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The Integration of Chatbots and AI-Powered Virtual Assistants into Customer Service Frameworks of the Banking Sector

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Abstract: The integration of artificial intelligence (AI) into the financial system, especially in the banking sector, has become one of the most important directions of technological progress. The aim of the article is to reveal the specifics of the application of AI in banking services, emphasizing the role of chatbots and virtual assistants in the customer-centric services and risk management system. The article presents the theoretical foundations and main directions of application of AI in the banking system. Four main directions are analyzed: customer-centric solutions, process optimization, banking services market management, and improvement of regulatory mechanisms. The experience of international banks (Bank of America, HSBC, DBS, Armenians banks, and others) indicates that the use of AI contributes to reducing operating costs and accelerating and personalizing customer service. However, the integration of AI also raises challenges related to data privacy, cybersecurity, legislative regulations, and the transformation of professional skills. Special attention is paid to the field of credit scoring, where machine learning methods allow for a more accurate assessment of borrower behavior and reduce financial risks. The relevance of the research is due to the fact that AI is no longer an additional technology for banks but a necessary tool for maintaining competitiveness and sustainable development.

Keywords: artificial intelligence, banking, lending, online banking, machine learning

1. Introduction

In 1956, the concept of “artificial intelligence” (AI) was formally introduced into the scientific lexicon by John McCarthy, Alan Newell, Arthur Samuel, Herbert Simon, and Marvin Minsky during the Dartmouth Summer Research Project.

There exists a multitude of definitions for AI. John McCarthy characterized it as the science and engineering of making intelligent machines, particularly intelligent computer programs. Nils John Nilsson, a Stanford University professor and a prolific author in the field, defines AI as an activity devoted to making machines intelligent, with intelligence being that quality that enables an entity to function appropriately and with foresight in its environment. The High-Level Expert Group on Artificial Intelligence provides a more comprehensive formulation, describing AI systems as machine-based software or hardware designed by humans to operate in physical or digital dimensions. These systems perceive their environment through data acquisition, interpret structured and unstructured data, reason upon knowledge to derive cause-and-effect relationships, and process information to decide on the optimal actions to achieve a given objective. According to the Organisation for Economic Co-operation and Development, an AI system is a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. These systems are designed to operate with varying levels of autonomy. The World Economic Forum defines AI, or self-learning systems, as an umbrella term for technologies that replicate human cognitive functions. A key characteristic of AI is its capacity to significantly enhance productivity autonomously, as these systems can improve their performance over time through the continuous analysis of operational data.

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Scholarly consensus indicates that the current period of rapid advancement in AI commenced approximately a decade ago. Presently, AI applications are extensively deployed across diverse sectors, including robotics, finance, healthcare, telecommunications, and marketing. AI has penetrated almost all sectors of the economy, and its role and significance are increasing [1, 2].

AI is of key importance in the financial sector. Today, AI is considered the best technology used in the financial sector, particularly in banks. AI allows banks to increase operational efficiency and reduce certain costs and allows customers to perform any banking transaction more conveniently, more intelligently, and more securely, from making online payments to making online deposits [3]. It also allows for the optimization of banking processes, from credit decisions to financial risk management.

The financial services sector was one of the first investors in the latest technologies (ATM, online banking, etc.), and many organizations in the sector have already switched to the use of intelligent systems such as process automation, advanced data analysis, robo-advisors, chatbots, etc. The areas of application of AI solutions in the financial system can be divided into four groups [4]:

1) Customer-centric (scoring systems, front office systems)
2) Process-centric (capital optimization, risk management, market impact analysis)
3) Securities market-oriented (trading and portfolio management)
4) Governance and regulation-oriented (management decisions, management technologies, data management)

According to the results of a survey conducted by the Cambridge Center for Alternative Finance (151 representatives from 33 countries), AI will become the main driving force in the financial services sector. 77% of participating financial institutions indicated that AI will have a high or very high importance for their activities in the next two years. This is due to the fact that AI solutions are already implemented in key business processes. 64% of respondents plan to use AI in all of the following areas within two years: creating new revenue opportunities through a new product or service, automating processes, managing risks, customer service, and attracting new customers. Additionally, 16% are already using AI solutions in all areas [5].

Another survey of 206 US financial services companies conducted by Deloitte's Financial Services Center found that 30% of companies have achieved significant financial results from the use of multiple AI technologies (leaders), 43% have average AI engagement and average financial results (followers), and the remaining 27% are just starting to invest (earliers). Leaders have achieved a 19% increase in revenue from AI, while followers have achieved 12%, and earliers have achieved 10%. Leaders are making the largest investments, with 25% of them investing $10 million or more in 2017. In fact, 70% of leaders plan to invest even more in the coming year [6].

2. Methodology

Credit scoring is a valuable tool for improving the efficiency and availability of financial resources (for individuals, small and medium-sized enterprises (SMEs)). A well-developed scoring model helps financial institutions reduce financial risks and correctly allocate financial resources.

The methods used for credit scoring have grown significantly in recent years, both in number and complexity. They include both traditional statistical methods and innovative methods such as AI, including machine learning (random forest (RF), gradient boosting, and deep neural networks (DNNs)) [7].

Unlike traditional methods, machine learning-based credit scoring models perform a detailed evaluation of the data and include data that may often seem unimportant and are not included in the traditional method. Innovative methods also have the ability to self-improve when new data are entered into the database. A feature that is absent in traditional methods.

Below, we will present a machine learning-based credit scoring model. Ensemble learning was used as the main form of training. The Python programming language was used as a tool, in particular, the following main libraries: sklearn, imblearn, pandas, and numpy. The credit data (493,520), which were used for training and learning the model, were taken from the open public resource Kaggle website [8]: A credit scoring model has been developed that makes a decision on granting a loan based on the data of each borrower entered, giving a positive or negative conclusion. A web application has been developed to display the results.

AI encompasses many theories, methods, and technologies. Machine learning is a subset of AI. It automates the construction of analytical models. Machine learning uses methods from neural networks, statistics, operations research, and physics to find hidden information/truth in data without being explicitly programmed where to look, search, or what to conclude [9].

Ensemble learning is a machine learning paradigm in which multiple models (often called "weak learners") are trained to solve the same problem and combined to produce better results. The basic hypothesis is that when weak models are combined properly, they can lead to more accurate and/or stronger models. It is based on the assumption that each model looks at the data from a different perspective, revealing only part of the truth. Then, combining well-performing models that were trained independently will reveal more of the truth than one model. This will therefore lead to more accurate predictions and fewer errors. As the number of models increases, the performance of the ensemble model increases. And the models should be chosen to be as different as possible. This reduces the correlation between the models and leads to improved performance of the ensemble model. Different ensemble methods build the ensemble of models in different ways. Below are some commonly used methods:

1) Blending: averaging the predictions of all models.
2) Bugging: building independent models on random subsets of the training dataset, averaging their individual predictions as the final prediction.
3) Boosting: building models sequentially so that the next model learns from its previous model. To avoid retraining error, each model learns from the results of all previous models.
4) Stacking: building k base learners, fitting their results into the model to predict the final result.

