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Recommendation system for financial decision-making using Artificial intelligence

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ABSTRACT

The rapid expansion of artificial intelligence (AI) in consumer markets presents challenges, particularly in how cognitive biases influence financial decision-making. These biases can lead to irrational spending, raising ethical concerns about AI's role in such applications. This research explores how AI can enhance decision-making effectiveness and support consumers in making more rational financial choices. The focus is on developing an intelligent financial management system that applies modern AI algorithms to analyze financial behavior, detect anomalies, and offer personalized recommendations. The article considers a system for generating personalized financial recommendations based on large language models, which uses transaction history, predicted costs, and anomaly information to generate individual advice. Techniques include using Isolation Forest for identifying atypical financial actions and a combination of ARIMA and LSTM models for budget forecasting. The research also considers integrating these models with large language models (LLMs) to generate personalized recommendations. The methodological part of the work includes an analysis of existing models and their areas of application, defining data types and structures for processing, developing a system that integrates the available models, and testing it. The process of generating recommendations is described, which includes the stages of processing input data, forming context, generating recommendations and evaluating them taking into account user characteristics, such as risk level, financial goals and preferences. The generated recommendations are aimed at optimizing the user's financial behavior and can be adapted to different income levels. Special attention is paid to the ethical aspects of the system, which include ensuring confidentiality, fairness and transparency, as well as the importance of supporting user autonomy in making financial decisions. The system promotes responsible financial behavior by helping to avoid impulsive spending and increasing financial awareness without manipulation or imposing specific decisions.

Keywords: Artificial Intelligence; machine learning; cognitive biases; financial decisions; ethics

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INTRODUCTION

The modern financial landscape faces numerous challenges, among which key issues include ineffective financial management and financial illiteracy, both among individual consumers and organizations. Many individuals lack sufficient knowledge to make sound financial decisions, making them vulnerable to aggressive marketing strategies. This is especially relevant in the context of increasingly sophisticated AI-enhanced marketing techniques that can manipulate consumer behavior, promoting irrational expenditures.

Research in behavioral economics shows that cognitive biases, such as loss aversion or framing effects, significantly impact consumer decision-making, often leading to deviations from rational behavior. This highlights the need for intelligent systems that can help consumers overcome these biases and make more informed financial decisions.AI is already demonstrating considerable potential in the financial sector, particularly through its ability to analyze large volumes of data and uncover hidden patterns. For example, systems that combine cognitive psychology with machine learning algorithms can personalize user experiences and offer recommendations based on an analysis of their behavior and preferences. This enables AI not only to predict consumer behavior but also to provide more accurate recommendations for financial planning, budgeting, and investing.

The goal of this study is to develop principles for creating financial recommendations using AI models, regardless of user's income levels.

1. LITERATURE OVERVIEW

At present, there is a significant body of work that provides extensive information about recommendation systems (RS).

In [1], theoretical studies for RS are described, along with new developments of applications, prototypes and real examples of such systems.

Recommendation systems play a crucial role in many areas: e-commerce websites, online shopping, dating apps, social media, digital marketing, online advertising, etc., as they provide users with personalized recommendations and feedback based on their preferences and choices [2].

Sources [3, 4] describe the main models underlying the construction of RS, highlight the primary sectors where such systems are used, and outline the distribution of publications for various application areas. It is noted that e-commerce, which can be considered a part of financial services, accounts for 17% of all reviewed studies.

Authors in [5] focus on the psychological mechanisms through which RS impacts user satisfaction. It is shown that the type of search goal interacts with the types of recommendations. Psychological reactance, a resistance that users may feel towards RS recommendations perceived as a threat to their freedom of choice, is also discussed as one of the primary reasons users reject recommendations.

In RS, there are two roles: predicting the value (how a user will rate a resource) [6]. The education sector is used as an example in this study.

When it comes to the financial sector, publications most often describe recommendations systems specifically for financial consulting. Financial consultants can improve the trading skills of investors; however, the presences of trading experience and professional complexity negatively correlates with the use of financial consultations, meaning that more experienced investors are less likely to use recommendations [7]. There is also study that found the connection between financial consultations and subjective well-being is stronger for households that have experienced income growth, individuals who do not consider themselves financially knowledgeable, and those with a weaker internal locus of control [8]. The foundation of the research is the idea that households face the need to make decisions with financial consequences every day, and the ultimate goal of decision-making is to achieve outcomes that enhance the quality-of-life experiences by individuals (subjective well-being).

