.

Результати дослідження свідчать, що запропонований метод, модель і ШІ-сервіс адаптивного опитування забезпечують підвищення точності та персоналізацію ризик-профілювання у порівнянні з традиційними методами. Інтеграція адаптивного вибору запитань та сучасних методів машинного навчання оптимізує процес опитування, забезпечує більш надійні інвестиційні рекомендації.

цифрова трансформація, машинне навчання, адаптивне опитування, ризиковий профіль інвестора, умовна логіка, континуальна шкала ризику, персоналізовані рекомендації

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