AI-Driven Financial Advisory Systems for Retirement Planning Among Displaced Populations

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Abstract. This paper presents a conceptual framework for an AI-powered financial advisory systems to address displaced populations' retirement planning challenges. The concept is based on approaches: 1) combining fine-tuned large language models and a retrieval-augmented generation, and 2) life financial events to provide personalized financial guidance for retirement planning, considering the cultural background, financial habits, remittances, and other input parameters of refugees. Data collection methodology includes interviews, displaced population surveys, and expert financial advisors. It is offered to test a pilot application of the AI-powered financial advisory system in Poland for Ukrainian migrants. The evaluation methodology combines quantitative metrics with qualitative assessment from end-migrants and financial professionals. The paper discusses the proposed system architecture, evaluation methodology, and potential challenges. Among the limitations are a relatively small sample size in the evaluation phase (30 participants), a short evaluation period (3 months), and a focus only on Ukrainian refugees in Poland. The generalizability of findings to other displaced populations and countries may be problematic. This research aims to contribute to developing innovative AI-powered solutions that

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[1] https://data.unhcr.org/en/situations/ukraine

[2] https://ces.org.ua/ukrainian_refugees_third_wave_research/

promote financial inclusion and improve the long-term financial well-being of migrant populations.

KEYWORDS: AI in finance, advisory system, retirement, displaced population

JEL CLASSIFICATION: D14, G53, I31, C63, F22

1 INTRODUCTION

Migration is a dynamic and ongoing phenomenon that shapes societies and economies worldwide. The reasons can differ: better economic opportunities, climate changes, political instability, wars and conflicts, etc. Problems of adaptation of migrants are usually related to integration to new communities, lowering of professional status, language and cultural barriers, education, job seeking, and access to finance. Moreover, migrants often enter the new country's job market later and have fewer opportunities to manage their retirement planning. The last most significant wave of migration was caused by the Russian invasion of Ukraine in 2022. According to the UN, as of January 15, 2025, 6.3 million Ukrainians have registered abroad[1]. Many Ukrainian refugees were adult women aged 35 to 44, making up 13% of all refugees[2]. This is a favorable age for those who haven't started saving for retirement yet. Because of low levels of financial knowledge, awareness about the host country's financial system and its rules, and the absence of access to financial advisors, migrants risk remaining below the poverty line during their retirement.

The increasing penetration of AI into the financial industry offers hope that this emerging financial technology can help overcome the challenges of migrants' financial adaptation and help them achieve their financial goals. AI technologies can provide data-driven insights, personalized financial advice, and automated tools that account for the complex variables unique to migrants' financial journeys. Potentially, AI can analyze cross-border pension systems, regulatory requirements of the host countries, and individual cultural patterns of financial behavior to generate tailored retirement plans. Moreover, AI-driven platforms can facilitate financial literacy by delivering native language and culturally sensitive financial education, helping migrants better understand and engage with available retirement options.

At the same time, challenges of AI adoption, such as data privacy concerns, ethical considerations, and the digital divide, must be addressed to ensure that AI solutions are accessible, fair, and secure for all individuals, regardless of their socioeconomic and cultural background.

Moreover, policymakers and financial institutions must collaborate to create regulatory frameworks that support AI-driven financial planning tools for migrants while ensuring compliance with international financial standards and safeguarding consumer rights.

2 LITERATURE REVIEW

A considerable amount of literature has been published on the application of AI in the financial industry during the last few years.

