



**ESRB**

European Systemic Risk Board

European System of Financial Supervision

# Analytical Knowledge Catalyst

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The views expressed in this presentation are our own and do not necessarily reflect those of the European Central Bank, the European Systemic Risk Board or its member institutions.



# Motivation

*"Further improvements in knowledge sharing would underpin the use of state-of-the-art analytical tools to provide a comprehensive view of systemic risk."*

(Report by the High-Level Group on the ESRB Review, December 2024)

- Since the GFC, authorities have invested heavily in granular data, IT infrastructure and analytical capabilities.
- Yet analytical knowledge is produced faster than institutions can capture and accumulate it, creating **"knowledge distance"**:



## Horizontal Distance:

Knowledge remains dispersed across **teams, notebooks, codebases and files...**



## Vertical Distance:

**Methods, assumptions and caveats** are lost as analysis moves towards decision-makers.

**The challenge is shifting from producing analysis to preserving and sharing the knowledge it generates.**

# Core idea: a knowledge layer for institutional analytics

Analytical artefacts  
reports · code · charts · models · references



**questions → data → methods → assumptions → caveats → findings → decisions**



Persistent, structured, and governed **knowledge objects**



Analytics produces results. **The Catalyst makes knowledge accumulate.**

# Architecture

A five-step Knowledge Production Pipeline

## 2. Enrich

AI extracts **metadata, assumptions, caveats, descriptions and summaries.**

## 4. Publish

Validated knowledge objects are published for **institutional discovery and reuse.**

## 1. Author

Analysts work in integrated computational documents, preserving a **single (distributed) source of analytical truth.**

## 3. Review

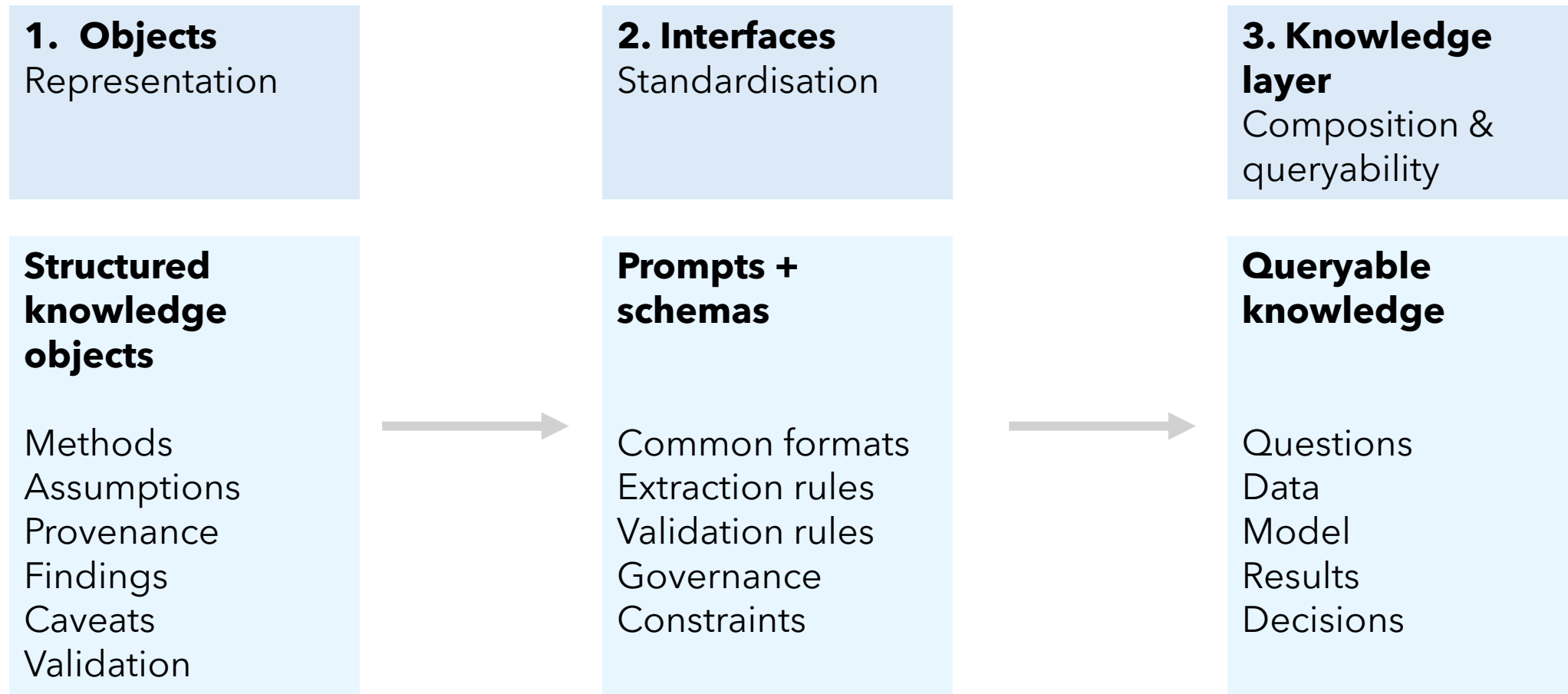
Human experts validate outputs for **accuracy, confidentiality, and policy relevance.**

## 5. Discover

Structured and reviewed resources become **searchable across the institutional knowledge base.**

# Architecture

## Analytical Knowledge as Computable Infrastructure



**AI acts as the translation layer, converting analytical work into structured, governed, connected and queryable institutional knowledge.**

# Conclusions and next steps

- The Analytical Knowledge Catalyst **is already helping us** capture knowledge as it is produced, making it persistent, searchable and reusable across the organisation.
- **Key risks remain:** semantic misinterpretation, unsupported inference and fabrication require strict human validation: AI enriches, experts review, institutions record.
- **Next step:** use **knowledge graphs** as the underlying representation layer, enabling increasingly complex and ***eventually near-real-time systemic risk queries***.

