UX Approaches to the Integration of Artificial Intelligence into User Scenarios of Digital Financial Platforms

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ABSTRACT

The article examines the integration of artificial intelligence tools into user scenarios of digital financial platforms from the perspective of user experience approaches. It investigates how the choice of forms of visualizing predictive data, the degree of autonomy of intelligent agents and the mechanisms for explaining results affect the perception of services, the level of trust and users' willingness to delegate routine operations to algorithms. It analyzes the balance between automation and the preservation of user control, as well as the role of adaptive personalization based on machine learning in shaping sustainable models of interaction with financial products.

Keywords: digital financial platforms, user interface, artificial intelligence, machine learning

INTRODUCTION

The rapid development of artificial intelligence (AI) is transforming the functional capabilities of digital financial platforms, expanding the range of tools available to users. However, its technical potential does not guarantee actual demand. For a significant share of clients, complex algorithms remain opaque, and their value is not sufficiently evident. Under these conditions, user experience (UX) approaches become an important intermediary between algorithmic complexity and real user scenarios, determining how effectively and meaningfully this functionality will be used.

The ability of interfaces to adapt the operation of AI systems to the cognitive characteristics of users of financial services, taking into account their tendency to avoid uncertainty, the need for rapid data interpretation and high requirements for reliability, becomes particularly important. Modern platforms increasingly use predictive models, automation of routine operations and personalized recommendations based on machine learning (ML), however, the effectiveness of these functions directly depends on how intuitive their mode of presentation is. The aim of this study is to analyze the main UX strategies for integrating AI into user scenarios of digital financial platforms.

METHODOLOGICAL APPROACHES TO VISUALIZING PREDICTIVE DATA

The visual environment shapes the user's final understanding of possible future scenarios and determines how effectively they will be able to apply the results of AI in their financial behavior. The predictive models underlying many functions are based on the probabilistic nature of data, which is inevitably associated with uncertainty, variability and sensitivity to initial conditions. Users, on the contrary, tend to seek fixed points of reference and to interpret a forecast as a deterministic result. This cognitive mismatch requires the development of solutions that simultaneously preserve statistical correctness and ensure interpretability and accessibility.

Empirical data confirm the importance of multi-layered visualization. For example, the study «Vistrust: a multidimensional framework and empirical study of trust in data visualizations», devoted to the mechanisms of trust in data visualizations, shows that the structure and clarity of presentation significantly affect the quality of information interpretation. The authors demonstrate that overly complex graphical forms reduce trust and provoke emotional rather than analytical reactions, whereas visualizations that allow information to be gradually «unfolded» foster cognitively grounded trust and improve understanding [1]. These findings directly relate to the tasks of financial platforms, where the user must navigate probabilistic forecasts under conditions of uncertainty, and where the interface becomes an important tool for supporting rational choice.

Effective UX approaches to presenting probabilistic models are based on the need to clearly distinguish between levels of uncertainty and the verifiable elements of a forecast. It is important for the user to understand not only the expected value but also the degree of confidence in each range. The visual tools used for this include semi-transparent interval bands, gradients indicating the probability of deviation from the baseline scenario, as well as event-sensitivity markers that reflect the impact of factors capable of significantly changing the dynamics of indicators. Such presentation makes it possible to eliminate common cognitive distortions, namely the tendency toward overconfidence, the erroneous interpretation of a point forecast as a guaranteed result, and the ignoring of «tail» scenarios.

A special place in the methodology is occupied by the use of graphic patterns aimed at increasing clarity and reducing cognitive load. Uncertainty ranges make it visually clear that a forecast is not a static value but a spectrum of possible results that depends on the chosen planning horizon and external conditions. Scenario forecasts that display several trajectories of the situation's development introduce the user into a space of alternative decisions, making it possible to correlate their personal risk appetite with the proposed behavioral options. Contextualized risks perform an auxiliary function. They indicate local zones of instability and help to avoid an oversimplified perception of indicator dynamics. The combination of these elements' forms in the user a deep understanding of the structure of forecasts that is unattainable with a static presentation of data.

The comparison of traditional and adaptive AI visualizations deserves special attention. These differences demonstrate how this transition affects the nature of data updates, the level of interactivity, the presentation of uncertainty, and the impact on the user's cognitive load (table 1).