As finance is a mega industry, many different ways of applying AI can exist. Some scholars started exploring AI for research and extending knowledge in finance. (Dowling & Lucey, 2023; Korinek, 2023) assess how using chat GPT impacts the research process in economics and finance. Researchers claim it is helpful for idea generation, data identification, and writing. However, it is weaker for coding, data analysis, and math. (Ganesh et al., 2024) call the Generative AI Agents for knowledge work augmentation in finance. A considerable number of studies are around the concrete application of AI in finance described on the theoretical level (Bahoo et al., 2024; Berradi et al., 2020; Ferreira et al., 2021; Gigante & Zago, 2023; Goodell et al., 2021; Huang et al., 2020; X. Li et al., 2023). For instance, (Bahoo et al., 2024) detected ten main research streams of AI application: (1) AI and the stock market; (2) AI and Trading Models; (3) AI and Volatility Forecasting; (4) AI and Portfolio Management; (5) AI and Performance, Risk, and Default Valuation; (6) AI and Bitcoin, Cryptocurrencies; (7) AI and Derivatives; (8) AI and Credit Risk in Banks; (9) AI and Investor Sentiments Analysis; (10) AI and Foreign Exchange Management.

A relatively large and growing body of literature has investigated the application of AI for forecast financial markets movements (for instance, Ali et al., 2021; Khattak et al., 2023; Sezer et al., 2020; Wang et al., 2018). AI can be used to predict cryptocurrency prices (Critien et al., 2022; Y. Li et al., 2022).

Weber et al., 2024 added that explainable artificial intelligence (EAI) in finance is focused mainly on the financial market. However, it is understudied in such areas as anti-money laundering. Misheva et al., 2021 implemented EAI models Local Interpretable Model Agnostic Explanations (LIME) and Quinn, (2023) introduced SHapley Additive exPlanations (SHAP) for lending services. Using a comparative survey, Yeo et al., 2023 categorized explainable methods of AI in finance and reviewed the problems of its adoption.

Mashrur et al., (2020) developed a taxonomy of financial-risk-management tasks and connected them with relevant machine learning methods. Beyond the described use, Ahmed et al., (2022) added in bankruptcy prediction, AI can be used.

2.1 AI for financial services

Hentzen et al., (2022) identified that AI for consumers of financial services is split between data-driven and theory-driven approaches, focusing on either testing AI algorithms for credit scoring or investigating consumer adoption of AI in banking. Herrmann and Masawi, (2022) studied how AI in banking has developed since the 2010s - it shifted from credit risk to more data-driven, algorithmic approaches. Kanaparthi, (2024) claimed that AI could help build trust between the financial institution and its customers by tailoring the product or service to the client's needs. Mogaji et al., (2022) explained how AI can better understand customer

needs and preferences to develop relevant services and make them more personalized. Srinadi, (2023) showed the importance of AI applications for detecting fraud in financial services. Lee, (2020) is convinced that AI can ensure access to finance and financial inclusion. However, there are the risks of market manipulation. A similar approach is provided by Mhlanga, (2020), who described how AI can assist vulnerable groups like women, youth, and small businesses with access to financial services. The more a client trusts the product, the more personal information the customer is ready to disclose. Lakkaraju et al., (2023) checked the answers of ChatGPT and Bard about financial services in different languages and revealed that there are gaps in providing reliable financial information.

2.2 AI for personal finance and financial literacy

There are studies where the revolutionary role of AI in personal finance is highlighted (A. G. Kim et al., 2025; Pangavhane et al., 2023; Vaduka et al., 2024). However, all humans must understand that AI is the only assistant in making decisions in personal finance, and AI is not the ideal instrument. Understanding the possible shortcomings of current LLMs for personal finance (Lo & Ross, 2024) proposed a framework for determining and exploring ways to overcome them.

As a personal adviser, AI is also getting smarter - Niszczota & Abbas, (2023) assessed the financial literacy of GPT-3.5 and GPT-4 and revealed that GPT-4 model got a near-perfect score of 99% while its financial literacy checking. Talamo et al., 2021 accented that effective design of AI-based decision-making systems requires a deep understanding of the real practices and decision-making processes of human actors, not just technological development. In addition to the described challenges, a problem of trust in robo-advisors is also presented and described by Zhu et al., (2023).

Works based on empirical data began to appear. Hean et al., (2025) studied the potential of LLMs for personal finance related to mortgages, taxes, loans, and investments in the United States.