For providing financial consultations, the GPT-4 bot can be used, which “offers specific investment portfolios that reflect an investor’s individual circumstances, such as risk tolerance, risk capacity, and preference for stability”.

There are other financial sectors where recommendation principles can be applied, such as banking, stocks, and insurance [10], in these areas, users are viewed as active entities who engage in interactions (such as browsing, selling, buying, rating etc.) within the system.

In [11], it was noted that a certain limit of development has been reached for recommendations systems in the financial sector. At the same time, such systems are “considered to be intelligent and experienced financial managers, well-informed and aware of each client’s financial situations, regardless of their location”. Further expenditures on their promotion can only be justified by economic impact.

Recommendation systems exist for banks; in particular, such system can provide personalized recommendations on spending opportunities near the user based on their credit card usage history and geolocation data [12], thereby taking context into account. However, the authors of the study highlight the aspect that user preferences are unstable and highly dependent on the user’s actual goal. Since these systems focus on money management and spending opportunities, there is a significant need to explain the systems’ results.

In [13] a recommendation system is presented for managing and utilizing three components of salary: savings, investments and expenses. The system focuses specifically on salary-related recommendations, but it concludes that such a system is useful when a person has a high income.

A large number of studies are dedicated to the development of recommendations systems for financial products. Specifically, [14] proposes an innovation that involves the seamless integration of Transformers, transfer learning and graph neural networks (GNN) to address issues faced by traditional methods, such as user cold start, data sparsity, and complex relationship modeling. In [15] generative adversarial networks (GANs) are considered as a predominant AI technique/model in various recommendation systems. In [16] an interpretable model for personalized financial service recommendations it proposed, based on self-attention mechanisms, by combining the long short-term memory (LSTM) model and the topic model Linear Discriminant Analysis (LDA) with AI support.

In [17], the need to understand the specifics of the recommendation system environment and the expected impact of the system on its users is emphasized. It is necessary to evaluate the quality of recommendation systems not only in terms of the accuracy of the recommendations provided but also by considering the diversity and novelty of the items included in the recommendations [5, 17]. Users are likely to follow recommendations only if they have developed trust in the system over time. Therefore, recommendations should also be evaluated based on whether the provided recommendation was utilized.

Acceptance of AI-generated recommendations is a function of attitudes toward AI, trust, perceived accuracy, and the level of uncertainty [18]. The described attitude-perception-intention model defines the basic psychological mechanism by which users decide to accept AI-supported advice.

Consumers often prefer human interaction in fields characterized by high consumer involvement, such as healthcare and financial services, over computer-generated advice [19]. However, AI is still rapidly being implemented in the financial sector. The concept of a robo-advisor has even emerged, offering “personalized risk analysis and real-time service adjustments based on self-service, requiring minimal human interaction” [20]. A robo-advisor essentially offers software for retail investors who lack sufficient experience or funds to hire a personal financial consultant [21]. As a potential enhancement, integrating Neuro-Linguistic Programming (NLP) technology into robo-advisor software could improve AI chatbots, increasing customer satisfaction and the likelihood that clients will follow portfolio guidance.

Privacy and security are important issue for recommendation systems. Even with excellent performance, users find it difficult to trust such systems due to opacity and privacy concerns [22].

In general, the ethical implications of using AI-based recommendation systems are a distinct area of research. For instance, [23] provides a conceptual assessment of human autonomy when using a universal recommendation system. The concept of human autonomy is defined in [24] as “the ability to be one’s own person, to live one’s life according to reasons and motives that are taken as one’s own, and not the product of manipulative or external forces that distort, thus being independent”. The conclusion of the study [22] is that not everything needs to be recommended, and people should be aware of the potential impact of automated recommendation technologies.

Thus, when designing recommendation systems to support financial decision-making, the following aspects must be considered; accuracy, completeness, privacy, and adherence to ethical standards.

2. USING AI MODELS TO ADDRESS THE ISSUE OF FINANCIAL RECOMMENDATION FORMATION

In the financial sector, AI is also used for detecting anomalous financial transactions and preventing fraud. The Isolation Forest model, which is well-suited for anomaly detection, can be applied to analyze consumer behavior, particularly to identify spontaneous expenses or impulsive financial decisions. Additionally, deep neural networks (CNN, RNN) are actively used to analyze consumer data and predict behavioral patterns, enabling the optimization of marketing strategies.