TABLE I Comparison Of Traditional And Adaptive Ai Visualizations In Financial Platforms [**2, 3**]

Characteristic	**Traditional**	**Adaptive**
The nature of data and updates	They are static, reflect data at a fixed point in time; they do not take into account the dynamics of context change.	They are generated in real time; they are automatically rebuilt depending on the update of data, user profile and current conditions.
Depth of analysis	They convey basic trends but are limited in displaying complex or probabilistic structures.	They are able to identify significant areas, annotate sudden changes, and take into account factors affecting the forecast.
Interactivity	Absent or minimal; visualization is used for passive viewing.	Supports interactive hints, scenario switches, disclosure of details by click; the user participates in data research.
Displaying uncertainty	It is presented rarely or simplistically, which creates the illusion of stability and determinism.	Demonstrates confidence intervals, forecast ranges, risk gradients; helps to correctly interpret the probabilistic nature of the data.
Consistency with the user profile	A single format for all categories of users, regardless of their level of experience and goals.	Adapts to individual preferences, level of risk, financial goals and style of interaction.
Impact on cognitive load	It can lead to overload or, conversely, oversimplification, distorting perception.	Reduces the load by step-by-step disclosure of information and intuitive user guidance on the structure of the forecast.
Influence on decision-making	Promotes superficial conclusions, does not reduce the risk of misinterpretation of trends.	Improves the accuracy of forecast understanding, speeds up decision-making, and strengthens trust in the AI system.
Role in the perception of AI work	The AI algorithm remains hidden, the logic of recommendations is not obvious.	Visualization reveals the structure of AI reasoning, annotates factors, increasing explainability and trust.

Thus, methodological approaches to visualization of predictive data form an important interpretative level that determines the quality of user interaction with predictive models. The more accurately visual solutions reflect uncertainty, identify risk factors, and allow the user to control the level of detail, the more likely it is to correctly perceive the forecast and build trust in the intelligent mechanisms of the platform.

Integration UX of Routine Operations Automation

The automation of routine operations in digital financial platforms relies on the functioning of specialized agent modules based on AI algorithms. They act as an intermediary link between computational models and practical user scenarios. The typologization of the most common classes of intelligent agents and their corresponding user scenarios is presented in table 2, which makes it possible to correlate the functional specialization of algorithms with practical automation tasks.

TABLE II: Main Types Of Ai Agents In Digital Financial Platforms [4, 5]

Type of AI agent	Description of functionality	Typical user scenarios
Automated budgeting	Analyzes historical transactions, identifies behavioral patterns, and predicts future expenses.	Monthly budget formation; automatic redistribution of limits.
Cost structure monitoring	It constantly monitors incoming transactions, classifies them into categories, and identifies abnormal or atypical transactions.	Automatic categorization of purchases; notifications of sudden changes in the cost structure; analysis of budget leaks.
Dynamic investment portfolio management	Uses optimization and forecasting algorithms to automatically rebalance assets.	Automatic reduction of deviations from the target structure; portfolio adjustment after market changes; recommendations on risk reassessment.

Embedding such agents into the interface requires strict adherence to UX principles aimed at reducing cognitive load. Users’ perception of automation is largely determined by how consistent and predictable the path is from receiving a signal to making a decision. Therefore, the design of automated scenarios seeks to minimize friction points, replacing long chains of actions with one-click solutions. These simplified confirmation models are particularly effective in processes where the logic of the algorithm’s operation is already familiar to the user. In such cases, the interface helps the user «glide» through the decision-making process without subjecting them to excessive reflection, while preserving a sense of control.

An important aspect is the ability of the interface to offer automated scenarios not as rigidly regulated operations but as adaptively configurable flows that adjust to the current context. For example, if the system detects regular fluctuations in the structure of expenses, it may suggest budget adjustments in the form of a compact pop-up block with a brief summary of changes and a single confirmation button. In investment products, similar UX patterns appear in the form of «quick adjustment» proposals for the portfolio: the user sees a concise visualization of deviations, a risk assessment and a button to apply changes. This makes it possible to highlight important facts while preventing the cognitive overload typical of complex financial tasks.