AI can also be a practical addition to robo-advisors or even substitute them. Thus, Tokic, (2018) studied the case of BlackRock who developed and implemented a fully automated investment program based on self-learning AI algorithms.
Shanmuganathan, (2020) explored longitudinal case study of robo-advisors in investment decisions and the impact of AI on behaviourial fiance.

2.3 The intersection of AI for personal finance and covering migrants' and refugee's

For migrants and refugees there are AI-based solutions to different issues are studied: integration, education, job sicking (Martin-Gutierrez et al., 2020); border security and data analysis for visas (Beduschi, 2021); case management of asylums (Ediae et al., 2024); tracking systems of diseases in refugees camps (Jarral et al., 2019); applications for refugee resettlement (Bansak et al., 2024; Freund et al., 2023).

Beyond the mentioned problems, the financial ones also exist. The most common financial problems of migrants are 1) financial inclusion or access to financial services (Dalal & Churchill, 2018; Datta, 2012; Dhawan et al., 2024; Ghazali & Leong, 2023; Schmich & Mitra, 2023); 2) financial literacy (Khan et al., 2022; Y. K. Kim et al., 2022); 3) savings and retirement (Harrysson et al., 2016); 4) debt management (Djaji´c & Vinogradova, 2014; Paul & Mandal, 2024; Platt et al., 2017). Also, Sengoelge et al., (2020) revealed the relationship between financial hardship and the common mental health problems of refugees.

In the context of our study, migrants and refugees are considered a part of the vulnerable population in host countries, considering their retirement planning (Harrysson et al., 2016). Older migrants have lower lifetime earnings because of late entry into the host country's labor market (Grant & Townsend, 2013). In some countries, migrants cannot access the public retirement system because of residence requirements (Curtis & Lightman, 2017). In many cultures, the younger generation supports the older one. Therefore, the ability to save for retirement is limited because they send money to their relatives (Liu et al., 2024b, 2024a).

It's crucial to mention that the cultural background of refugees matters in managing their financial problems (Gatina, 2012; Haliassos et al., 2017; Ventura & Ventura, 2021; Wanner et al., 2024). Our previous studies about Ukrainian labor and war migrants in Poland (Polishchuk et al., 2023, 2024) showed that they have certain patterns of financial behaviour caused by their cultural background. The Ukrainians have a short period of financial planning (they do not get used to think for long-term perspective), usually their incomes cover mainly food, they are pretty disciplined in paying regular accounts (rent, loans, utilities, etc.), most of them manage their personal finance intuitively. It's a tradition to send remittances to support their elder relatives. Ukrainians tend to borrow money from their relatives and friends instead from financial institutions.

At the same time, there are a limited number of research papers related to AI in the finance of refugees with financial problems. Some of them showed that fintech and intelligent technologies were able to overcome income inequality, giving poor people access to finance (Demir et al., 2022; Wanner et al., 2024). However, there is an absence of papers specifically addressing AI-driven solutions for the retirement planning of migrants of certain origin and financial mindset.

Therefore, the **aim** of this study is to develop a concept of a solution based on AI for migrants and refugees to overcome their challenges related to retirement planning.

3 THEORETICAL EXPLORATION OF HOW AI CAN ADDRESS MIGRATION-SPECIFIC RETIREMENT PLANNING CHALLENGES

The theoretical base of the AI model for retirement planning is the life event approach, where secure retirement plays a crucial role. Financial planners and advisors widely use this approach. AI-based solutions can help resolve the retirement planning challenges of migrants in different ways. It is possible to generate personalized retirement plans based on

user-specific data (sex, age, marital status, number of dependents (children and elder relatives), etc). For example, when planning retirement, it is essential to calculate the migrant's net worth and analyze cash flow (income and expenses). The specific cost of migrants is sending remittances to their home countries.

The retirement planning is different for migrants and refugees compared to locals and has a different context. However, its algorithm will be the same (see Table 1).