AI also plays an important role in financial recommendation systems that help users choose the best financial products or services. Algorithms based on collaborative filtering and deep learning methods are used to analyze user behavior and create targeted offers that meet their needs. These systems can significantly improve the quality of financial decisions by reducing the impact of cognitive biases on consumer behavior.

2.1. Detection of anomalous expenses using isolation forest

The concept of Isolation Forest was used as the basis for detecting anomalous user expenses, with its core idea being the isolation of anomalies from normal data.

To achieve this goal, a binary tree is initially created by randomly selecting features and distributing values. The next step is to determine the anomaly score by calculating the path length from the root of the tree to the terminal node. The shortest paths are considered anomalies.

The mathematical basis for calculating the expected path length is the following formula:

$$E\big(h(x)\big) = c(n) + \frac{2loglog\ (n-1) - \frac{2(n-1)}{n}}{n},$$

where $c(n)$ is the average path length for unsuccessful searches in a binary tree; $h(x)$ is the path length for point x in the isolation tree (the number of edges traversed from the root to the terminal node).

$$c(n) = 2H(n-1) - \left(\frac{2(n-1)}{n}\right),$$

where $H(i)$ is the harmonic number, calculated as:

$$H(i) = \sum_{k=1}^{i} \frac{1}{k}.$$

The anomaly score for a point is calculated based on the average path length across all trees:

$$s(x,n) = 2^{-\frac{E(h(x))}{c(n)}},$$

where $s(x,n) \approx 1$, if the point is an anomaly; $s(x,n) \approx 0.5$, if the point is normal.

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2.2. Budget prediction using ARIMA and LSTM

To predict user budget expenses, a combination of two models was used: ARIMA (Auto Regressive Integrated Moving Average) and LSTM (Long Short-Term Memory). Both models are designed to work with time series data but have different approaches to solving the problem. In this context, ARIMA was used for short-term forecasts, and LSTM for long-term forecasts, allowing for more accurate and stable predictions. The first stage of prediction is data preparation. This includes data cleaning, handling missing values, and standardizing the data format. The main focus is on removing trends and seasonality from the data series, as these factors can affect the accuracy of the forecast.

2.2.1. ARIMA model

The ARIMA model consists of three components:

• AR (AutoRegressive) component, which models the dependency between an observation and several previous observations.

• I (Integrated) component, used to eliminate non-stationarity.

• MA (Moving Average) component, which models the dependency between an observation and the forecast error.

Mathematically the ARIMA(p, d, q) is described by the equation:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t,$$

where y_t is the value of the series at time t, ϕ_i are the coefficients of the AR component; θ_j are the coefficients of the MA component ϵ_t is the random error term, c is a constant.

The process of building an ARIMA model includes determining the orders p, d, q. The parameter p represents the order of the autoregressive component, i.e., the number of previous values used for forecasting; it is represented in the formula by the coefficients ϕ_i for values y_{t-i}. The parameter d denotes the degree of differencing, which determines how many times the series needs to be differences to ensure stationarity; this operation is performed on the time series before applying the formula. The parameter q indicates the order of the moving average component, meaning the number of previous random errors considered in forecasting; it is represented by the coefficients θ_j for the error terms ϵ_{t-j}. After determining these parameters, usually selected using the Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC), the model is trained on the training data and used for short-term forecasting.

2.2.2. LSTM model

For long-term forecasts, the LSTM model is used, which is a type of recurrent neural network (RNN). The LSTM model can capture long-term dependencies in time series data due to its specific architecture, which includes memory cells and mechanisms for forgetting and retaining information. Mathematically, the behavior of a single LSTM block is described by the following equations:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$
$$C_t^{\sim} = tanh\ tanh\ (W_C \cdot [h_{t-1}, x_t] + b_C)\ ,$$
$$C_t = f_t * C_{t-1} + i_t * C_t^{\sim}$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$
$$h_t = o_t * tanh\ tanh\ (C_t)$$

where f_t is the forget vector i_t is the input vector, $C_t^{\sim}$ is the new candidate for the cell state value; C_t is the updated cell state, o_t is the output vector; h_t is the vector of output values from the LSTM block; W_f , W_i, W_C, W_o are weight matrices; b_f, b_i, b_C, b_o are bias vectors.

The LSTM network is trained on historical spending data to create long-term forecasts, taking into account long-term dependencies between observations.