# Navigating AI Adoption in Central Banks: Insights from Bank Indonesia

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**Alvin Andhika Zulen**  
**Bank Indonesia**

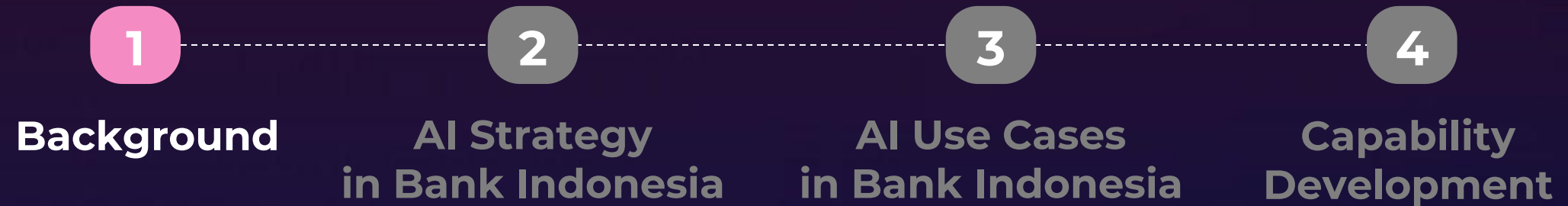
13<sup>th</sup> IFC Biennial Conference  
Basel, 20-21 August 2026

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do not necessarily reflect the views of Bank Indonesia*

# Outline



# Outline



# AI is evolving **Fast** .... Why?

What are the pillars behind today's **AI surge**?



**The Rise of GenAI**  
**AI is accessible**  
**and smarter**



**Faster Computation**  
**Complex task run fast**  
**(near real time)**  
**using GPU/TPU**



**Explosion of Data**  
**Endless fuel for models**

# Can Central Banks **Keep Up?**

Central banks face rising complexity and institutional pressures. **AI can help, but capturing value requires a clear strategy ...**

## Challenge central bank face



The size of the financial system continues to grow



Money movement, payments, and bank runs are accelerating, making crises unfold in hours or days