Table 1: Stages of Planning for Retirement and Possible options for migrants

Stages of Plan for Retirement	Possible options
Identifying goals	Save enough money for the desired lifestyle
	Traveling
	Buying a retirement home (at homeland)
	Returning to homeland
	Starting a second carer
Retirement expenses forecast	75% of a person's pre-retirement standard of living
	Person's expenditures today, adjusting for downward (lower cost for children, education, wardrobe, paid-off mortgage)
If the migrant/ refugee can afford to retire	Number of years of retirement span (longer, shorter)
	Number of years to retirement (longer, shorter)
	Savings and retirement plan before displacement
	Inflation rate (higher/lower)
	Rates of return (higher/lower)
Place of living	Home country
	Host country
	Home and host countries
	Affect on health/ safety/ transportation costs/taxation
Health care and other insurance issues	Medicare (hospital insurance and medical insurance)

*Adjusted from Nissenbaum et al., 2004

It is also important to note that, when building AI-based solutions for migrants, cultural background will be taken into consideration. Lack of financial literacy and limited access to financial advisors because of high-cost services and language barriers can push migrants to use AI models to shape their retirement plans. Given these challenges, there is a pressing

need to develop AI-based solutions that provide accessible financial guidance. However, creating effective AI systems requires comprehensive data that reflects refugees' unique circumstances and established financial planning principles.

4 DATASET COLLECTION METHODOLOGY

Developing a practical framework for applying AI to manage savings for retirement requires a comprehensive dataset that captures Ukrainian refugees' unique financial challenges and expert financial planning guidance. This section outlines our data collection methodology and dataset construction approach.

The data collection process involves two primary sources of data, carefully selected to ensure comprehensive coverage of the financial advisory needs of displaced populations. The foundation of our data collection rests on structured interviews with Ukrainian refugees currently residing in Poland countries. We will conduct semi-structured interviews with 30 Ukrainian refugees (aged 25-65) to understand the most common patterns of financial behaviour, considering their pension planning and shaping hypotheses for further surveys of Ukrainian refugees in Poland. The questions of the survey will capture detailed financial information based on Table 1 and focused on retirement planning intentions. The survey will include questions on monthly income, employment status, expense patterns, savings, assets, financial goals, risk tolerance, family status, remittances, number of dependents, and specific financial challenges in host countries. We plan to recruit participants from diverse demographic groups, including various age ranges and differing financial knowledge and investment experience levels.

Four certified financial advisors with experience in refugee financial integration will participate in the study to complement the refugee interviews. These experts will conduct mock advisory sessions addressing common financial scenarios identified through the refugee surveys. This expert knowledge is crucial to our training data, providing professional insights into financial planning for displaced populations.

We implement a multi-stage processing pipeline to transform the collected interview data from refugees and expert advisory sessions into structured training instances. The system architecture for processing financial advisory data is illustrated in Figure 1, which demonstrates the flow from refugee interviews and expert recommendations as raw data inputs through a data preprocessing stage to the final structured training dataset.

