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MODEL OF TECHNOLOGICAL MATURITY OF ARTIFICIAL INTELLIGENCE USE IN BANKING INFORMATION SYSTEMS

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Abstract. *The paper proposes a model of technological maturity for the use of artificial intelligence (AI) in banking information systems. The model combines user engagement, productivity, and economic efficiency indicators with security and quality requirements. Maturity levels and criteria for transitioning between them are formed, evaluation metrics (ER, DR, ROI) and practical interventions for scaling AI in a regulated environment are provided.*

Keywords: technological maturity, artificial intelligence, banking information systems, adoption, quality control, information security.

I. INTRODUCTION

The use of artificial intelligence in banking information systems has gradually shifted from isolated experiments to broader application scenarios in recent years. AI tools are used to support software development processes, analyze text data and customer inquiries, work with internal knowledge bases, and automate operational and compliance processes. At the same time, in a regulated banking environment, the mere technical availability of such tools does not guarantee their systematic and sustainableuse.

In practice, there is often a gap between providing access to artificial intelligence tools and achieving measurable results from their use. This gap is due to insufficient formalization of work processes, the lack of clearly defined criteria for quality and effectiveness, increased information security requirements, and uneven levels of user engagement with AI. As a result, the potential of the technology is only partially realized, and the scaling of AI use is not systematic.

The purpose of this work is to develop a model of technological maturity for the use of artificial intelligence in banking information systems. The proposed model allows for a structured description of the stages of AI development, the definition of criteria for transition between them, and the formation of a system of indicators for assessing the level of user engagement and the achieved effect. Particular attention is paid to the formation of practical recommendations for increasing the maturity of AI use in a regulated environment.

II. DATA AND METHODS

The proposed model of technological maturity is based on a combination of quantitative and qualitative indicators. Quantitative indicators are used to assess the level of user engagement with artificial intelligence tools, the amount of time saved, and the overall economic effect. In addition, proxy metrics of engineering productivity are taken into account, in particular the dynamics of change flow in software repositories. Qualitative indicators reflect the level of maturity of organizational processes, including the presence of information security standards, quality control mechanisms, action logging, as well as approaches to user training and support.

The engagement rate (ER) characterizes the share of regular users, which includes irregular and daily users, in the total number of users. The daily rate (DR) reflects the share of users who use artificial intelligence tools on a daily basis. The economic effect of using AI is assessed through the indicator of annual working time savings H_{year} and its financial equivalent S_{year}. The return on investment is determined using the ROI indicator, which is calculated as the ratio of the economic effect obtained to the annual costs of using the tools.

The calculation of key indicators is carried out according to the following ratios:

$$ER = (\frac{N_{occasional} + N_{daily}}{N_{total}}) \cdot 100\ \%; \quad (1)$$

$$DR = \frac{N_{daily}}{N_{total}} \cdot 100\%; \quad (2)$$

$$H_{year} = \sum (N_i \cdot h_i \cdot 52)\,; \quad (3)$$

$$S_{year} = H_{year} \cdot C_{hour}\,. \quad (4)$$

To illustrate the approach to assessing the economic effect of using artificial intelligence tools, an example of calculating annual working time savings for specific user groups is provided. Table 1 shows the initial data and the results of calculating annual time savings based on the number of users and average weekly time savings.

Table 1. *Example of calculating annual working time savings from using AI tools*

User group	N (persons)	h (hours/week)	Annual savings: N·h·52 (hours/year)
Daily users	67	4,1	67·4,1·52 = 14 271
Irregular users	70	2,0	70·2,0·52 = 7 280
Total ($\boldsymbol{H_{year}}$)			21 551

III. RESULTS AND ANALYSIS

3.1. User engagement and adoption rate

The level of actual use of artificial intelligence tools should be interpreted as a user engagement funnel, reflecting a gradual transition from non-use to daily use. This approach allows the implementation process to be managed through targeted organizational and training interventions aimed at transitions between different user groups: from those who do not use AI tools to inactive access holders, irregular users, and, ultimately, daily users.