Policy, supervision, and operations are becoming more complex

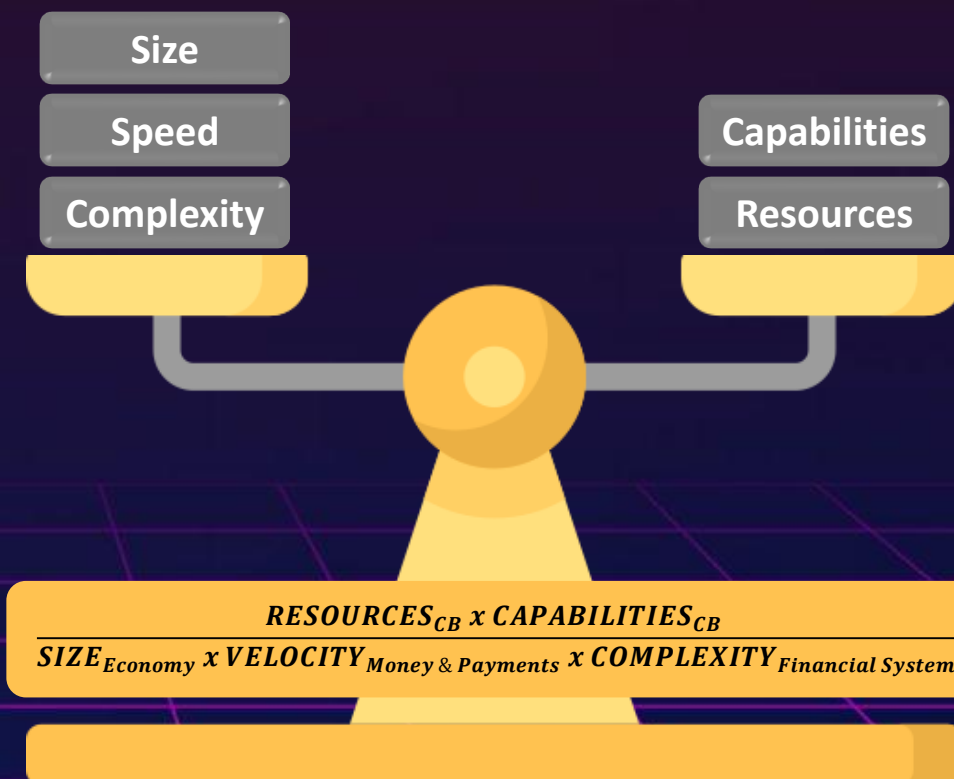


Constraint on resources and talents capacity



Traditional & rigid business process

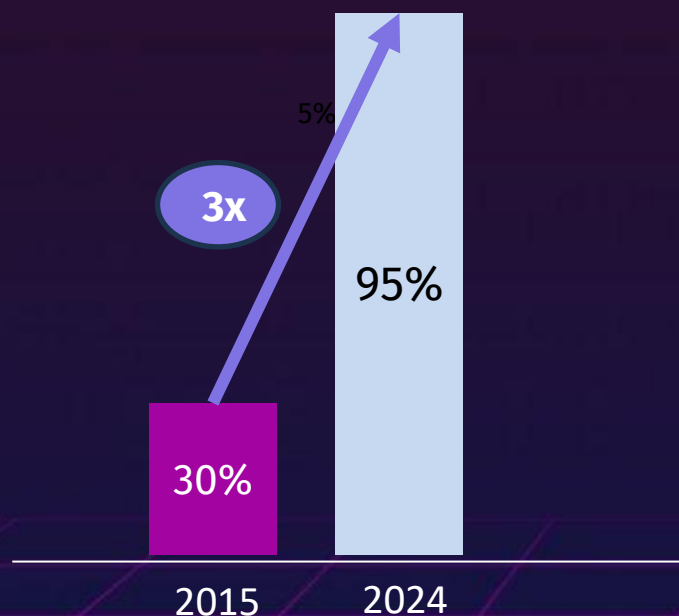
As size, velocity, and complexity rise while resources are flat, **central banks must dramatically enhance capabilities to keep up!**



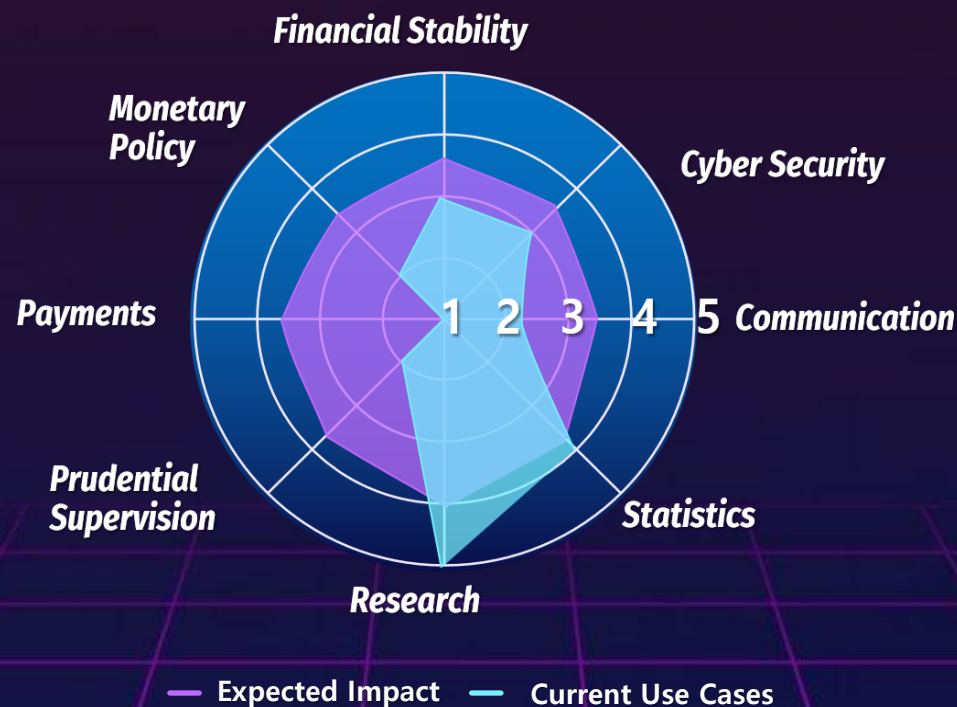
# Ai in Central Banks

AI has become one of the **drivers of innovation and digital transformation in central banks**, in line with the growing interest in AI utilization and the increasing variety of use cases...

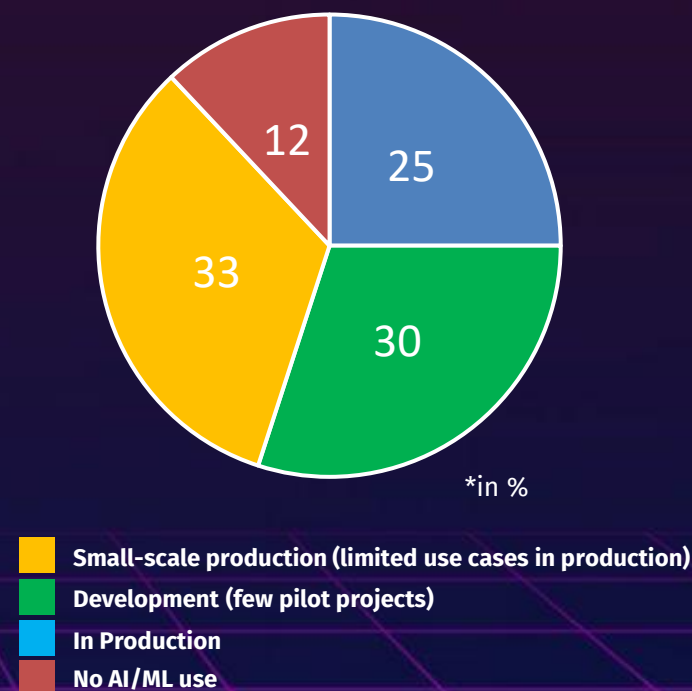
Increasing number of central banks are showing interest in adopting AI...