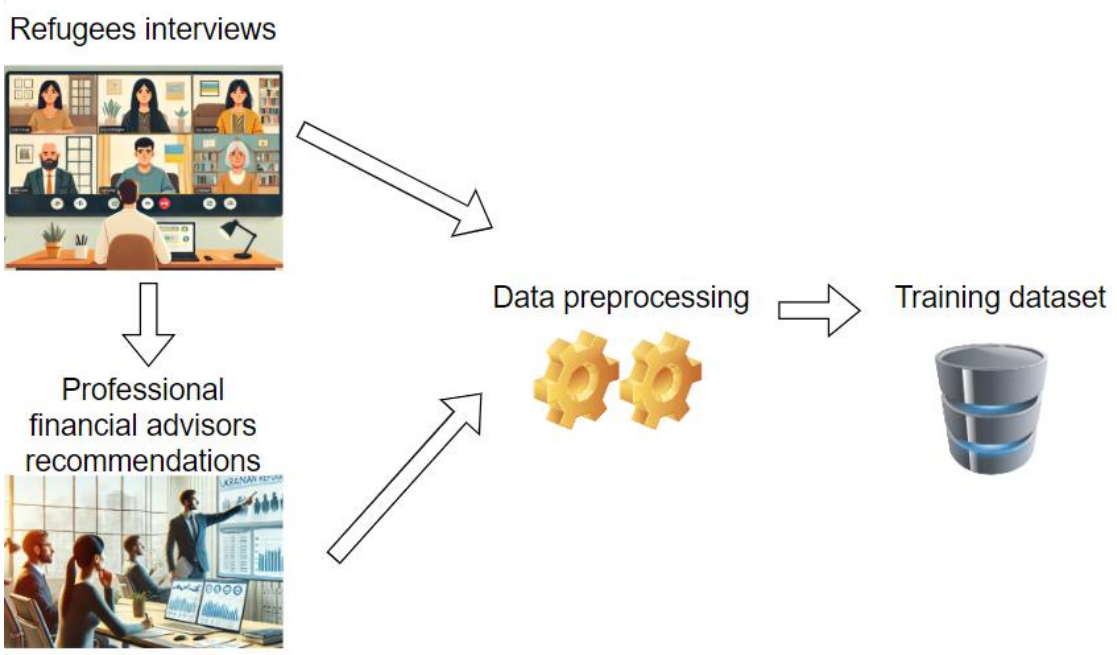


Figure 1: Dataset collection methodology for AI-Driven System for Migrant Retirement Savings

We will also introduce controlled perturbations to the collected data, such as varying the number of dependents, adjusting income levels, or modifying expense categories to simulate diverse user contexts and enhance the model's generalization ability. Additionally, we plan to leverage the expertise of financial advisors to create additional training examples by extrapolating from existing scenarios. For instance, advisors can provide alternative recommendations for the same financial context, introducing variability in the output space (Assefa, 2020).

The collected data undergoes careful processing to create a specialized format suitable for fine-tuning large language models. Each training instance combines contextual information with input-output pairs structured to capture the complexity of financial advisory scenarios. The examples of training data are shown in Table 2.

Table 2: Examples of training data and labels for fine-tuning the model

Training example	**Input of user data and question**	**Output with finance advises**
1	User Context: Monthly income: €2200; Current savings: €4000;	Let's create a practical savings plan based on your current situation of €2200

Training example	Input of user data and question	Output with finance advises
	Monthly expenses: Housing €800; Utilities €150; Food €400; Transportation €100; Remittances €100; Healthcare €50; Other €200. Has two dependent family members. Gender: Male Lives in Poland for 6 months. User question: I currently spend almost all my monthly income and can't save anything. I need to start retirement savings, but I don't know where to start	monthly income and €1800 expenses. First, establish an emergency fund targeting €5400 (3 months of expenses). Start by saving €200 monthly. Your housing cost is 36% of your income, above Poland's recommended 30% threshold. Consider: 1. Apply for "Family 800+" program if your children are eligible. 2. Open an IKZE (Individual Retirement Account) with a minimum €50 monthly contribution to benefit from tax advantages. 3. Use regulated money transfer services like Western Union or TransferWise to reduce fees for remittances. 4. Register with NFZ (National Health Fund) to reduce healthcare costs.
2	User Context: Monthly income: €1800; Current savings: €1000; Monthly expenses: Housing €600; Utilities €120; Food €350; Transportation €80; Remittances €50; Healthcare €40; Other €150. Single-person household. Recently arrived in Poland. Gender: Female User question: How should I start saving for my retirement, given my current financial situation?	With €1000 in savings and being new to Poland, focus first on building an emergency fund before retirement planning. Aim for 3–6 months of expenses (€4,170-3,340). Consider these steps: 1. Open a high-interest savings account with a Polish bank (like PKO BP or ING Bank Slaski). 2. Once the emergency fund is established, start an IKZE (Individual Retirement Security Account) for tax benefits. 3. Use comparison sites like Compareremit.com for the best remittance rates. 4. Register for NFZ healthcare coverage to reduce medical expenses. 5. Consider a Mikrorachunek tax account for more manageable tax payments.