2.2.3. Combination of forecasts

The final step is the combination of forecasts obtained from the ARIMA and LSTM models. For this, a weighted average method is used, where the results of both models are combined to obtain the final expense forecast.

The formula for the final forecast is as follows:

$$y_t^{\wedge} = \alpha \cdot y_t^{ARIMA^{\wedge}} + (1 - \alpha) \cdot y_t^{LSTM^{\wedge}},$$

where α is the weight coefficient that determines the influence of each model on the final result.

The combination of ARIMA and LSTM allows for consideration of both short-term and long-term trends, enhancing the accuracy of user expense forecasts.

2.3. LLM for generating financial recommendations

A large language model (LLM), such as LLaMa 3.1, can be effectively used to generate personalized financial recommendations based on the analysis of previous financial data, spending anomalies, and budget forecasts. This section provides a detailed look at the approach to using LLM for this task and presents a diagram describing the process of integrating the LLM model into the overall system architecture.

2.3.1. Data collections and preparation

To generate personalized recommendations, it is important to ensure high-quality input data.

This data includes:

– historical transaction data of the user;

– data on detected spending anomalies;

– budget expenditure forecasts based on ARIMA and LSTM models;

– additional parameters, such as the user's financial goals, risk tolerance, and typical spending patterns.

The data is transferred to the LLM after preprocessing, which includes normalization, categorization, and extraction of the key features.

2.3.2. Generation of personalized advice

After configuring the LLM, the model can use the available data to create personalized recommendations.

The recommendation generation process proceeds as follows:

1. Processing input data: The LLM receives input data, including transaction history, projected expenses, and anomaly information.
2. Context formation: The model defines the context based on the user's current financial status, forecasts, and identified anomalies.
3. Generating recommendations: Based on the context, the model generates several options for financial advice, taking into account both the user's short-term and long-term goals.
4. Evaluation of recommendations: Each recommendation is evaluated in terms of its alignment with the user's individual characteristics, such as risk level, financial goals, and preferences.

The generated recommendations are delivered to the user through the system interface as structured suggestions, including explanations and an assessment of the potential consequences of each decision. The user can select one of the suggestions or request additional recommendation of the initial set does not meet their needs. The recommendations are adapted to the user's financial capacity, providing valuable advice for individuals with various income levels, from low to high. Since the analysis, forecasting and advice generation occur within the context of the user's specific financial operations, the system will be beneficial regardless of the user's income level.

Fig. 1 illustrates an example of a request to the LLM to obtain a personalized financial recommendation. Fig. 2 shows an example of the model's response based on the provided context.

Figure 3 demonstrates the interaction of AI components within the financial system. In the initial stage, the system receives input data on the user's financial transactions, which then pass through the data preprocessing module. This module is responsible for data cleaning, normalization, and preparation for further analysis by the models.

3. ENSURING COMPLIANCE WITH ETHICAL PRINCIPLES IN THE SYSTEM

Ethics is an important aspect in designing recommendation systems (RS) for supporting financial decisions, as it affects how much users trust the system and how willing they are to accept recommendations as objective and unbiased.

In [25], an analysis of ethical issues created by recommendation systems is conducted. The study describes how ethical consequences can arise in a recommendation system: its operations can (negatively) impact the utility for each of its stakeholders and/or violate their rights. Ethical impacts can be immediate (e.g., an inaccurate recommendation leading to reduced utility for the user) or expose relevant parties to future risks (such as the influence of potentially irrelevant or harmful content).

The authors of [26] analyze recommendation system technology from the perspective of methods used to address issues in the following areas: privacy, personal data, fairness, transparency, personal identity, and the proper functioning of society.

An AI-powered system must ensure a balance between its ability influence the user and the user's autonomy, promoting more rational financial behavior. One of the ethical advantages of such a system is its ability to help users become aware of their financial habits without judgement, offering the opportunity for an objective analysis of spending and savings, regardless of income level.

An AI-based recommendation system can promote responsible financial behavior by enhancing the user's financial awareness and helping them avoid potentially irrational expenditures. In an aggressive marketing environment, where users are constantly exposed to advertising, an ethically built recommendation system allows users to maintain control over their financial decisions. AI algorithms analyze data to ensure the accuracy and usefulness of recommendations, avoiding manipulation and supporting user's long-term financial goals. This helps users navigate a complex informational landscape where marketing influences often lead to impulsive purchases and irrational spending.