Particular importance is acquired by the concept of «invisible» AI, when algorithms operate in the background without requiring constant user involvement and without undermining the user’s sense of control over their financial situation [6]. From a UX perspective, this means the need for a precise balance between system autonomy and transparency of its behavior. Supporting this mode implies including in the interface concise explanations, periodic summaries of completed operations and visual indicators of algorithm activity that do not occupy a central place on the screen but are available at the moment when there is a need for verification. In this case, AI is perceived not as an intrusive external agent but as an embedded «service layer» of the platform, providing background optimization and reducing the number of manual actions without creating a sense of loss of control.

The assessment of the effectiveness of UX integration scenarios inevitably goes beyond subjective impressions and is associated with measurable changes in user behaviour and the platform’s operational indicators. On the one hand, an important aspect is the reduction of time spent on performing typical operations and the decrease in the number of errors related to the human factor. On the other hand, more complex effects must be taken into

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account, such as increased stability of financial behaviour, reduced dispersion of outcomes as a result of avoiding impulsive decisions, and a higher share of users who regularly use the service's advanced functions. Taken together, these parameters make it possible to consider automation UX integration as an integral part of the architecture of a financial platform, where AI is implemented as a consistent transformation of routine user scenarios into manageable, transparent and predictable ones. processes.

Adaptive user Personalization using ML

Adaptive personalization based on ML algorithms has become one of the mechanisms for improving the effectiveness of digital financial platforms, since it ensures the alignment of the interface, functionality and recommendations with the user's individual behavioural patterns. It is formed at the intersection of several methodological approaches (fig. 1).

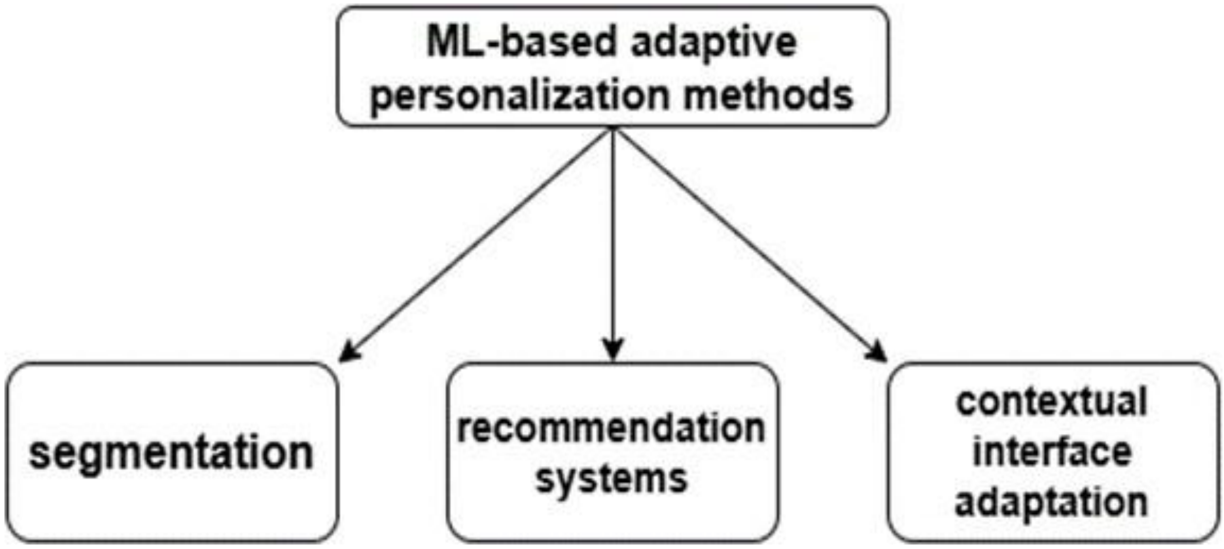

Fig. 1. Methods of adaptive personalization based on ML

A central place is occupied by user audience segmentation. In digital financial platforms, we are talking about dynamic classification based on multifactorial behavioral models. The algorithms analyse transactional activity, income structure, risk attitude, frequency of using certain tools and level of financial literacy, forming flexible clusters that can change over time. Unlike traditional methods, such models reflect real patterns of interaction with the system, which allows the platform to offer the user precisely those scenarios that correspond to their current financial capabilities, interests, and level of engagement.