Training example	Input of user data and question	Output with finance advises
3	User Context: Monthly income: €2500; Current savings: €8000; Monthly expenses: Housing €900; Utilities €180; Food €450; Transportation €120; Remittances €200; Healthcare €60; Other €250. Family of three with one child in school. Gender: Male User question: What is the best way to allocate my savings towards retirement planning?	With €8000 in savings covering over four months of expenses, you can focus on retirement planning: 1. Open both IKE and IKZE accounts to maximize tax benefits: - Contribute €300 monthly to IKE (2024 limit: 20,805 PLN). - Add €200 to IKZE (2024 limit: 8,322 PLN). 2. Apply for "Family 800+" benefit for your child. 3. Consider PPE (Employee Capital Plans) if applied by a Polish company. 4. For remittances (€200), use multi-currency accounts like Wise or Revolut to save fees. 5. Ensure complete family registration with NFZ for comprehensive healthcare coverage.

Data privacy will be a critical focus throughout the collection and processing pipeline. All collected data will be anonymized at the earliest stage. Participants' consent will be obtained before data collection, and secure storage systems will be used to protect sensitive information. Measures will also be taken to minimize identifiable information in the structured training data, ensuring ethical standards are maintained from data collection to final processing.

To ensure systematic development and evaluation of the AI-powered financial advisory system, we have developed a comprehensive implementation plan spanning 12 months. Table 3 outlines the key phases, activities, participant selection criteria, and identified methodological limitations.

Table 3: Examples of training data and labels for fine-tuning the model

Component	Name	Duration	Details
Phase 1	Initial step	Months 1-2	Institutional review board approval. Recruitment of participants and financial advisors.

Component	Name	Duration	Details
			Development of interview guides and questionnaire.
Phase 2	Data collection	Months 3-5	Conduct refugee interviews and survey. Expert advisory sessions. Initial data processing.
Phase 3	System development	Months 6-8	AI model training. Interface development. Security implementation.
Phase 4	Testing and evaluation	Months 9-12	System testing. User feedback collection. Expert evaluation.

The selection of participants is guided by specific criteria to ensure diversity and relevance. Ukrainian refugees are chosen based on a minimum of six months of residence in Poland, varied educational backgrounds, different employment statuses, and a mix of urban and rural locations. Financial advisors are selected based on at least five years of experience, prior work with migrant clients, and cross-cultural advisory expertise in Poland.

5 FRAMEWORK FOR APPLYING AI TO MANAGE SAVINGS FOR RETIREMENT

The proposed AI-powered financial advisory system to manage savings for retirement employs a sophisticated architecture designed to provide personalized financial guidance to Ukrainian refugees, as illustrated in Figure 2. At its core, the system combines fine-tuned language models and a retrieval-augmented generation (RAG) approach to deliver accurate and contextually relevant financial advice (Gupta et al., 2024). Recent research demonstrates that combining retrieval-augmented generation with domain-specific fine-tuning can significantly improve the accuracy and reliability of AI-generated financial advice (Zhang et al., 2024). As in Raj et al., 2024, we plan to implement a dynamic knowledge retrieval system that allows the model to access and reference relevant financial regulations and country-specific information for different EU countries.