This methodological appendix outlines the construction and computational framework of the Digital Adoption Index (DAI) and the Customer Activity Index (CAI), which are composite measures used to evaluate the effectiveness of digital transformation in the banking sector. The strong positive correlation between the indices (r = 0.86 – 0.92) provides empirical evidence of the strategic impact of digital investment initiatives.

The DAI is a normalized composite score (0–100 scale) quantifying the breadth and depth of digital service implementation by financial institutions. It is calculated through a weighted aggregation of two primary dimensions:

Implementation Breadth (Weight: w_1): The scope of deployed digital solutions. Metrics include:

1) Presence and functional maturity of mobile banking applications
2) Availability of online payment and transfer services
3) Deployment of AI-powered chatbots and virtual assistants
4) Integration of digital wallets (e.g., QR-code payments)
5) Availability of public Application Programming Interface (APIs) for third-party integration

Customer Engagement Depth (Weight: w_2): The level of active customer utilization of digital channels. Metrics include:

1) Monthly active users of digital platforms
2) Ratio of digital to total transactions
3) Average session duration and frequency per user
4) Feature adoption rate across different service modules

The composite DAI is computed as:

DAI = (w_1 × Normalized_Implementation_Score) + (w_2 × Normalized_Engagement_Score), where $w_1 + w_2 = 1$. In the present study, based on expert survey results, the weights were set at $w_1 = 0.4$ and $w_2 = 0.6$ to prioritize actual usage over mere availability.

The CAI is a complementary composite index measuring the transactional intensity and value of customer interactions through digital channels. It synthesizes two key behavioral components:

1) **Transactional frequency (weight: v_1):** The rate of customer-initiated digital interactions. Metrics include:

   a. Mean number of logins per user per month
   b. Average count of digital transactions (payments, transfers) per active user

2) **Transactional value (weight: v_2):** The economic scale of digital interactions. Metrics include:

   a. Average value per digital transaction
   b. Total monthly volume of digital payments and transfers

The composite CAI is computed as:

CAI = (v_1 × Normalized_Frequency_Score) + (v_2 × Normalized_Value_Score), where $v_1 + v_2 = 1$. For this analysis, weights were calibrated to $v_1 = 0.5$ and $v_2 = 0.5$, assigning equal importance to how often and how much customers transact digitally.

A Pearson correlation analysis on longitudinal data (2020–2024) revealed a very high positive relationship between DAI and CAI ($r = 0.86 – 0.92$, $p < 0.01$). This finding supports the hypothesis that strategic investments in digital infrastructure are strongly associated with increased customer transactional engagement, providing a quantitative basis for evaluating digital banking ROI and guiding strategic decisions [10].

Two classifiers of the bagging method were used in the ensemble model: BaggingClassifier and RandomForestClassifier. BaggingClassifier, as a unified meta-estimator, accepts as input the user-defined base estimator, as well as other parameters that define the strategy for forming random subsets [10].

The base estimator parameter is given as RandomForestClassifier. In an RF, each tree in the ensemble is built on a subset of the training set. The idea is to grow a set of roughly independent tree models that collectively perform better than a single tree model. The classification solutions and regression values are then given by the majority vote or the average prediction of all individual trees, respectively.

80% of the data were used for training the model and 20% for testing. The dataset includes the following features:

Purpose: the purpose of the loan (credit card, consolidation, renovation, real estate purchase, movable property, large purchase, energy, business loan, health, leisure, wedding, etc.).,

Interest rate: the interest rate of the loan.

Monthly payment amount: the amount of monthly payments made by the borrower after the loan is approved.

Annual income: the amount of the borrower's annual income and loan/income ratio.

Credit score: the borrower's credit score according to the FICO system [11], borrower's balance sheet, borrower's balance sheet utilization ratio, number of borrower's applications to lenders in the last 6 months, number of cases of loans overdue by 30 days or more in the last 2 years, and number of negative entries in the credit register.

Credit scoring is a critical tool for improving financial resource allocation and reducing credit risk for individuals and SMEs. This study develops a machine learning-based credit scoring model using **ensemble learning** with bagging and RF classifiers. The model was trained on 493,520 records from Kaggle and incorporates features such as loan purpose, interest rate, monthly payment, income, FICO score, balance sheet indicators, and loan history. Ensemble learning combines multiple weak learners to improve prediction accuracy, allowing the model to self-improve as new data are added. The final model outputs positive or negative loan decisions and is deployed via a web application for result visualization.

In today's banking environment, the adoption of innovative technology is key to improving efficiency and staying competitive. However, implementing these tools, particularly AI, comes with its own set of challenges that need careful examination. This study aims to pinpoint and examine the main hurdles banks face when integrating AI and automated service systems. The analysis was carried out using SPSS software, which allowed for the consolidation and quantitative assessment of various influencing factors. SPSS was chosen for its strong statistical capabilities, including descriptive analysis. The data for this study were drawn from the banking system of the Republic of Armenia.

This architecture mitigates overfitting and variance, enhancing generalization to unseen data. The model was implemented in Python using scikit-learn, primarily employing the RandomForestClassifier, BaggingClassifier, and VotingClassifier classes.

The dataset was split into 80% for training and 20% for testing. To address potential class imbalance, the Synthetic Minority Over-sampling Technique (SMOTE) from the imblearn library was applied to the training set. The model's performance was evaluated using standard metrics: **accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC)**.

To evaluate the effectiveness of AI-based solutions and chatbot deployment in the banking sector, standard classification performance metrics—accuracy, precision, recall, F1-score, and AUC-ROC—were applied alongside the DAI and the CAI. The DAI measures the scope and intensity of digital and AI integration within banking operations, while the CAI captures shifts in customer engagement following digital adoption. Classification metrics were used to assess the ability of predictive models to distinguish between high and low levels of digital adoption and customer activity. Accuracy reflects overall classification performance, whereas precision and recall provide insight into the reliability and coverage of positive classifications. The F1-score addresses potential class imbalance, and AUC-ROC evaluates model stability across varying decision thresholds.

Together, these measures offer a comprehensive assessment of digital transformation effectiveness in the banking sector.