On the basis of these segmented structures, recommender systems are deployed, providing targeted support to the user in decision-making. They combine predictive models with the analysis of preferences and historical data, generating individualized prompts, investment proposals, warnings about financial risks and recommendations for cost optimization [7]. Unlike generic advice from financial consultants, ML-based recommendations adapt not only to the user's profile, but also to the dynamics of their behaviour.

Contextual interface adaptation reinforces the effect of these models, as it provides a direct reflection of personalization in the visual and structural organization of the user environment. Such solutions change the placement of elements, information density, levels of detail and the priority of displayed modules depending on current tasks and context. For example, for a client who makes frequent payments, the interface may automatically foreground quick transfer functions, while for a user with an active investment portfolio it may display analytical charts and predictive indicators on the main screen. Contextual adaptation not only reduces cognitive load but also strengthens the sense of «naturalness» of interaction when the interface anticipates and structures the user's actions.

The effectiveness of such systems is largely determined by how well the interface can explain the logic of personalized decisions. User trust in AI recommendations increases when the system demonstrates cause-and-effect relationships. Incorporating explainability into UX becomes a necessary condition not only for

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understanding recommendations but also for maintaining the perception of control over the situation, especially in financial services where the risk of errors is particularly sensitive. Taken together, the dynamics of adaptive personalization can be represented as a closed loop (fig. 2).

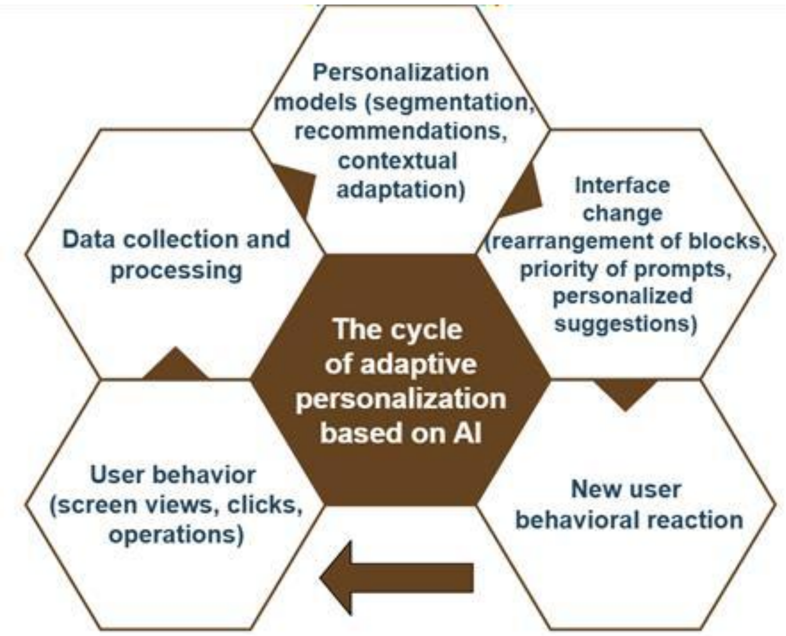

Fig. 2. Adaptive personalization cycle based on AI

The balance between automatic interface adaptation and the preservation of room for user choice forms a stable interaction structure. The user must be able to influence the depth of personalization, adjust settings, decline suggestions or return to a more standard interface structure. At the same time, the adaptation process itself should not become the focus of attention. The most effective systems operate «gently» and unobtrusively, without disrupting familiar interaction patterns. Such equilibrium prevents both a sense of pressure from the algorithm and fatigue from the need to constantly confirm changes. According to digital banks and investment services, it is personalized UX mechanics that are decisive for the regular use of forecasting, budgeting and investment functions.

A telling example is the experience of Bank of America, where the introduction of the virtual assistant Erica was accompanied by a deliberate focus in the interface on simplicity, transparency and explainability of interaction. As of April 2024, since the launch of the virtual assistant, approximately 800 million requests from more than 42 million customers have been processed and more than 1,2 billion personalized information and recommendations have been provided, and the total number of interactions has exceeded 2 billion (fig. 3).