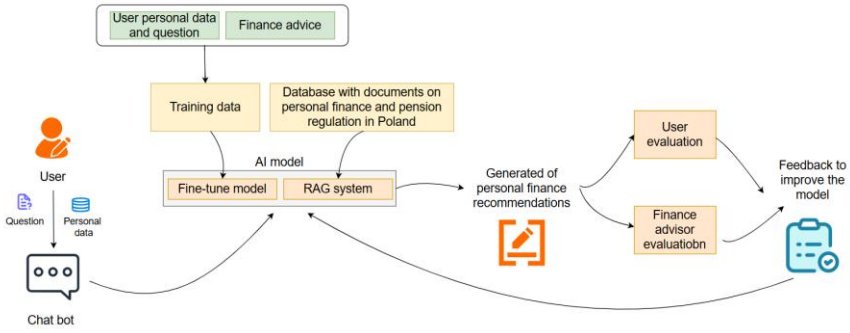


Figure 2: The proposed AI-powered financial advisory system to manage savings for retirement

The system begins with a user interface implemented as a chatbot, where users can input their personal financial data and questions. The chatbot processes and structures these inputs into a format suitable for the underlying AI model.

The AI model's architecture incorporates two primary components working in tandem. The first component is a fine-tuned language model adapted to handle financial advisory scenarios. This model would be trained on the carefully curated dataset in Table 2. The second component is an RAG system that augments the model's capabilities by accessing a comprehensive database of personal financial literature. This dual approach ensures the system's recommendations will be contextually appropriate and grounded in established financial principles.

The system will generate personalized financial recommendations and undergo a two-tier evaluation process: first, they will assessed by actual users who provide feedback, and second, they will be reviewed by professional financial advisors who evaluate the technical accuracy and appropriateness of the recommendations. This evaluation framework creates a feedback loop continuously improves the model's performance.

6 SYSTEM EVALUATION METHODOLOGY

The evaluation of our AI-powered financial advisory system requires a comprehensive approach that combines quantitative metrics with qualitative assessment from both end-users and financial professionals. Building on the established methodologies from Yuan et al., 2024, we propose a multi-faceted evaluation framework that assesses the technical accuracy and practical utility of the financial advice provided.

For quantitative evaluation, we will employ several key metrics. The overall system accuracy (SA) will be calculated as a weighted combination of expert evaluation scores (EES) and user satisfaction scores (USS):

$$SA = \alpha \cdot EES + (1 - \alpha) \cdot USS \tag{1}$$

where α is the weighting coefficient (typically set to 0.6 to prioritize expert validation while maintaining significant user input).

For each generated financial advice *i*, the EES is computed as:

$$EES_i = \frac{RA_i + EI_i + RC_i + RS_i}{4} \quad (2)$$

where:

RAi is the risk assessment accuracy from 0 to 1;

EIi is the expected income rate of the offered financial instrument from 0 to 1;

RCi is the regulatory compliance from 0 to 1;

RSi is the refugee sensitivity from 0 to 1.

The USS is computed as:

$$USS_i = \frac{C_i + P_i + U_i}{3} \quad (3)$$

where:

Ci is the clarity score from 0 to 1;

Pi is the practicality score from 0 to 1;

Ui is the usefulness score from 0 to 1.

The primary evaluation will be conducted through a structured trial period involving 30 Ukrainian refugees residing in Poland, stratified across different income levels, family situations, and host countries. Each participant will interact with the system over a three-month period, presenting their real financial scenarios and receiving AI-generated advice. Following each interaction, participants will complete a detailed evaluation questionnaire addressing the recommendations' clarity, practicality, and perceived usefulness.

To ensure technical accuracy and compliance with financial regulations, a panel of four certified financial advisors will conduct an expert evaluation of the system's outputs. These professionals will assess a random sample of 100 AI-generated recommendations against a standardized rubric covering key aspects such as accuracy of financial calculations, appropriateness of risk assessment, compliance with Poland financial regulations, consideration of refugee-specific circumstances, and alignment with professional planning standards.

7 DISCUSSION AND LIMITATIONS

The development of an AI-powered financial advisory system for migrants' retirement planning represents a significant step toward addressing the unique financial challenges faced by displaced populations. Our proposed framework and evaluation methodology reveal several key insights and implications for research and practice. Using a pilot case of Ukrainian migrants in Poland, the offered system can demonstrate the potential of adjusting their financial patterns (preferably short-term planning, avoiding retirement planning,

sending remittances to relatives in Ukraine etc.). This aligns with findings from Wanner et al., (2024) and Haliassos et al., (2017) regarding the importance of cultural context in financial decision-making among migrant populations.