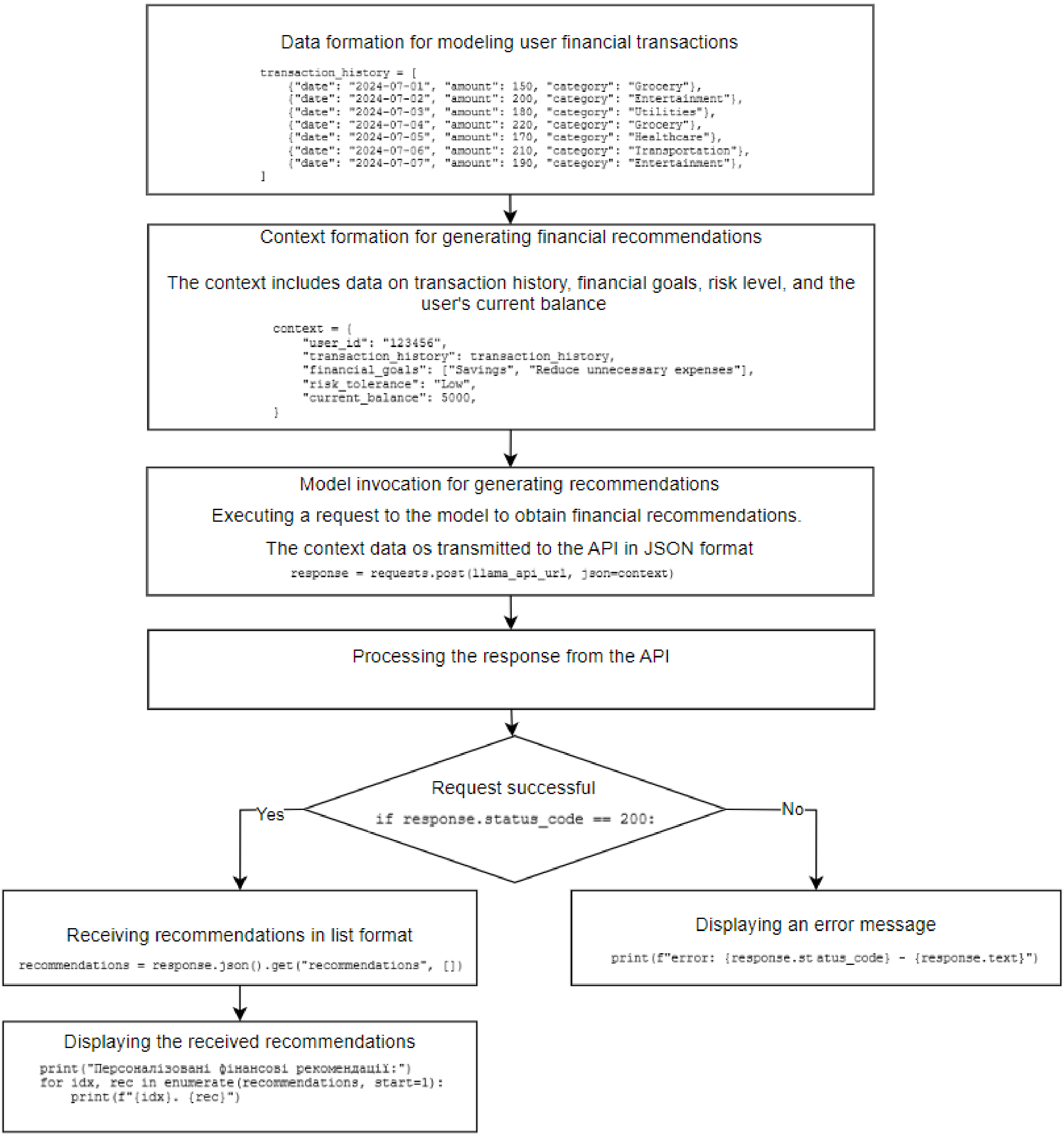

Fig. 1. **Diagram of the request implementation to the LLM for obtaining a personalized financial recommendation**

***Source*: compiled by the authors**

```
{
  "recommendations": [
    "Consider increasing your monthly savings by 10% by reducing
entertainment expenses.",
    "Review unused subscriptions and cancel them.",
    "Invest part of your balance in high-reliability assets for
long-term growth."
  ]
}
```