Fig. 3. Statistics on the operation of the virtual assistant Erica [8]

An analysis of the bank's public reports shows that the growth in interactions is accompanied by qualitative changes in user behaviour. Clients have begun to more frequently review their financial activity, respond promptly to alerts and use built-in tools for analysing the structure of expenses. Taken together, these data demonstrate that well-designed UX integration of intelligent functionality enhances both quantitative indicators of digital activity and the quality of users' financial behaviour, while simultaneously having a positive impact on the platform's operational metrics and strategic outcomes.

In order to empirically verify the theoretical propositions, put forward, this study conducted a comparative analysis of digital financial platforms implementing various models of AI UX integration. The comparison was carried out on the basis of a structured analysis of user scenarios, logic of interface transitions and forms of representation of intelligent functions (table 3).

TABLE III The Results of a Comparative Analysis of AI UX Implementations On Digital Financial Platforms

Parameter	**Chime**	**SoFi**	**PayPal**
The basic UX pattern	Insights and notifications with assistant elements	Analytical dashboards	Contextual recommendations and flashcards
Entry point to AI	Operation feed, push notifications	Main screen, analytical sections	Notifications and activity sections
Visualization of forecasts	Brief text insights, simple graphics	Interactive charts, trends	Simplified charts and indicators
Displaying uncertainty	Mostly verbal	Through ranges and comparisons	Limited
Degree of autonomy	Average	Low–medium	Average
The level of explainability	Brief explanations	Factors and causes of changes	Brief reasons
Estimated cognitive load	Low	Medium–high	Average

The comparison confirms that the UX architecture is a determining factor in converting the algorithmic potential of AI into practical value for the user. Assistant-centric solutions enhance emotional-intuitive trust, dashboard-oriented solutions build cognitive-analytical trust, while hybrid architectures provide a balance between ease of use and depth of perception of intellectual functions.

The results obtained allow us to formulate a number of practical recommendations for developers of digital financial platforms. Integration of AI functionality should be carried out as part of complex user scenarios with a priority on contextual presentation of information, multi-level disclosure of information and a clear definition of forecast uncertainty. When designing an interface, it is advisable to focus on the principle of managed autonomy, in which automated actions are accompanied by brief explanations and the possibility of rapid user intervention without increasing cognitive load. Particular attention should be paid to matching the depth of personalization to the user's level of digital and financial literacy, as well as introducing clarity as a standard UX component of recommendations. Their implementation increases the likelihood that intelligent functions will be perceived as an auxiliary service layer, which ultimately increases the trust, sustainability and practical value of AI on digital financial platforms.

CONCLUSIONS

In modern digital ecosystems, AI is ceasing to be an autonomous technological superstructure and is becoming a structural element of human interaction with the financial environment. Under these conditions, UX becomes the main channel through which algorithms gain access to everyday decisions that affect the allocation of resources, risk assessment and planning horizons. The visualization of predictive data, the automation of routine operations and adaptive personalization based on ML models form a new configuration of interfaces in which AI acts not only as a source of services but also as a hidden participant in the user's dialogue with the system. The effectiveness of such solutions is determined by how transparently the interface reveals the probabilistic nature of forecasts, points out the limitations of algorithms, and provides a balance between automation and maintaining user control over important actions.

In turn, UX integration of AI is considered as an independent direction in the design of digital financial products, requiring a combination of behavioral, technological, and organizational perspectives. Multi-level visualization of uncertainty, the introduction of agent scenarios understandable to users and the development of adaptive personalization mechanisms based on explainable rules create the preconditions for increasing trust, interaction stability and the time horizon of using the platform's intelligent functions.

Promising areas of further research include quantifying the impact of AI integration UX patterns on user financial behavior, analyzing the long-term dynamics of trust in intelligent systems depending on the degree of explainability and autonomy of algorithms, as well as studying cross-cultural and demographic differences in the perception of functions. Of additional interest is the development of UX audit techniques for AI services and the formation of regulatory and methodological principles for responsible integration. The implementation of these directions creates the basis for the transition to a systematic, human-centered implementation of intelligent technologies in digital financial ecosystems.

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