The types of AI use cases are also becoming more diverse...

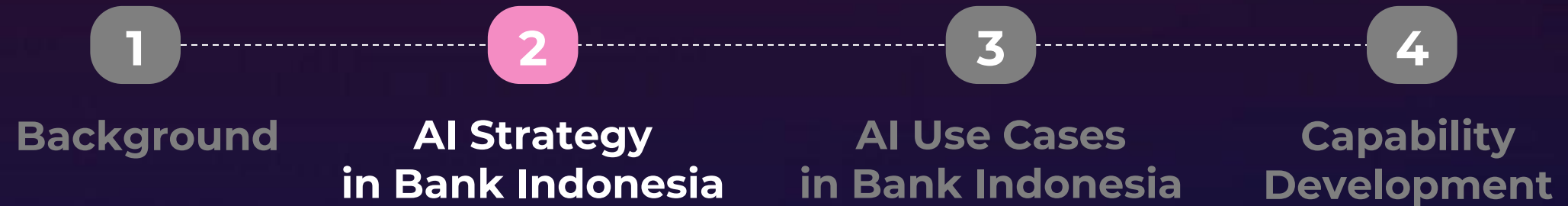


However, most are still in the experimentation stage...



Source: BIS & IFC AI/ML Survey (2015, 2020, 2024)

# Outline



# Bank Indonesia's AI Journey

Bank Indonesia's AI transformation has unfolded through strategic stages, building a data and organizational foundation, strengthening AI/ML capabilities, and accelerating enterprise-wide adoption...

1

## BUILD STRATEGIC FOUNDATION

Laying the **groundwork** for AI

- ✓ **Organisasi:** Establishment of the Data Innovation and Digitalization Department (DIDD)



- ✓ **Teknologi:** Development of Enterprise Data Platform: **Data Lake; Data Catalog; Data Analytical Tools**



2

## STRENGTHEN AI/ML CAPABILITIES

Turning strategy into **actions**

- ✓ **Regulatory Reform (Data & AI):** AI governance (balancing the trilemma of innovation, speed, and risk)



- ✓ **Strategic Plan:** Formulation of BI's AI Master Plan 2025-2030

**RIKABI**

- ✓ **Data Foundation:** Development of AI-ready metadata



- ✓ **AI use case**, e.g.:
  - Nowcasting/forecasting
  - Text mining
  - Network analysis



3

## ACCELERATE ENTERPRISE AI ADOPTION

From adoption to **innovation at scale**

- ✓ **High impact & strategic use cases (*leapfrog*)**, e.g the use of unstructured data, GenAI, and Agentic AI



- ✓ **Human Capital & Community Development:**

- Activation of the AI Innovation Community (KIKA)



**300+**  
Employees

- Human capital development through training and certification

# BI's Strategy to Capture AI Value

The AI paradox shows that AI adoption does not automatically generate added value that is significant and commensurate with the investment made. To address this challenge, **BI focuses on three main strategies to maximize the utilization of AI...**



## Prioritize for Value

Focus on the high-value  
AI initiatives



## Iterate & Learn Fast

Adapt quickly through  
rapid experimentations and  
technology adoption



## Govern & Scale Responsibly

Ensure responsible  
use of AI with strong  
governance

# Prioritize for Value through BI's AI Roadmap

AI adoption at Bank Indonesia is carried out through the **development of AI use cases** supported by **AI capabilities (data, methodology, technology, and human resources)**, together with **governance** to ensure AI development is carried out responsibly...

## Main Strategy (3AI)

### Leveraging AI for Policy

AI supports the formulation and implementation of central bank policy and institutional policy

### Optimizing AI for Productivity

AI supports employees' task execution, helping improve their effectiveness and productivity