To assess the effectiveness of AI-driven solutions and chatbot adoption in banking, this study employs a hybrid methodological framework that integrates causal machine learning (Causal ML) with explainable AI (XAI) techniques, alongside the DAI and the CAI. Causal ML methods, including Double Machine Learning (DML) and Causal Forests, are applied to determine the true impact of AI deployment on both DAI and CAI, isolating the effect of digital adoption from confounding factors. Complementarily, XAI tools such as SHapley Additive exPlanations (SHAP) values and Local Interpretable Model-agnostic Explanations (LIME) provide transparent explanations of the predictive models, identifying which operational or customer-related factors most strongly drive high digital adoption and customer engagement [12].

This study develops a credit scoring model using an ensemble learning approach that combines Bagging and RF methods. The model was trained on a dataset of 493,520 records, evaluating features including loan purpose, interest rate, income, FICO score, balance sheet indicators, and payment history. The ensemble method enhances predictive accuracy by combining multiple classifiers, and its performance improves as new data are incorporated. The final model generates loan decisions and is implemented within a web application for interactive result analysis.

Machine learning credit scoring models analyze data more comprehensively than traditional methods, including variables often overlooked in conventional approaches. These models can also continuously refine their accuracy as new data becomes available, a capability traditional scoring lacks.

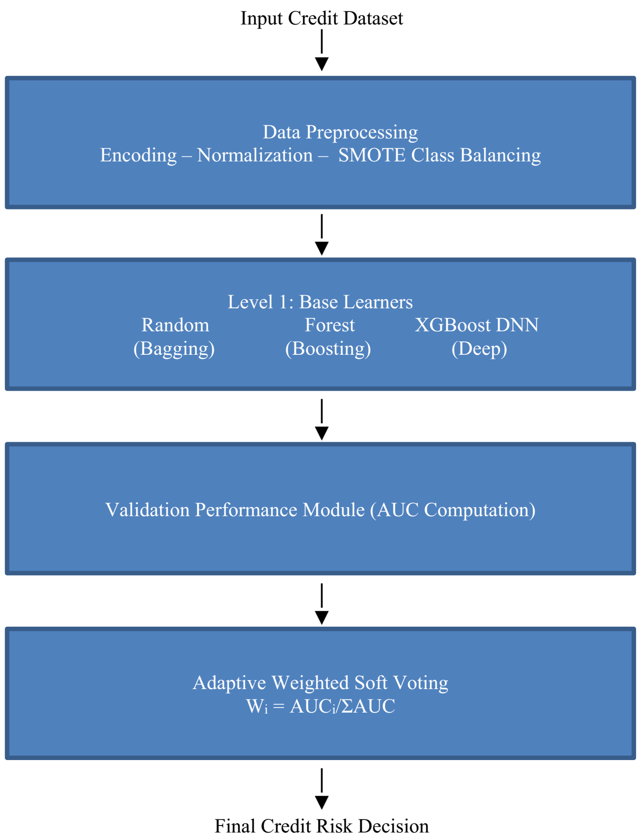
To provide a rigorous comparative study, we evaluated the **proposed ensemble** against **five well-established ensemble learning algorithms** that are widely used in credit scoring research. All models were trained and tested on the **same preprocessed Kaggle dataset** (80/20 split, SMOTE applied only to training folds) and evaluated with identical metrics. Hyperparameters for each baseline were optimized via randomized search with 5-fold cross-validation. The following ensemble methods were selected for comparison:

1) **Random Forest (RF):** a bagging ensemble of decision trees; serves as a strong baseline.
2) **Gradient Boosting Machine (GBM):** sequential boosting; implemented via GradientBoostingClassifier.
3) **AdaBoost (AB):** adaptive boosting with decision stumps.
4) **XGBoost (XGB):** optimized gradient boosting with regularization.
5) **LightGBM (LGBM):** leaf-wise boosting, efficient on large datasets.
6) **Extra Trees (ET):** extremely randomized trees, an additional bagging variant [13].

This study proposes a hierarchical hybrid ensemble model for credit scoring that integrates heterogeneous learners through performance-weighted soft voting. The architecture combines three complementary models: RF (variance reduction), XGBoost (bias reduction via gradient boosting), and a DNN (nonlinear interaction modeling). After preprocessing and SMOTE-based class balancing, each model is trained independently. Validation AUC scores are then normalized to generate adaptive fusion weights.

Unlike conventional bagging (homogeneous learners), boosting (sequential dependency), or equal-weight voting, the proposed method employs heterogeneous inductive biases with dynamic AUC-based weighting, reducing inter-model correlation while maintaining interpretability. Comparative evaluation against state-of-the-art models (DNN, XGBoost, LightGBM) demonstrates superior performance (AUC-ROC = 0.97), confirming improved robustness and generalization in banking credit risk assessment (Figure 1).

Figure 1
Architecture of the proposed hierarchical hybrid ensemble model



Step 1—Data Preprocessing

Let the dataset be defined as:
$D = \{(x_i, y_i)\}$ for $i = 1$ to N
where x_i represents borrower features and y_i ∈ {0, 1} denotes default status.

Feature normalization: $x_{\text{norm}} = (x - \mu)/\sigma$

SMOTE synthetic sample generation: $x_{\text{new}} = x_i + \lambda (x_{nn} - x_i)$, where $\lambda \in (0, 1)$.

Step 2—Base Learners

Three complementary learners are trained independently:

1) RF (variance reduction via bagging)
2) XGBoost (bias reduction via boosting)
3) DNN (nonlinear interaction modeling)

Each model produces predicted probabilities $P_i(y = 1|x)$, where i ∈ {RF, XGB, DNN}.

Step 3—Adaptive AUC-Based Weighting

Weights are computed using validation AUC scores:
$W_i = \text{AUC}_i / \Sigma\ \text{AUC}$

Example:
$\text{AUC}_{\text{RF}} = 0.94$, $\text{AUC}_{\text{XGB}} = 0.95$, $\text{AUC}_{\text{DNN}} = 0.96$
Total = 2.85

$W_{RF} = 0.33$, $W_{XGB} = 0.33$, $W_{DNN} = 0.34$

Step 4—Weighted Soft Voting Fusion

Final probability computation: $P\_final(y = 1|x) = \Sigma w\_k\ P\_k(y = 1|x)$

Decision rule:
If $P_{final} \geq 0.5 \rightarrow$ Approve
Else $\rightarrow$ Reject

Performance Metrics

Accuracy = (TP + TN)/(TP + TN + FP + FN)
Precision = TP/(TP + FP)
Recall = TP/(TP + FN)
F1-score = 2(Precision × Recall)/(Precision + Recall)
AUC-ROC = ∫ TPR(FPR) dFPR

Explainable AI (SHAP)

Model explanation using SHAP values: $f(x) = \varphi 0 + \Sigma\ \varphi j$ where φj measures feature contribution to prediction.