Fig. 2. **Example of the model's response based on the provided context**

***Source*: compiled by the authors**

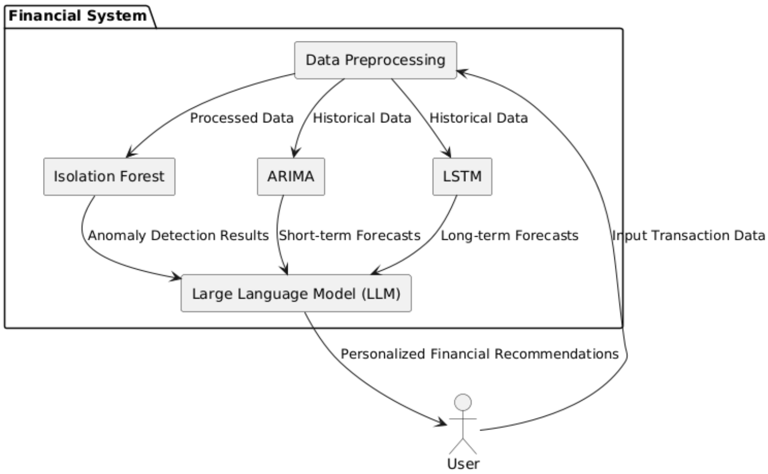

Fig. 3. **Diagram of the interaction of AI components within the system**
***Source*: compiled by the authors**

The ethical nature of the system is reinforced by its focus on the user's interests. Instead of evaluating or judging financial behavior, the system provides structured, well-founded advice that helps users better understand their spending patterns, identify potential saving opportunities, and optimize their budget. Importantly, the recommendations are tailored to the user's individual goals and preferences, preserving their independence and autonomy in making financial decisions. The system does not impose specific actions but instead offers a variety of options from which the user can choose that best meet their needs and goals.

4. IMPLEMENTATION OF THE RECOMMENDATION SYSTEM

The architecture of the system is built on an event-driven approach with a high-level of module independence. The overall operations principle of the system, which supports core financial operations, integration with banking systems, as well as data cleaning and preparation processes for further AI module analysis, is that each module operates autonomously. For example, the Budget Module remains operations even if the AI module is temporarily unavailable, and vice versa. The AI module is responsible for key functions such as detecting anomalous expenses, forecasting future expenses during budgeting, generating personalized financial advice, and recommending alternative spending options. The Build-Train-Deploy pattern is used to integrate the AI model into the microservices architecture, supported by AWS SageMaker, which automates model training, testing, and deployment [27].

A database has been developed to store data that provides input information for the recommendation system, with its Entity-Relationship Diagram (ERD) model shown in Fig. 4, illustrating the main entities of the financial platform and the relationships between them. The diagram covers various aspects of the system's operation, including user management, transactions, budgets, financial goals, subscriptions, and categories.

Fig. 5 and Fig. 6 provide examples of the screen forms of the developed system.

The system's software implementation is built on a modular architecture, including several components, each responsible for a specific part of the functionality. The main components are the AI Module, Budget Module, API Gateway, Authentication Module, and other integrations with cloud services such as AWS Glue and AWS SQS.

The AI Module is implemented in Python using libraries like scikit-learn, TensorFlow, and statsmodels. Python was chosen for this module due to its powerful data processing capabilities, ease of integrating machine learning algorithms, and support for a wide range of analytics libraries.

The Budget Module is implemented in Java using the Spring Framework to ensure fast and reliable processing of user financial transactions. This module allows adding new transactions, creating budgets, and retrieving expense data. Using Spring facilitates easy configuration of REST APIs for interaction with other modules and the client side. The choice of Spring is based on its effectiveness for building scalable web applications and microservices. Additionally, using Java ensures reliability and a high level of security in data processing.

The API Gateway is implemented with Spring Cloud Gateway, allowing efficient routing of requests between different microservices in the system. This solution provides a centralized entry point for all client requests and enables the application of security policies and load balancing.