As shown in Figure 1, the structure of user engagement in the sample with a total number of $N_{total} = 400$ developers is uneven. In particular, 180 people do not use artificial intelligence tools, 83 are inactive license holders, about 70 belong to the group of irregular users, while approximately 67 people use AI on a daily basis.

Based on the data provided, the DR indicator is $67/400, or\ 16{,}75\%$. The share of regular users (irregular + daily) forms the ER indicator ≈ $(70 + 67)/400 = 34{,}25\%$. In addition, an aggregated indicator of current engagement of 62% is used with a target of 80% +, reflecting the transition from partial integration to systematic use of AI tools.

The discrepancy between ER and the aggregate indicator highlights the need to establish «activity» criteria in measurement policies (e.g., weekly active users and monthly active users). Practically manageable goals should be to increase the share of daily users and reduce the share of inactive access owners. The practical conclusion for managing the level of technological maturity is that the main effect of using AI tools is generated by a cohort of regular users. Accordingly, the managed goals should be to increase the share of daily users and reduce the share of inactive access owners.

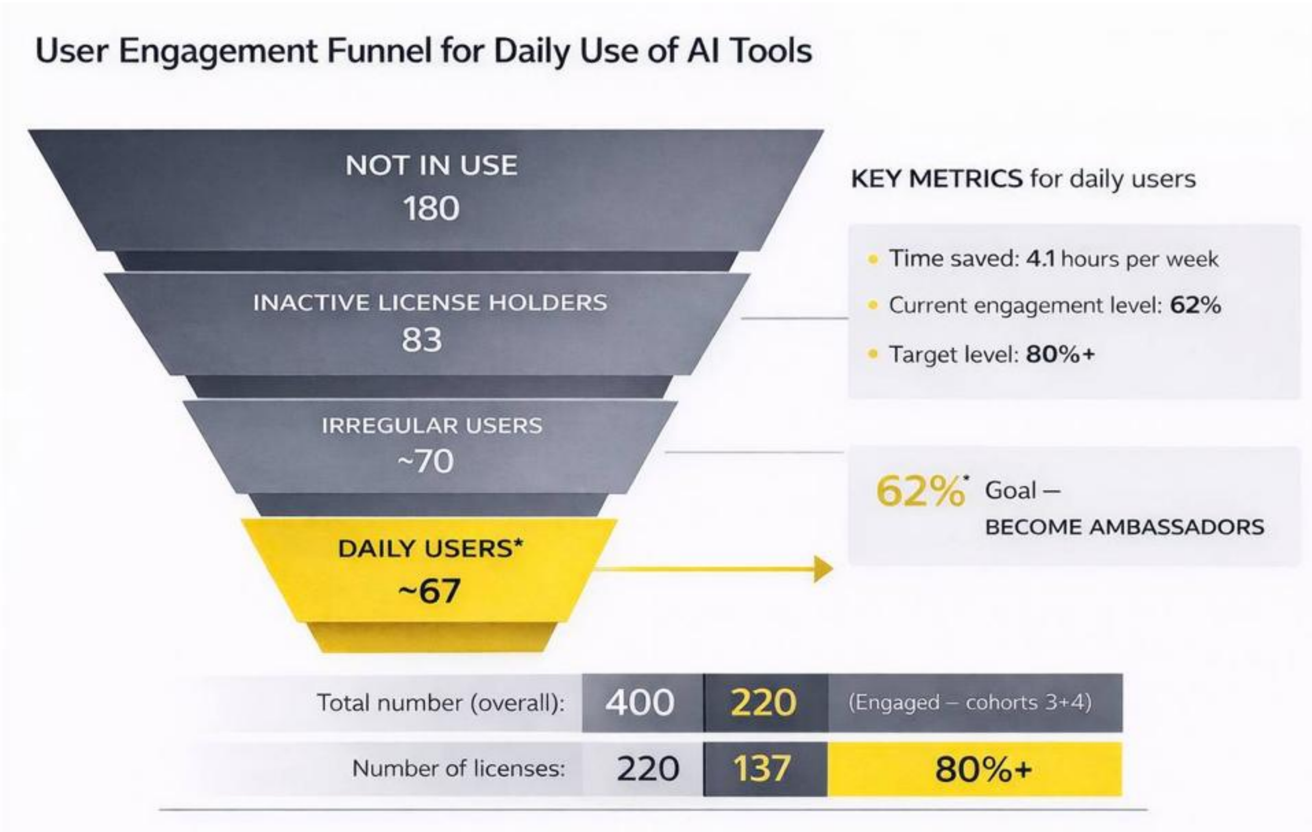

Figure 1. *Funnel for attracting users to levels of technological maturity in AI use*