To collect data for further fine-tuning, we use interviews and surveys to cover the gap of a limited sample of similar qualitative studies in financial advisory systems research (Zhu et al., 2023). The system's ability to account for migrant-specific circumstances, such as remittance obligations and cross-border pension considerations, represents a significant advancement over traditional retirement planning tools. This addresses the gaps that Liu et al., 2024a identified regarding the impact of familial obligations on retirement savings capacity among migrant populations.

Combining fine-tuned language models with RAG is particularly effective for providing personalized financial advice. This approach allows the system to maintain accuracy while adapting to individual circumstances, addressing concerns raised by (Lo & Ross, 2024) and (Gupta et al., 2024) about the limitations of current LLMs in personal finance applications.

While the proposed system's design aims to provide accurate and reliable financial advice, the actual effectiveness and user engagement levels must be validated through empirical testing. Therefore, professional financial advisors and users are proposed to be invited for validation of generated financial decisions. The need to balance comprehensive financial analysis with user-friendly interaction presents an ongoing challenge similar to those identified by (Talamo et al., 2021) and (Zhang et al., 2024) in their study of AI-based decision-making systems.

Our implementation reveals important considerations regarding data privacy and the ethical use of AI in financial advisory services. The structured data collection methodology and encryption protocols address many of the concerns raised by previous studies (Zhu et al., 2023) regarding trust in automated financial advisors. However, the challenge of maintaining data privacy while gathering sufficient training data remains a significant consideration for future implementations.

Several limitations of the current study, similar to Whitaker (2024), present opportunities for future research. The relatively small sample size (30 participants) in the evaluation phase may not fully represent the diversity of migrant experiences and financial situations. The three-month evaluation period may not be sufficient to assess long-term impacts on retirement planning behavior. Additionally, due to the focus on Ukrainian refugees in Poland, the generalizability of findings to other migrant populations and regions may be limited. Variations in digital literacy among participants may influence their ability to engage with the survey system.

8 CONCLUSION

The objective of this study was to propose the concept of an AI-driven solution for migrants and refugees to support their retirement planning. The concept of an AI-powered financial advisory system was developed to address this need. By applying this concept, the fintech

product can influence the financial behavior of migrants, addressing gaps such as a lack of financial knowledge, limited access to financial advisory services, and cultural and regulatory differences in host countries.

For the pilot case, we proposed focusing on the retirement planning needs of Ukrainian refugees in Poland. A fintech solution based on this AI-powered financial advisory system concept can effectively address the financial challenges faced by migrants, acting as an assistant and financial advisor for retirement planning. From a technical perspective, the proposed system leverages Retrieval-Augmented Generation and fine-tuned language models to provide personalized financial advice. Its ability to account for migrant-specific circumstances, such as remittance obligations and cross-border pension considerations, distinguishes it from traditional financial advisory tools. A user-friendly interface built upon this AI-powered system can empower migrants to make informed decisions regarding retirement planning and other financial goals.

However, implementing this solution presents challenges at the regulatory level, including data privacy concerns, compliance with financial regulations across jurisdictions, and ensuring accessibility for diverse user groups. These hurdles must be addressed to guarantee the system's practicality and widespread adoption. Future research will focus on: 1) testing and validating the concept of the AI-powered financial advisory system through pilot programs and stakeholder collaborations; 2) implementing and evaluating the system's ability to manage retirement savings for Ukrainian migrants in Poland, with consideration for enhancing scalability in other countries; 3) exploring the use of different large language models to optimize accuracy during the evaluation phase.

This research contributes to the growing discourse on financial inclusion and AI-driven solutions for vulnerable populations by demonstrating the potential of integrating advanced machine learning techniques with domain-specific knowledge.

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