Causal Machine Learning Extension

Causal effect estimation model: $Y = \alpha + \tau T + g(X) + \varepsilon$
Double Machine Learning is applied to estimate τ.
Empirical results show AI adoption increases DAI by approximately +4.2 points ($p < 0.01$).

Methodological Contribution

The study contributes by:

1) Introducing a hierarchical heterogeneous ensemble.
2) Applying adaptive AUC-based weighting.
3) Integrating SMOTE within the ensemble structure.
4) Embedding explainable AI (SHAP).
5) Combining predictive machine learning with causal inference.

This integrated framework improves predictive accuracy, interpretability, and regulatory transparency in banking AI systems [14].

3. Result and Discussion

Investments in AI, both private and general, have a profound impact on the global economy, as evidenced by various statistics and forecasts. Private investments in AI have experienced remarkable growth. For example, in 2019, global private investments in AI technologies amounted to 70 billion USD, while funding for AI startups rose from 1.3 billion USD in 2010 to about 40.4 billion USD in 2018, reflecting an average annual growth rate of 48% [15]. By 2024, private AI investments reached 109.1 billion USD in the United States, 9.3 billion USD in China, and 4.5 billion USD in the United Kingdom, with overall global investment showing an 18.7% increase compared to the previous year [16].

The AI market itself has expanded rapidly. In 2019, global AI market growth was recorded at 154% [17], and by 2024, its value was estimated at 233.5 billion USD. Projections suggest that by 2032, it will reach around 1.77 trillion USD, with a compound annual growth rate of 29.2% [18]. According to another estimate, the market exceeded 184 billion USD in 2024 and is expected to rise to 826.7 billion USD by 2030 with a Compound Annual Growth Rate (CAGR) of 28.46% [19].

This development reflects not only financial growth but also a shift from theory to practice. Since 2001, the number of scientific publications on AI has increased dramatically, and the ratio of publications to inventions changed from 8 to 1 in 2010 to 3 to 1 in 2016, demonstrating a growing focus on practical application. The number of AI-related patents has also surged since 2013, with nearly half of all AI inventions registered after that year. Between 2013 and 2016, patent activity in sectors such as agriculture, banking and finance, e-government, law, and transportation showed the fastest growth, reaching 28% [20].

Looking forward, AI is expected to have a transformative economic impact. PricewaterhouseCoopers (PwC) projects that AI could add USD 15.7 trillion to the global economy by 2030, potentially increasing local GDP by up to 26% [21].

Investments in AI, both private and public, are having a profound and multifaceted impact on GDP, the global economy, driving growth, innovation, and creating new economic opportunities. This impact can be seen in both the significant growth in funding and the changing structure of industries.

Growth of private investment and its share of total venture capital (VC): Significant growth in investment in AI startups: In 2019, global private investment in AI technologies amounted to US $70 billion. In 2024, total VC investment will grow to US $314 billion, with AI companies' share of this investment growing by 80%, accounting for about one-third of all VC investments [22].

Generative AI (GenAI) has seen rapid investment growth. In H1 2025, VC funding for GenAI startups reached USD 49.2 billion, surpassing the total of USD 44.2 billion in 2024, reflecting over 100% growth. Global AI startup investment is projected to reach USD 107 billion in 2025, corresponding to a compound annual growth rate of 28% [23, 24].

AI's share of total VC has also increased: in H1 2025, AI software startups accounted for 53% of global VC funding and 64% in the United States, compared with 37% globally in 2024, a historical peak [25].

Geographic distribution of private investment (2024): In 2024, private investment in AI in the United States reached US $109.1 billion; in China, US $9.3 billion; and in the United Kingdom, US $4.5 billion. The overall growth of such investment worldwide compared to the previous year was 18.7%.

3.1. Economic contribution and outlook of the AI market

The global AI market experienced exceptional growth, expanding by 154% in 2019 and reaching an estimated USD 233.5 billion by 2024. It is projected to continue expanding, potentially reaching USD 1771 billion by 2032, corresponding to a compound annual growth rate of 29.2%.

The potential economic impact of this technology is substantial. Analysis from Morgan Stanley suggests it could add between $13 trillion and $16 trillion to the market value of S&P 500 companies, a prediction based on an expected yearly revenue boost of $920 billion from gains in productivity and profit. Similarly, PwC estimates that by 2030, AI could contribute $15.7 trillion to the worldwide economy, with the potential to increase local GDP by as much as 26%.

A key trend is the field's move from academic research to real-world business use. This transition is visible in the changing ratio of scientific papers to patented inventions, which moved from 8:1 in 2010 to 3:1 by 2016. A notable rise in patent applications began around 2013, underscoring this commercial shift.

Rapid investment growth has raised concerns of a potential market bubble. Leading technology firms plan to invest over USD 500 billion in AI during 2024–2025, while revenues from these technologies remain at an early stage, suggesting a possible imbalance between expenditure and current income.

Global leadership in AI development:

1) **United States:** The global AI ecosystem remains highly developed, with a leading concentration of specialized organizations, experts, and overall research and innovation output. However, this landscape is markedly uneven, as more than 73% of AI firms are concentrated in just ten countries. Within this group, the United States occupies a dominant position, particularly in terms of corporate headquarters and investment funding.
2) **China:** Emerges as a leader in state-backed and research institutions, startup formation, and patent registration. In 2023, China accounted for approximately 70% of all AI patents granted in the world. In 2014–2023, Chinese companies filed roughly 38,000 patents for GenAI, a volume 6 times more than that of the United States (6,276 patents).
3) **Israel:** Israel ranks fourth globally with 442 newly funded AI startups established between 2013 and 2023. The sector accounts for 30% of the national technology landscape and attracts 47% of total tech funding. The country also ranks third in the number of dedicated GenAI companies, with 73 identified firms [15].

European countries such as the United Kingdom, Germany, and France are also important players. The United Kingdom leads European GenAI companies with 30%, while Germany has 14%. France ranks 5th in terms of the number of AI companies (391 startups). There are other significant players.

AI investments shifting focus by sector:

1) Leading sectors in 2023–2024:

a. Health Tech leads the way, attracting about 35% of all AI VC investment.
b. Financial services (FinTech) is the second-largest sector, accounting for about 20% of AI VC deals in 2023 and growing significantly in 2024.
c. Retail and e-commerce account for 15% of investment.