3.2. Productivity and quality control in a regulated environment

For daily users, the average time savings is 4.1 hours per week. In addition, proxy performance metrics are recorded (for example, a +60% increase in pull requests during a selected period), as well as a 10-fold reduction in the time required to perform routine tasks. However, in banking information systems, increased speed must be accompanied by enhanced quality control.

A dual-loop control model is recommended: (1) automated verification loop (security standards, architectural rules, logging, compliance with conventions), (2) expert review loop (verification of business logic, edge cases, integrations, regulatory implications). Maturity increases with the presence of a feedback loop, where typical errors are used to update verification rules and AI interaction templates.

3.3. Economic efficiency and thresholds for transition between levels

Economic feasibility is assessed based on annual labor savings. Given the current parameters of $H_{year} = 21{,}551$ hours/year and an average hourly cost of $C_{hour} \approx 35 - 36$, the result is $S_{year} \approx \$\,750 - 776$ thousand per year. Annual tool (license) costs are estimated at ≈ $ 53 thousand, resulting in an $ROI\ of\ \approx 15\times$.

For practical use of the model, transition thresholds are proposed: level 1 (experimental) – DR < 5% and no standards; level 2 (controlled access) – $DR\ 5 - 10\%$ and basic security policies; level 3 (partial integration) – $DR\ 10 - 20\%$, $ER\ 25 - 50\%$ and formalized scenarios; level 4 (systemic use) – $DR > 20\%$, ER > 50% and integrated quality control loops, audit and governance.

Table 2. *Quantitative indicators of engagement and effectiveness (aggregated data)*

Indicator	Meaning
Total number of users (N_{total})	400
Number of licenses	220
Not in use	180
Inactive license holders	83
Irregular users	≈ 70
Daily users	≈ 67
DR (daily / total)	16,75%
ER (irregular + daily/ total)	≈34,25%
Average time savings (daily)	4,1 hours/week
Annual time savings (H_{year})	21 551 hour/year
Financial effect (S_{year})	≈ US$750–776 thousand /year
Cost of tools	≈ US$53,000/year
ROI	≈ 15×
Current engagement (aggregated)	62%
Target indicator	80%+

Table 3. *Model of technological maturity of AI use in banking information systems*

Level	Signs	Criteria (thresholds)	Key mechanisms
1. Experimental	Isolated attempts, lack of standards and control	DR < 5%	Pilots, risk assessment, basic training
2. Controlled access	Access granted, significant proportion inactive	DR 5-10%; lowering inactive	Security policies, onboarding, library of basic scenarios
3. Partial integration	Stable scenarios in individual processes	DR 10-20%; ER 25–50%	Tests/reviews, request templates, mentoring, quality metrics
4. Systematic use	AI – the standard «default» tool	DR > 20%; ER > 50%; goal 80%+	Governance, audit, logging, dual-circuit quality control, continuous improvement

IV. DISCUSSION AND CONCLUSIONS

The proposed model of technological maturity provides a tool for assessing the actual state of AI use in banking information systems, where security and quality control are critical. The practical value of the model lies in the ability to link adoption with manageable goals (DR, ER), economic effect (H_{year}, ROI), and process maturity (control contours, governance).

To increase maturity, it is advisable to use interventions linked to transitions in the funnel: (1) for inactive users – short scenarios of "first success" and removal of access barriers; (2) for irregular users – standards for teamwork with AI, templates, and mentoring; (3) for daily users – quality control tools, auditing, and development of internal ambassadors. The target of 80%+ is achieved when the use of AI becomes part of standardized processes and is supported by a system of metrics.

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