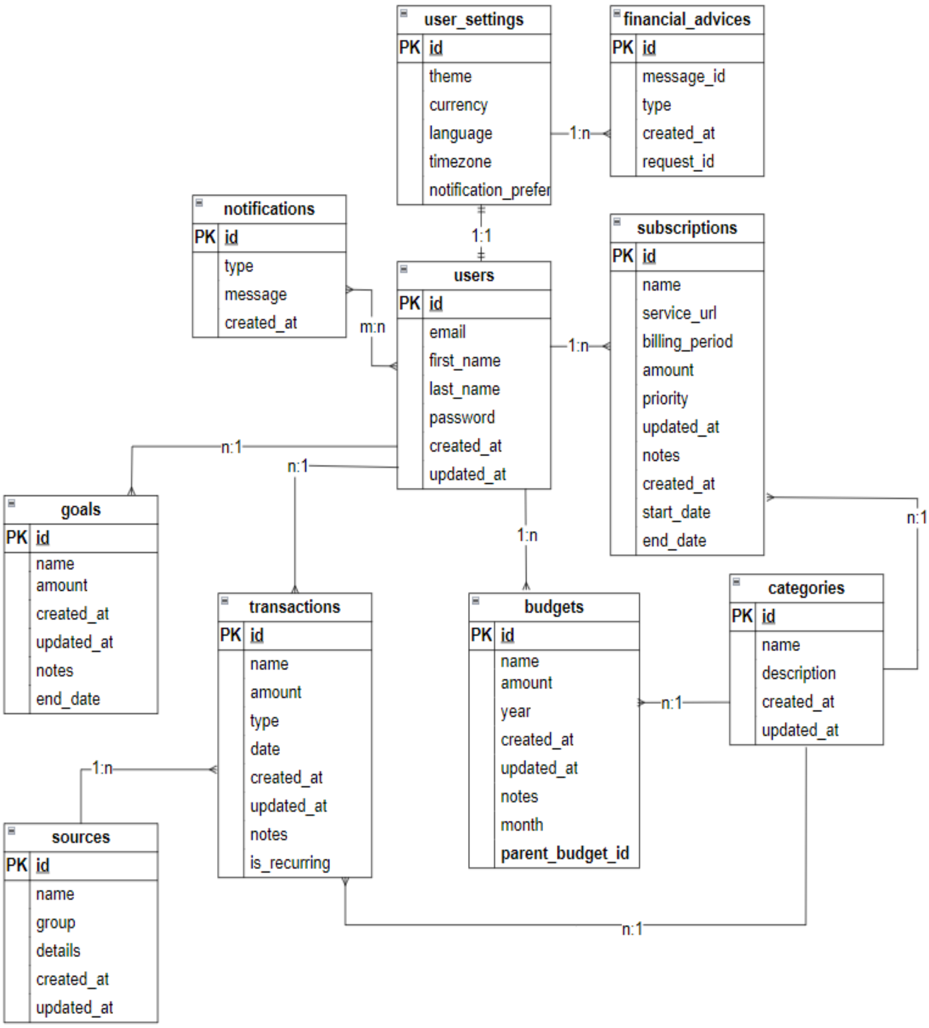

Fig. 4. **ERD for the recommendation system**
***Source*: compiled by the authors**

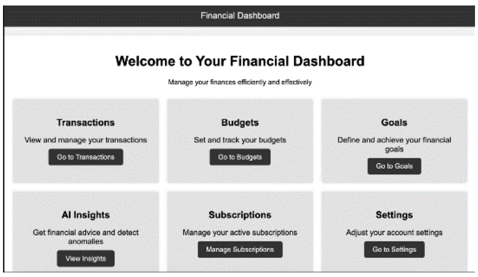

Fig. 5. **Main page**
***Source*: compiled by the authors**

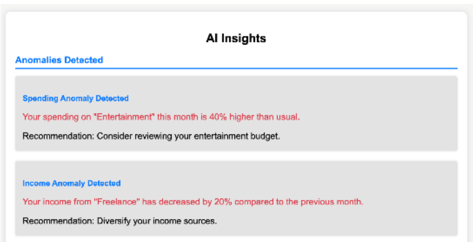

Fig. 6. **Use of AI models for anomaly detection**
***Source*: compiled by the authors**

Spring Cloud Gateway was chosen for its ease of configuration and ability to scale with the system, which is critically important to ensure continuous availability of services.

To ensure reliable user authentication, OAuth 2.0 is used, which allows for controlling access to the system's protected resources via tokens. Implementing OAuth 2.0 on the basis of Spring Security makes it easy to integrate authentication with other modules and ensures reliable control over access to important data. Spring Security was chosen for this task due to its seamless integration with OAuth 2.0 and its ability to quickly adapt to different levels of user access.