### Empowering AI for Public Services

AI supports the delivery of services to a broader public and stakeholders

+

## Core Capabilities

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Data



Methodology



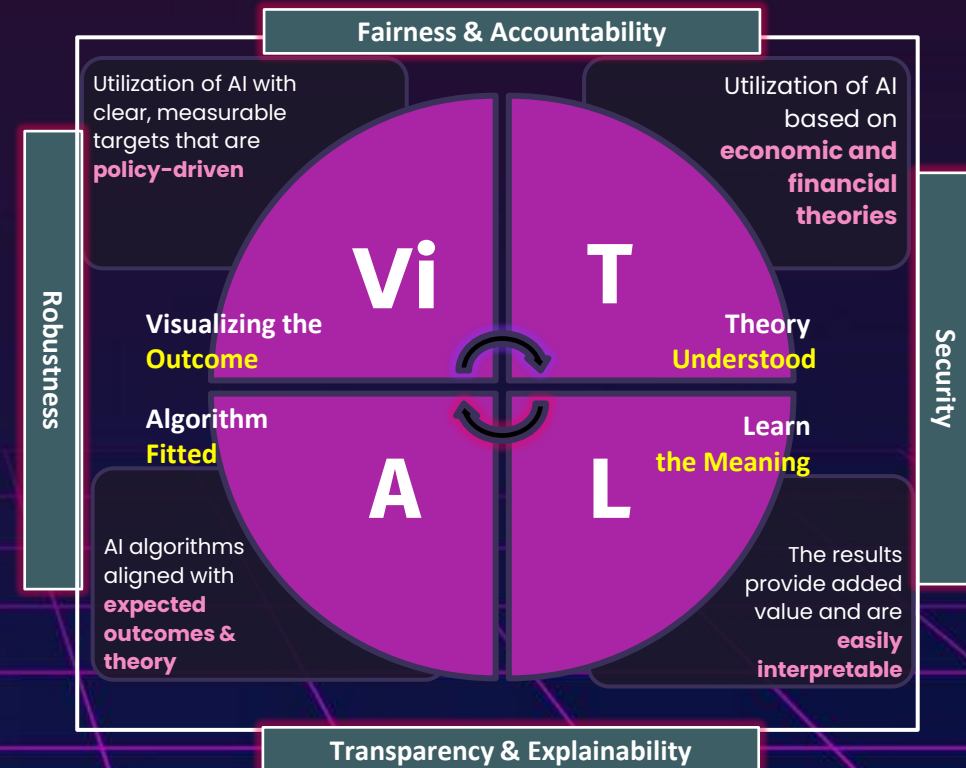
Technology



Human Resource

+

## Guiding Principle



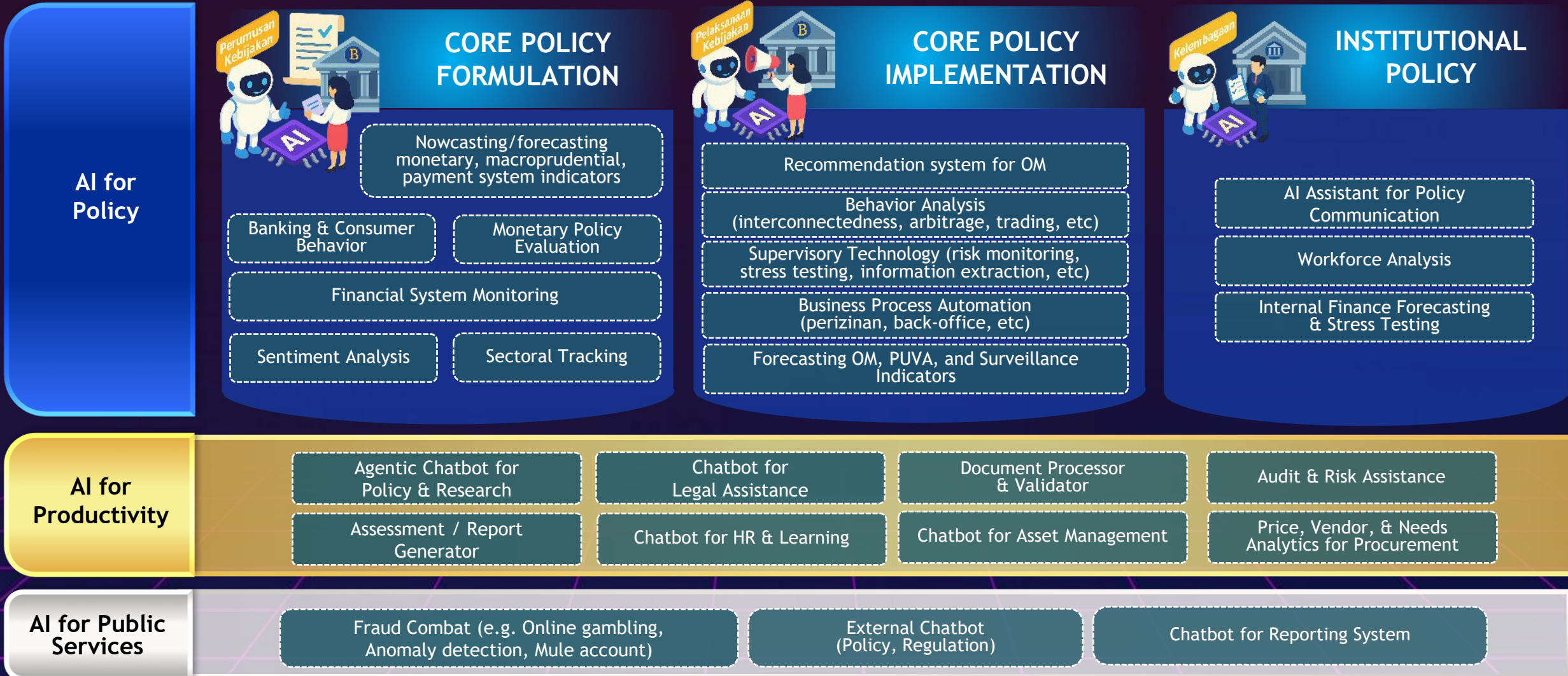
# Outline



# Use Case Portfolios

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AI development is directed toward **more transformative use cases** (changing how work is done) and the **application of higher-complexity methodologies**, including Generative AI and Agentic AI...