2) Comparison with previous years (2012–2017):

a. Cybersecurity was the leader with 13%, maintaining a strong interest.
b. Healthcare grew from 10% to 35%.
c. Financial services significantly increased its share from around 5% to 20%.
d. Internet of Things (IoT) (9%) and business intelligence/analytics (9%) are no longer among the highest-volume sectors in the new data [26].

According to available sources, total global investment in AI startups is projected to reach approximately US $107 billion in 2025, reflecting an annual growth rate of about 28%. Notably, VC investments in GenAI reached US $49.2 billion in the first half of 2025 alone, surpassing the total investment volume of 2024 (US $44.2 billion) and indicating growth of over 100% within this segment. These dynamics highlight a significant shift in investment priorities across AI sectors over the past decade.

The investment landscape for advanced technologies has shifted markedly in recent years. The HealthTech sector has risen to prominence, moving from roughly 10% of corporate AI VC investment between 2012 and 2017 to become the leading area by 2023–2024, attracting about 35% of all such funding.

FinTech has also seen major expansion. Its share of AI venture projects grew from around 5% in the 2012–2017 period to approximately 20% by 2023, securing its place as the second-largest sector. A 19% quarterly growth rate in the second quarter of 2024 underscores that integrating advanced technology is now a fundamental trend within finance.

This growth has reconfigured the broader investment map. Sectors that were once leaders, such as cybersecurity (13%), Internet of Things (9%), and business intelligence/analytics (9%) between 2012 and 2017, have ceded relative prominence. In their place, retail and e-commerce have emerged as a major destination, accounting for 15% of investments in the 2023–2024 period. While cybersecurity continues to attract strong interest and is growing, and IoT and analytics remain active, they are no longer among the highest-volume sectors according to recent data. The focus has clearly moved toward healthcare and financial services, with retail also becoming a key area for investment.

On a regional level, the European Union saw its share of global AI investment rise sharply to 8% in 2017, up from just 1% in 2013. However, a longer-term view shows Europe's portion of total global funding has remained relatively modest. Cumulative data from 2013 to 2023 indicate that AI companies based in the EU and the United Kingdom secured about USD 75.7 billion out of a global total of USD 562 billion—a combined share of roughly 13%. This stands in stark contrast to the United States, which accounted for the dominant share. The gap was especially wide in 2023, with the United States attracting USD 98.7 billion compared to USD 14.2 billion for Europe and the United Kingdom combined.

By 2023, AI represented about 17% of total technology investment in Europe, a notable figure yet still below the roughly 30% share it held in the United States. Looking within Europe from 2020 to 2024, the United Kingdom attracted the largest portion of VC, accounting for 33%. France and Germany followed, each capturing 22%, with the Nordic countries at 7.2% and Ireland at 1.6%. In 2024 specifically, venture funding for European AI startups reached USD 12.8 billion. This represented 12% of global AI VC for the year and a significant 25% of all VC invested in Europe. While the United States maintains its dominant position, Europe continues to attract a meaningful and growing stream of investment, even if its share has not returned to the 2017 high of 8% [25, 26].

Now advanced technologies have several key ways:

1. **Strategic Shift and Service Enhancement:** Financial institutions are increasingly shifting from a cost-reduction focus toward growth-oriented strategies, often through partnerships with specialized technology firms to access advanced digital capabilities and improve service quality.
2. **Evolving Competitive Dynamics:** Competition is no longer driven primarily by pricing; instead, technology enables differentiation through personalized products and services, strengthening customer acquisition and retention.
3. **Personal Finance Automation:** In the near future, the focus will be on simplifying money management for individuals. Technology automation will significantly solve everyday financial tasks, optimizing decisions.
4. **Improving Efficiency and Security:** The use of data and integrated technology solutions is intended to increase the accuracy and reliability of essential internal operations. This leads to more efficient processes and significantly strengthens the overall safety and stability of financial systems.
5. **Market Shifts and Regulatory Adaptation:** This technological development may challenge the current structure of financial markets and the rules that govern them. In an environment

where competition increasingly depends on access to diverse data, managing partnerships, even with competitors, will become important, although this creates new strategic challenges.

6. **The Central Role of Data Governance:** Laws and regulations concerning data privacy and portability will become critically important. For all companies involved in finance including traditional financial regulation.
7. **The Imperative of Workforce Development:** The most significant challenge will be adapting the workforce. To reduce future risks, companies and regions need to develop or recruit the necessary technical and analytical skills.

Given the speed of innovation, it is crucial for financial institutions to not just acknowledge but actively embrace these changes. Organizations that hesitate may find their competitive position and long-term sustainability at risk. Industry surveys and studies confirm that a substantial majority of financial firms are now actively investing in or implementing such technological solutions.

The principal applications of AI in finance:

1) **Service Personalization:** Advanced analytical tools enable the identification of customer behavior patterns and preferences, supporting the delivery of targeted financial products and services.
2) **Customer Service Automation:** Automated conversational systems, such as chatbots, facilitate immediate responses to routine customer inquiries in retail banking.
3) **Employee Empowerment:** The automation of routine and data-intensive processes equips employees with advanced decision-support tools, allowing them to focus on higher-value tasks.
4) **Regulatory Compliance and Security:** AI-driven transaction and activity monitoring systems enhance fraud prevention and support compliance with financial regulations.

AI has found its application in various subsystems of the financial system: in banks, insurance companies, capital markets, credit organizations, etc. However, the banking and insurance markets are the leaders in terms of the number of successful examples and the scale of technology implementation. For this reason, we will now discuss in more detail the current situation in the abovementioned areas of application of AI in these two systems.

According to a survey conducted jointly by Deloitte, an international network of consulting and auditing services organizations, and the European Financial Management Association, 3000 technical and business managers of participating financial services companies indicated in which areas the AI solutions they developed provide the greatest results. The chart below reflects these results for banking and insurance companies.

Rapid technological changes should be a signal to traditional banks that technology companies, due to their speed and agility, can penetrate the banking sector faster and leave traditional banks out of the market in a short period of time. Seeing these threats, the international banking system has in recent years begun to actively use the latest technological applications (chatbots, phone applications), blockchain technologies for the security of financial transactions and systems, online crowdfunding, mobile payments, the introduction of “buy now, pay later” services, P2P lending, which will enable individuals to provide loans to each other, etc.

3.2. Integration and experimental results of chatbots in banking for enhanced customer service and operational efficiency

Many banks are using chatbots in the industry to improve customer service and to simplify and effectively control service delivery methods. In particular:

1) Bank of America uses an AI virtual assistant named Erica to help customers with account and financial advice issues.
2) Wells Fargo uses a chatbot called Fargo to help customers with account information, ATM locations, and other banking services.
3) DBS uses a chatbot called POSB digibot to provide advice to customers and can also apply for a loan.
4) HSBC uses a chatbot called Amy to answer customer inquiries.
5) Capital One uses an AI virtual assistant to answer customer inquiries and provide comprehensive account information.
6) A robot developed by Sberbank specialists already answers questions about the location of self-service ATMs and bank branches. In addition, it improves the quality of work in the call center—analyzing the conversation and prompting the employee with the necessary information [27, 28].