For processing large volumes of transaction and budget data, AWS Glue is used to perform ETL (Extract, Transform, Load) operations to prepare data for further analysis in the AI Module. Glue Crawler automatically determines the schema of data stored in S3 and makes it available for further processing.

AWS SQS is used for message queuing between microservices. This enables asynchronous event processing and reliable message transmission, for example, about anomalies in financial expenses.

Terraform is used to automate the creation of AWS infrastructure, including configuring SQS queues and S3 buckets. This makes it easy to set up and scale the cloud infrastructure to meet system requirements.

The client side of the system is implemented in React.js, providing an interactive and fast user interface. React enables the construction of Single Page Applications (SPA), ensuring quick response and dynamic data updates without page reloads. React.js was chosen for its popularity, performance, and extensive capabilities for integration with REST APIs.

CONCLUSIONS

The use of AI models for a system that generates personalized financial recommendations is described. The Isolation Forest model is applied to detect anomalous transactions, using a tree-like structure to isolate deviations in the user's financial behavior. This enables the model to effectively identify potentially spontaneous or uncharacteristic expenses.

In parallel, ARIMA and LSTM models are used to forecast future expenses. ARIMA provides short-term forecasts, accounting for seasonal fluctuations and dependencies in time series, while LSTM, with its ability to capture long-term dependencies, is used for more stable long-term forecasts.

The data generated by these models is fed into a large language model (LLM), which integrates anomaly results, short-term, and long-term forecasts to produce personalized financial recommendations. These recommendations are tailored to the user's specific financial goals and behavior and can help optimize the budget, reduce risks, or increase savings.

The system ensures high accuracy through the combination of various AI models (ARIMA and LSTM for forecasting, Isolation Forest for anomaly detection, and LLM for generating advice), completeness by training on user's transactions and financial operations, as well as privacy and security by adhering to OAuth 2 standards and OWASP Top 10 principles. The systems' ethical aspect is reflected in its support for users in managing their finances rationally, without judgement of their decisions.

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Рекомендаційна система для прийняття фінансових рішень з використанням штучного інтелекту

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АНОТАЦІЯ

Стрімке поширення штучного інтелекту (ШІ) на споживчих ринках створює серйозні виклики для суспільства, зокрема в контексті використання когнітивних упереджень, що впливають на ухвалення фінансових рішень споживачами. Ці упередження можуть призводити до нераціональних витрат, що ставить під сумнів етичність застосування ШІ у подібних сферах. У цьому дослідженні розглядається, як ШІ може не тільки підвищувати ефективність ухвалення фінансових рішень, але й допомагати споживачам приймати більш обґрунтовані та раціональні рішення. Основна увага зосереджена на розробці інтелектуальної системи управління фінансами, яка застосовує сучасні алгоритми ШІ для аналізу фінансової поведінки, виявлення аномалій та надання персоналізованих рекомендацій. У статті розглядається система генерації персоналізованих фінансових рекомендацій на основі великих мовних моделей, яка використовує історію транзакцій, прогнозовані витрати та інформацію про аномалії для створення індивідуальних порад. Зокрема, досліджуються моделі машинного навчання, такі як Isolation Forest для ідентифікації атипових фінансових дій, а також поєднання ARIMA та LSTM для прогнозування бюджетів. Дослідження також розглядає можливість інтеграції цих моделей із використанням великих мовних моделей (LLM) для генерування персоналізованих рекомендацій. Методологічна частина роботи включає аналіз існуючих моделей і сфер їхнього застосування, визначення типів та структури даних для обробки, розробку системи, що інтегрує наявні моделі, та її тестування. Описано процес формування рекомендацій, що включає етапи обробки вхідних даних, формування контексту, генерації рекомендацій та їх оцінки з урахуванням характеристик користувача, таких як рівень ризику, фінансові цілі та уподобання. Генеровані рекомендації спрямовані на оптимізацію фінансової поведінки користувача та можуть бути адаптовані до різних рівнів доходів. Окрему увагу приділено етичним аспектам системи, що включають забезпечення конфіденційності, справедливості та прозорості, а також важливості підтримки автономії користувача у прийнятті фінансових рішень. Система сприяє розвитку відповідальної фінансової поведінки, допомагаючи уникати імпульсивних витрат та підвищуючи фінансову обізнаність без маніпуляцій чи нав'язування конкретних рішень.
Ключові слова: штучний інтелект, машинне навчання, когнітивні упередження, фінансові рішення, етичність.

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