This document outlines the key areas where Machine Learning(ML) technologies are applied within payment systems, provides specific market examples, and details the challenges associated with their implementation.

1. Key areas of machine learning usage in payments

Machine Learning has become a core technology in modern payment ecosystems, enabling real-time decision-making, risk mitigation, and service optimization. Below are the three most impactful application areas.

1.1. Fraud detection and prevention

- **Problems:**
  - Detection of fraudulent transactions and complex social engineering attacks.
  - Identification of abnormal behavior patterns, such as unusual locations, new devices, or irregular transaction timing.
  - Reduction of false declines (blocking legitimate customers) caused by rigid, traditional rule-based systems.
- **How ML helps:**
  ML models analyze transaction history and behavioral patterns in real-time. This allows systems to detect anomalies and adapt to new fraud schemes significantly faster than static rules.

1.2. Intelligent payment routing (smart routing)

- **Problems:**
  - Low payment approval rates resulting from technical failures or suboptimal routing paths.
  - High transaction costs caused by inefficient acquiring strategies.
  - Reliance on manual retry logic that fails to adapt to real-time network conditions.
- **How ML helps:**
  ML models dynamically select the optimal routing path for each transaction based on historical performance data, issuer behavior, and real-time system availability.

1.3. Credit scoring and personalization

- **Problems:**

    - Slow, cumbersome, and inflexible credit approval processes.
    - Limited personalization of financial products for the end-user.
    - Over-reliance on traditional, often delayed, credit bureau data.
- **How ML helps:**
  ML models assess creditworthiness by utilizing transaction history, behavioral data, and contextual signals. This enables financial institutions to make instant credit decisions and generate personalized offers.'

2. Examples of ML application

The following companies demonstrate successful implementation of Machine Learning across the areas described above:

- **PrivatBank (Fraud detection):**
  PrivatBank integrates machine learning into its risk management systems to monitor millions of daily transactions. The models evaluate transaction context, such as location, device characteristics, and frequency to calculate real-time risk scores; if suspicious activity is detected, transactions are automatically blocked or sent for customer confirmation via the mobile app, effectively reducing fraud losses while minimizing inconvenience for legitimate users.
- **Adyen (Intelligent payment routing):**
  Adyen utilizes machine learning within its payment optimization suite (RevenueAccelerate) to analyze global transaction data. Their models determine how each payment request should be formatted and routed through acquiring banks and card networks, automatically retrying transactions via alternative paths if a failure is predicted, thereby maximizing conversion rates for merchants.
- **Monobank (Credit scoring):**
  Monobank relies on ML-based scoring models to calculate and adjust credit limits for customers without requiring physical branch visits. By analyzing transaction history, credit bureau data, and behavioral signals within the application, the bank can provide instant credit decisions and continuously adjust limits based on the user's repayment capacity.
- **PrivatBank (Personalization – «Pay in installments»):**
  The bank applies ML to automatically manage installment limits for millions of customers. The system continuously analyzes income inflows, spending patterns, and repayment discipline to dynamically update available

installment amounts, allowing customers to receive personalized credit offers without submitting additional applications.

3. Challenges of applying Machine Learning

Despite the clear operational benefits, adopting ML in payment systems involves navigating several critical challenges:

- **Data quality and integration:**
  Payment data is often distributed across fragmented legacy systems. Incomplete, siloed, or inconsistent data can lead to inaccurate model predictions and poor decision-making.
- **Model explainability and compliance:**
  Financial regulators strictly require transparency in automated decisions. Complex ML models often function as "black boxes," making it difficult for institutions to explain the specific reasons behind credit rejections or transaction blocks to both customers and auditors.
- **Latency and scalability:**
  Payment decisions must be executed within milliseconds to ensure a smooth user experience. ML models must be rigorously optimized to operate at scale without increasing transaction processing time (latency).
- **Concept drift:**
  Fraud patterns and user behavior evolve rapidly. Models are subject to "concept drift," requiring continuous retraining, monitoring, and maintenance, which increases operational and infrastructure complexity.
- **Macroeconomic instability and crisis periods:**
  Payment and credit ML models are typically trained on historical data that assumes relatively stable economic conditions. Crisis periods, such as economic downturns, regulatory interventions, or wartime measures like credit holidays, can significantly disrupt customer behavior and financial patterns, leading to reduced model accuracy and increased reliance on manual oversight. These atypical data segments differ substantially from long-term trends, making them difficult to model and limiting the ability of many algorithms to generalize and produce reliable forecasts. Nevertheless, such data often cannot be excluded due to business or regulatory constraints and is sometimes deliberately retained to ensure models can respond appropriately to rare but high-impact crisis situations.