# AI Use Cases in Bank Indonesia

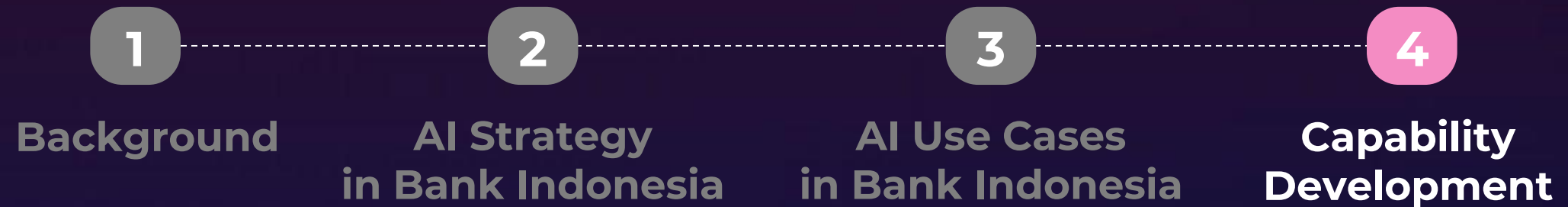
| # | Use Case                                                  | Scope                                                                                                                                 | Cluster                                       | Data Source                                          | Methodology                                                                                                                           | Period  |
|---|-----------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------|------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------|---------|
| 1 | <b>Job Vacancy Indicator using Advertisement Data</b>     | Constructing a job vacancy index as an indicator of labor demand, available monthly with 1-week lead over conventional data releases. | Leveraging AI for Policy – Core Policy Making | Online job portals and print media.                  | Text mining, through processing of job-vacancy advertisement text files.                                                              | Monthly |
| 2 | <b>Property Price Indicator using Advertisement Data</b>  | Faster, broader-coverage indicator of secondary property market developments, complementing the Residential Property Price Survey.    | Leveraging AI for Policy – Core Policy Making | Online property portals.                             | Text mining, through processing of property listing advertisement text files.                                                         | Monthly |
| 3 | <b>GDP Indicator Forecasting</b>                          | Forecasting GDP indicator as a proxy for quarterly GDP projections.                                                                   | Leveraging AI for Policy – Core Policy Making | Survey data, market data, banking data, fiscal data. | Machine learning — data preprocessing, feature engineering, feature-importance analysis.                                              | Monthly |
| 4 | <b>Enhancing Nowcasting using Unstructured Data</b>       | Refining nowcasting/forecasting models for economic & financial indicators via sentiment indices from unstructured news data.         | Leveraging AI for Policy – Core Policy Making | Bank Indonesia's Cyber Library and Bloomberg News.   | LLMs for sentiment analysis & embeddings transformation (sentiment inference, keyword-based filtering, sentiment index construction). | Monthly |
| 5 | <b>Interbank Interconnectedness in the Payment System</b> | Mapping the network structure among payment-system participants to identify sources of systemic banking risk.                         | Leveraging AI for Policy – Core Policy Making | BI-RTGS settlement transaction data (interbank).     | Data mining using Core-Periphery structural model, with SVM classification.                                                           | Weekly  |

# AI Use Cases in Bank Indonesia

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| #  | Use Case                                                   | Scope                                                                                                               | Cluster                                       | Data Source                                                                                         | Methodology                                                                     | Period         |
|----|------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------|-----------------------------------------------|-----------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------|----------------|
| 6  | <b>Behavior Analysis in Money and Forex Market</b>         | Dynamic visualization of banking sector behavior in the money market and forex market.                              | Leveraging AI for Policy – Core Policy Making | Daily banking transaction reports.                                                                  | Entity resolution modelling combined with network analysis.                     | Daily          |
| 7  | <b>Fraud Combat</b>                                        | Identifying illegal transaction patterns and accounts associated with online gambling within the payment system.    | Empowering AI for Public Services             | BI Payment System Infrastructure transaction data; web-scraped data on suspected gambling accounts. | Hybrid AI/ML approach — clustering, classification, and graph machine learning. | Daily          |
| 8  | <b>Policy Credibility Indicator</b>                        | Measuring public/stakeholder perception of BI's credibility in monetary, macroprudential, and payment system policy | Leveraging AI for Policy – Core Policy Making | Bank Indonesia's Cyber Library.                                                                     | Machine learning — sentiment analysis.                                          | Quarterly      |
| 9  | <b>AI Assistant for Money &amp; Forex Market Analytics</b> | Automating and improving the quality of data and knowledge discovery/analysis on money and forex market data.       | Optimizing AI for Productivity                | Market transaction data; unstructured documents; domestic/global news.                              | Agentic AI Orchestrator — Prompt-to-SQL, Document RAG, and Internet Search.     | Near real time |
| 10 | <b>HR Policy Chatbot</b>                                   | Providing a GenAI-based chatbot within BI's internal HR application to improve understanding of HR regulations.     | Optimizing AI for Productivity                | Bank Indonesia HR regulations; FAQs; HR pocketbook.                                                 | GenAI with Retrieval-Augmented Generation (RAG).                                | Real-time      |

# Outline



# Human Capability-Building Program

- The success of AI transformation depends not only on technology, but also on **strengthening human capital capability, strategic policy direction and top-management commitment**, and **institutional support**.
- KIKA serves as a vehicle for **accelerating the adoption of AI** in alignment with Bank Indonesia's strategic direction.