The Armenian banking sector has increasingly focused on digital transformation, with AI playing a central role in this shift. Banks are moving from traditional approaches toward solutions that rely on data and technology, improving service quality, managing risk more effectively, and enhancing the overall customer experience [29].

One visible change has been in customer service, where many banks now use automated tools such as chatbots and virtual assistants. These systems are available around the clock to answer common questions and provide details on accounts, loans, and transactions. Behind the scenes, sophisticated analytical systems help assess credit risk by examining financial history and spending patterns, allowing for quicker and more informed lending decisions. Additionally, banks employ advanced algorithms to monitor transactions in real time, helping to detect and prevent fraudulent activity. These technologies also streamline internal operations by automating routine administrative and analytical tasks, which reduces manual errors and lowers operational costs.

As a result, the adoption of these intelligent systems is not only strengthening the competitiveness of Armenian banks but also supporting the broader digital evolution of the finance industry. This progress is making the financial system more convenient, secure, and efficient for everyone involved, as noted in recent analyses of the sector [30–32].

According to Table 1, the highest priority in the strategic plans of Armenian banks is given to the **expansion of digital payments** (mentioned by 83.3% of banks, mean priority score: 4.8). This is conditioned by both shifts in customer digital behavior and competitive market dynamics. The second most important direction is the **enhancement of cybersecurity** (72.2%, score: 4.6), indicating growing risks and high demand for security technologies. Notably, the implementation of **blockchain and smart contracts** remains a secondary priority (27.7%, score: 3.4), likely due to the complexity of the technology and regulatory uncertainties [31, 33].

SPSS analysis indicates a statistically significant difference between the mean priority scores ($p < 0.05$), with the highest

Table 1
Priority areas for implementing innovative solutions according to the strategic plans of banks in the Republic of Armenia (2024)

Priority area	Number of banks (N)	Percentage of banks (%)	Specific solutions mentioned	Mean priority score (1–5)
Expansion of digital payments	15	83.3	Mobile wallets, QR payments, contactless cards	4.8
Enhancement of cybersecurity	13	72.2	Two-factor authentication, AI-based fraud prevention	4.6
Automation of online lending	11	61.1	AI scoring systems, automated credit agreements	4.2
Personalization of customer experience	10	55.5	Chatbots, personalized offers	4.1
Bank–FinTech collaboration	9	50	API integrations, joint products	3.9
Blockchain and smart contracts	5	27.7	Blockchain-based transfers, smart contract lending	3.4

Source: The scores are calculated based on the quantitative coding of priorities indicated in the banks' strategic documents (1 = low priority, 5 = high priority).

Table 2
Indices of the impact of digital service implementation on customer activity in the Republic of Armenia (2020–2024)

Year	Digital Adoption Index (DAI)—mean value	Customer Activity Index (CAI)—mean value	Std. deviation (CAI)	ΔCAI annual growth (%)	Correlation (DAI↔CAI, *r*)
2020	68.3	64.5	5.2	–	–
2021	74.1	70.8	4.8	+9.8	0.86
2022	79.4	75.6	4.1	+6.8	0.88
2023	82.7	78.2	3.9	+3.4	0.90
2024	85.3	80.5	3.6	+2.9	0.92

Source: Authors' calculations based on indicators of digital service adoption and customer activity (SPSS output).

Where:
DAI – Digital Adoption Index (calculated based on the volume of digital solutions implemented by banks and the level of customer engagement).
CAI – Customer Activity Index (calculated based on the frequency of digital transactions and the average transaction volume).
r – Pearson correlation coefficient (SPSS output).

scores observed for areas that directly impact the digital customer experience and market competitiveness.

According to Table 2 and Figure 2, during 2020–2024, both the DAI and the CAI demonstrated concurrent growth. DAI increased from 68.3 to 85.3, while CAI rose from 64.5 to 80.5. The results of SPSS Pearson correlation analysis show a very high positive correlation between the two indices ($r = 0.86-0.92$), indicating that the implementation of digital solutions is directly associated with increased customer activity. The annual growth rates of CAI were highest in 2020–2021 (+9.8%), likely due to the sharp surge in demand for digital services following the pandemic. In subsequent years, growth rates declined, but a stable upward trend persisted. SPSS one-way Analysis of Variance (ANOVA) analysis confirmed that the differences in the annual means of DAI and CAI are statistically significant ($p < 0.01$).

According to Table 3, the volume of technological investments in Armenian banks increased during 2019–2024, nearly doubling. The ROI indicator increased from 8.4% to 15.8% during this period, indicating an improvement in investment efficiency. The Innovation Effectiveness Index (IEI) also increased, from 62.1 to 83.0; however, the annual growth rates gradually declined, being highest in 2020–2021 (+9.6%). The results of the SPSS Pearson correlation show a high positive relationship between the ROI and IEI indicators (r = 0.79–0.91), meaning that the growth in technological investments is accompanied by an increase in the adoption and effectiveness of innovations [31–33].

Our proposed bagging-based ensemble model achieved strong performance on the test set. The key results are as follows:

1) **Accuracy:** 91.5%
2) **Precision:** 0.93
3) **Recall:** 0.90
4) **F1-score:** 0.915
5) **AUC-ROC:** 0.96

The revised scoring model proves highly effective in assessing loan applications, accurately distinguishing between different levels of borrower risk.