## Steering Committee: Board of Governor

BINS

DIDD

DSDM

**KIKA's  
Role**

KIKI

AI Expert

AI Champion

1

Acts as an AI Champion within its department.

2

Identifies problems and opportunities for AI adoption within the department.

3

Supports AI development — particularly experimentation — and its rollout within the department.

4

Builds individual competence and drives improved AI capability within the department, e.g. through knowledge sharing.

## CAPACITY BUILDING

MODULE 1

### DATA ANALYTICS

Foundational competence in **data and metadata management, data integration, and data processing** aligned with international standards and internal requirements.

MODULE 2

### ARTIFICIAL INTELLIGENCE

**AI/ML methods**, including **Traditional AI, Generative AI, and Agentic AI**, for extracting information and generating contextual insights from multimodal data.

MODULE 3

### CENTRAL BANK USECASES

**Application of data analytics and AI** to BI's business processes through **formulating practical, high-impact use case proposals** that add value for the organization.

### CERTIFICATION



# AI Playbook

The **AI Playbook series** was developed to **build foundational knowledge and technical expertise on AI**, enabling BI employees to effectively understand, develop, and apply AI-based solutions...

## AI Playbook Series 1



- For general audience from various backgrounds.
- Introduces fundamental AI concepts as a foundation for understanding.

## AI Playbook Series 2



- For practitioners and employees seeking to deepen their AI knowledge.
- Provides more technical and practical guidance for applying AI.

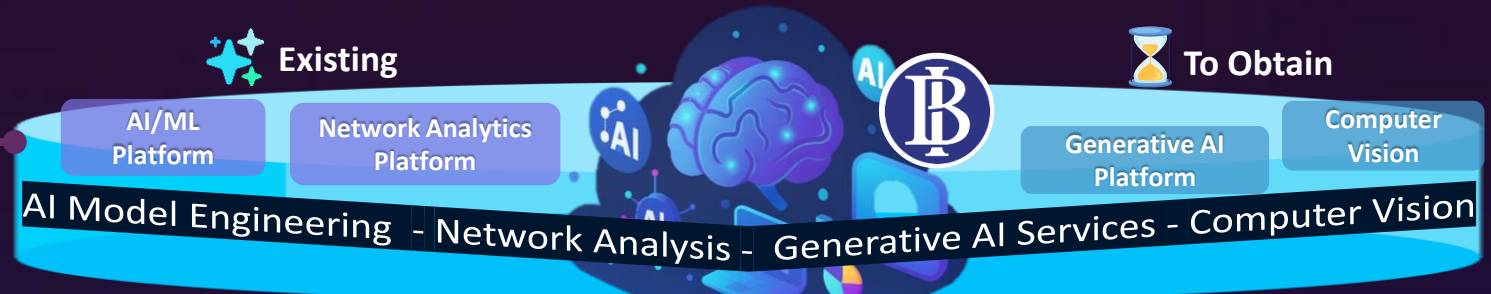
# AI Technology at Bank Indonesia

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- Developing AI use cases at scale depends on **three foundational technology layers** — AI, Data, and Infrastructure — working in tandem.
- While existing tools already satisfy part of this need, keeping pace with the speed and diversity of business demand requires a **deliberate strategy to acquire newer technology**, particularly a GenAI Platform and Cloud Computing capacity.

## 1. AI TECHNOLOGY

Ready-to-use **AI Services**  
with robust engineering  
platform



## 2. DATA TECHNOLOGY

Integrated **Data Services**  
serving end-to-end data  
management



## 3. INFRASTRUCTURE

Future-proof **Infrastructure**  
adapting to latest AI advancements



# AI Governance: Risk-Based Approach

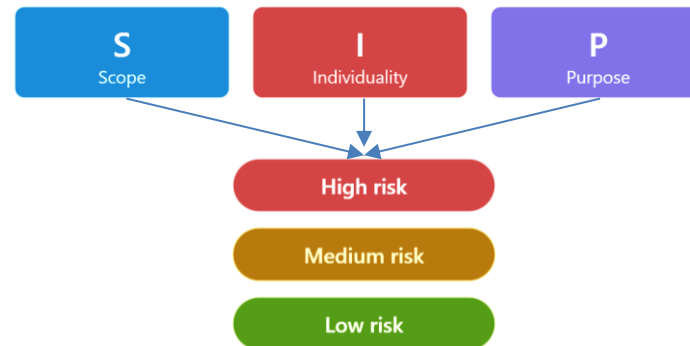
AI governance is not “one-size-fits-all” but rather “context-specific”. It must consider the actors involved (development or utilization areas), the level of risk (determined by Scope–Individuality–Purpose), and the type of AI object (Managed AI – Self-managed – Personal).

## BI's Duality: Developer or User



Governance approaches will differ depending on the role being performed, whether as a developer (development area) or as a user (utilization area).