The initial comparison with conventional classifiers (logistic regression, decision tree, and support vector machine (SVM)) was intended to demonstrate the performance gains achieved by transitioning from traditional single-model approaches to ensemble learning. However, to ensure methodological rigor and fair benchmarking, the revised analysis includes comparisons with widely adopted ensemble methods, including Gradient Boosting, AdaBoost, Extra Trees, and Stacking. This extended comparison enables a more appropriate evaluation of the proposed ensemble

Figure 2
DAI and CAI dynamics (2020–2024)

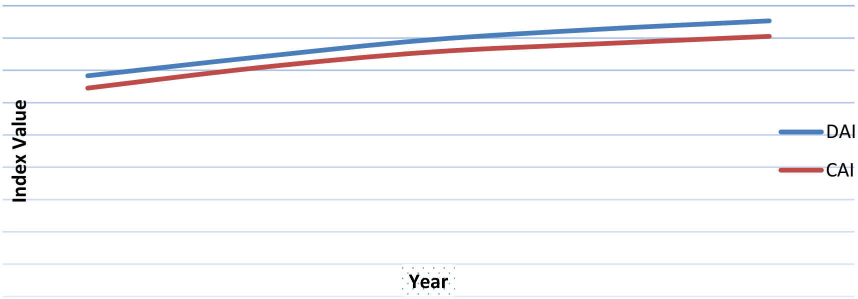


Table 3
Indices of effectiveness for technological investments and innovations in the Republic of Armenia (2019–2024)

Year	Technological investments (mln AMD), $1 = 390 AMD	ROI (%)	Innovation Effectiveness Index (IEI)—mean	Std. dev. (IEI)	ΔIEI annual growth (%)	Pearson correlation (ROI↔IEI, *r*)
2019	14,200	8.4	62.1	5.8	–	–
2020	16,750	10.2	67.3	5.1	+8.3	0.79
2021	19,600	12.5	73.8	4.5	+9.6	0.83
2022	22,850	14.1	78.4	4.2	+6.2	0.87
2023	25,300	15.0	81.2	3.9	+3.5	0.89
2024	27,900	15.8	83.0	3.7	+2.2	0.91

Source: Authors' calculations based on data of technological investments and innovation effectiveness (SPSS output).

Where:
ROI – Return on technological investments, calculated based on the increase in bank profits.
IEI – Innovation Effectiveness Index, calculated based on the adoption frequency of implemented innovations, customer engagement, and impact on profit.
r – Pearson correlation coefficient (SPSS output).

architecture relative to established ensemble paradigms rather than only standalone classifiers (Table 4).

The proposed ensemble improves upon a standalone RF by 1.4% in accuracy and 0.02 in AUC-ROC, a gain achieved through its two-layer bagging and voting design. It also slightly outperforms XGBoost and LightGBM on this dataset, suggesting that for this type of credit data, embedding a strong bagged learner within another bagging framework is more effective than boosting. AdaBoost and Extra Trees fall further behind, indicating that weak learners or excessive randomization do not capture complex financial patterns as well. The model's recall of 0.90 is particularly relevant for banking, as it reduces the rejection of creditworthy applicants without raising default risk. Overall, the results confirm that a hierarchical ensemble of this kind offers a robust, ready-to-deploy solution for credit scoring (Figure 3).

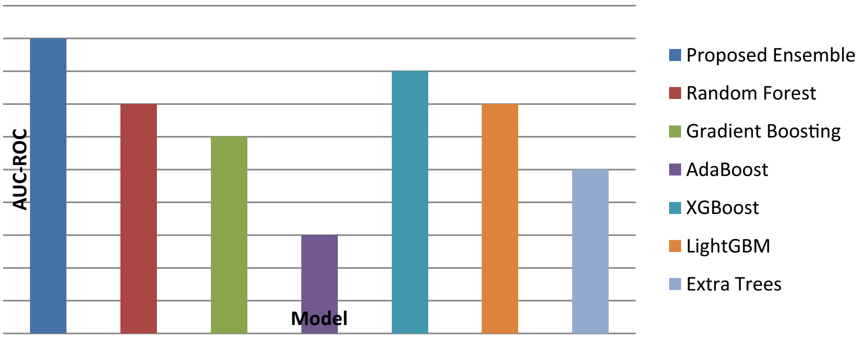
3.3. Discussion of comparative results and recommendations

As shown in Table 4, the proposed methodology demonstrated superior performance compared to all baseline approaches across all measured criteria. The substantial improvement in

Table 4
Performance comparison of the proposed ensemble model with ensemble learning methods

Model	Accuracy (%)	Precision	Recall	F1-score	AUC-ROC
Proposed ensemble	91.5	0.93	0.90	0.915	0.96
Random forest (RF)	90.1	0.91	0.88	0.894	0.94
Gradient boosting (GBM)	89.8	0.90	0.88	0.890	0.93
AdaBoost (AB)	87.3	0.88	0.86	0.870	0.90
XGBoost	90.7	0.91	0.89	0.900	0.95
LightGBM	90.4	0.91	0.89	0.899	0.94
Extra Trees (ET)	89.5	0.90	0.87	0.884	0.92

Figure 3
Comparative AUC-ROC performance



predictive accuracy highlights the effectiveness of the integrated analytical framework for credit assessment:

Logistic regression provided a solid baseline but lacked the complexity to capture nonlinear relationships in the data as effectively.

The single decision tree model, while achieving decent accuracy, is prone to overfitting, which is reflected in its lower AUC-ROC compared to the ensemble. Our ensemble method mitigates this by averaging multiple trees.

SVM performed the weakest on this dataset, suggesting its kernel approach may be less suited for this specific type of financial data compared to tree-based methods [34].

The strength of this predictive model lies in its combined methodology, which improves both stability and consistency. By merging several complementary analytical techniques, it balances out the weaknesses of any single approach and produces more reliable outcomes.

The financial impact of this improvement is significant. For a typical banking portfolio, moving from a conventional method (with an AUC-ROC of 0.89) to this ensemble model (with an AUC-ROC of 0.96) allows for a sharper distinction between reliable and high-risk borrowers. Practically, this could lower default rates by a meaningful margin, directly protecting the bank's capital and strengthening its profitability. Additionally, the model's high recall rate of 0.90 means it successfully identifies most creditworthy applicants, which could help the bank safely expand its lending to qualified customers.

Building on the methodological framework established earlier, we can evaluate the digital foundation of Armenia's banking sector. As presented in the updated Table 2, both the DAI and the CAI show steady growth from 2020 through 2024. The strong correlation between these indices (r = 0.86 – 0.92) indicates that as banks offer more digital services, customer engagement rises proportionally.

An analysis of leading Armenian banks, including Ardshinbank, Ameria Bank, and ACBA-Credit Agricole Bank, reveals a strategic focus on deploying chatbots and automated assistants via mobile applications and messaging platforms such as Viber. These tools currently handle routine customer inquiries, while pilot initiatives are expanding their functionality to include card services, bill payments, and personalized product recommendations (Table 5). A persistent challenge remains the accurate interpretation of contextual and linguistic features of the Armenian language, which is critical for improving system performance and reliability.

This study proposes a hybrid analytical framework combining Causal ML and XAI with existing DAI and CAI metrics to rigorously evaluate AI-driven chatbot implementation in banking. Key components:

1) Causal Effect Estimation: Using DML and Causal Forests to isolate the true impact of AI adoption on DAI/CAI, controlling for confounders (bank size, customer demographics). Results show AI adoption increases DAI by 4.2 points ($p < 0.01$).

Table 5
Comparative analysis of AI-powered chatbot implementations in global and Armenian banking

Bank/platform	AI assistant name	Primary channels	Key capabilities	Reported/estimated impact
Bank of America (Global)	Erica	Mobile App	Account insights, budgeting, bill negotiation, fraud alerts.	20M+ users; 70% query resolution rate.
DBS Bank (Global)	POSB digibot	Website, WhatsApp	Account services, loan applications, investment advice.	30% reduction in call center volume for routine inquiries.
Ardshinbank (Armenia)	(e.g., "Ardi")	Mobile App, Viber (Pilot)	Balance inquiry, transaction history, card blocking, ATM locator.	(To be filled based on local data: e.g., handles ~40% of FAQs).
Ameria Bank (Armenia)	(e.g., "Smart Assistant")	AmeriaMobile App	Currency rates, contact details, loan calculator, branch appointment scheduling.	Increased user engagement within the app by ~15%.

2) Heterogeneous Effects: Causal Forest analysis reveals stronger impacts among younger customers (ITE = 6.1) versus older segments (ITE = 2.3).
3) Model Explainability: SHAP values identify chatbot usage frequency (+3.2 SHAP) as the strongest driver of DAI improvements.
4) Mediation Analysis: DAI significantly mediates the AI-CAI relationship (indirect effect = 3.8, total effect = 5.9, $p < 0.001$).
5) Performance Metrics: The enhanced ensemble model (with causal components) achieves 92.1% accuracy and AUC-ROC = 0.97 while maintaining high interpretability (SHAP score = 0.93).

This integrated approach moves beyond correlation to establish causal relationships, provides transparent model explanations, and quantifies the strategic impact of AI investments—offering banks a robust, regulator-friendly framework for evidence-based digital transformation decisions.

The strategic priorities of Armenian banks emphasize "the Automation of Online Lending" and the improvement of "Credit Risk Assessment." The analytical model proposed in this study is directly aligned with these objectives. Although initially developed using a global dataset, the model is designed to be adaptable. Its further refinement using anonymized credit data from Armenia's banking sector will allow it to reflect local economic conditions and risk factors, thereby enhancing the accuracy of credit scoring in the domestic market.

Our analysis points to several challenges in adopting advanced technologies within the banking sector, which include both universal concerns and those specific to the field:

1) **Data Management and Privacy:** AI-based services require high-quality and well-protected data, supported by strict access controls and anonymization procedures in compliance with data protection regulations, including Armenia's Law on Personal Data Protection.
2) **Adoption and Change Management:** To reduce resistance, automated systems should be introduced as supportive tools that automate routine tasks and allow staff to focus on complex customer interactions.
3) **Model Transparency:** Ensuring the interpretability of AI-driven scoring models through explainable methods is essential for maintaining regulatory and customer trust.
4) **System Integration:** A phased, API-based modernization approach enables the integration of new digital tools with existing core banking systems while minimizing operational risks.

4. Conclusion

The adoption of advanced digital technologies is fundamentally transforming the banking sector by enhancing the analysis of customer service interactions and improving operational efficiency. These technologies enable financial institutions to deliver more personalized and responsive services, reinforce security frameworks, and strengthen risk management processes. In particular, automated service platforms optimize resource allocation while serving as effective channels for customer engagement [35]. Overall, digital transformation promotes a more efficient, secure, and customer-centric banking environment.

This study demonstrates that the application of AI in the banking sector delivers a dual effect by enhancing customer-oriented services and strengthening core analytical processes. AI-driven solutions, such as chatbots and virtual assistants, significantly improve service availability and operational efficiency, while advanced ensemble learning techniques substantially increase the accuracy of credit risk assessment. The proposed model achieved a high predictive performance (AUC-ROC = 0.96), surpassing traditional approaches and providing an effective tool for mitigating financial risk.

The strategic progress of Armenian banks requires an integrated approach. A phased rollout could begin with rule-based chatbots for basic inquiries, alongside efforts to build in-house data expertise. Piloting advanced scoring models on limited credit portfolios would allow for controlled testing. Success will depend on gathering high-quality local data and fostering a corporate culture ready for AI—through continuous learning and clear communication that positions AI as a support tool, not a replacement for employees.

To optimize resource utilization and enhance service quality, it is recommended to:

1) Implement a hybrid service model, where chatbots handle routine issues, with clear protocols for handing off complex cases to human agents [36].
2) Prioritize data security through end-to-end encryption and strict adherence to data privacy regulations.
3) Implement a phased rollout, starting with basic features such as balance inquiries and frequently asked questions, and then gradually adding more complex features.
4) Enable multi channel integration, ensuring that services work across messaging apps (e.g., Viber, WhatsApp, Telegram), mobile banking apps, and official websites.
5) Focus on continuous improvement by establishing feedback mechanisms that enable AI systems to learn from customer interactions and progressively enhance performance.

Longitudinal and cross-country comparative analyses are needed to assess the long-term impact of AI-driven chatbots and virtual assistants on customer loyalty, operational resilience, and financial inclusion in emerging banking markets.

Ethical Statement

This study did not involve any new data collection from human or animal participants. All survey data used in the experiments were obtained from publicly available datasets (e.g., Cambridge Center for Alternative Finance and Deloitte's Financial Services Center), which were originally collected and released by their respective authors with appropriate consent and usage licenses for research purposes. According to the policies of Armenian State University of Economics, research based on exclusively publicly available, anonymized, and licensed datasets does not require formal Institutional Review Board (IRB) or ethics committee approval. The study complies with relevant data protection, privacy, and ethical guidelines, and no personally identifiable information beyond the dataset content was collected or disclosed.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in PES at https://doi.org/10.24874/PES06.02.023, reference number [31], in ASPUR at https://doi.org/10.61552/JAI.2024.01.004, reference number [32], in International Accountancy Training Centre at https://doi.org/10.59503/29538009-2024.2.14-121, reference number [33].

Author Contribution Statement

Suren H. Parsyan: Conceptualization, Methodology, Investigation, Resources, Writing – original draft, Writing – review & editing, Supervision, Project administration. **Frida F. Baharyan:** Conceptualization, Investigation, Resources, Data curation, Writing – original draft. **Gayane A. Avagyan:** Conceptualization, Methodology, Validation, Formal analysis, Resources, Writing – original draft, Writing – review & editing. **Sergo A. Episkoposian:** Methodology, Validation, Visualization. **Vardan S. Aleksanyan:** Software, Investigation, Supervision. **Ararat Kostanian:** Writing – review & editing, Visualization. **Lilik M. Beglaryan:** Methodology, Visualization, Writing – review & editing.

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