## The higher the risk, the stricter the governance



The implementation of risk classification based on use cases<sup>1</sup> enables Bank Indonesia to determine the level of governance that should be applied to AI.

<sup>1</sup> The concept of “use case risk” is adopted from the EU AI Act, which uses risk levels to determine the required governance framework.

## 3 AI Objects with Different Characteristics



### MANAGED AI

Developed by the IT Dept. and/or the Use Case Owner Business Unit.



### SELF-MANAGED AI

Developed by the Use Case Owner Business Unit.



### PERSONAL AI

No development involved. Third-party AI is directly utilized by employees.

AI governance also considers the characteristics of 3 (three) types of AI objects used within Bank Indonesia, which determine the potential risks and the types of mitigation measures required.

# THANK YOU TERIMA KASIH

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**Alvin Andhika Zulen**  
**Bank Indonesia**

13<sup>th</sup> IFC Biennial Conference  
Basel, 20-21 August 2026



EUROPEAN CENTRAL BANK

EUROSYSTEM

# Improving Financial Market Data Discoverability with AI- Generated Metadata and Semantic Search

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**13th IFC Biennial Conference**

BIS, Basel, Switzerland

**20–21 August 2026**

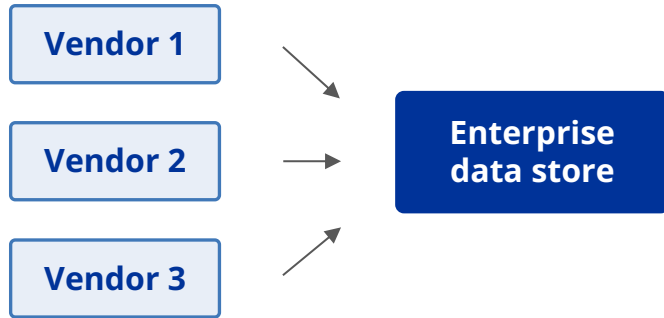
Disclaimer: This paper should not be reported as representing the views of the European Central Bank (ECB). The views expressed are those of the authors and do not necessarily reflect those of the ECB.

A low-angle, upward-looking photograph of a modern skyscraper with a glass facade, reflecting the sky and clouds. The building is the European Central Bank building in Frankfurt.

**Juraj Botkuljak**  
European Central Bank

# The problem

Central banks often pool commercial data from multiple external vendors into one enterprise store



Each dataset has a different schema. **How do you (or your AI agents) find the data?**

The problem can be broken down into **two sub-problems**.

**1**

Building the data catalogue

**2**

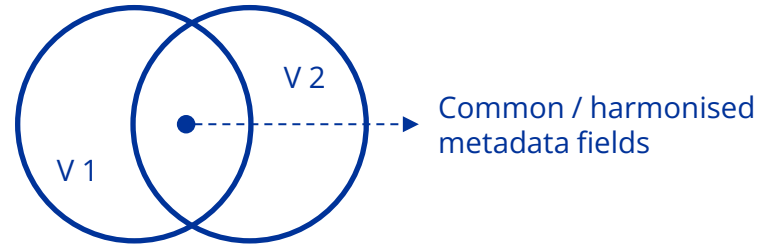
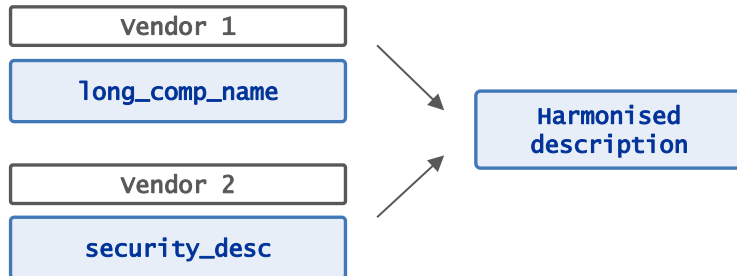
Indexing the catalogue

# Building the data catalogue | Naïve approach

A data catalogue lists **entities** – symbols – along with *definitional metadata*

We store both **vendor-specific** and **harmonised metadata**.

A simple approach to schema harmonisation: **transformation rules**.

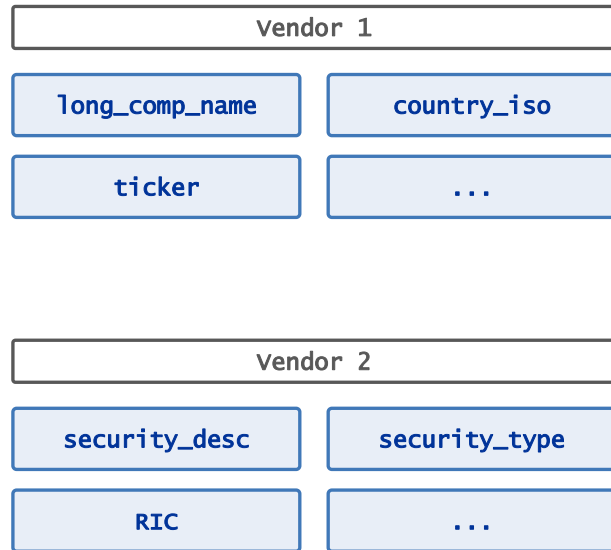


| Vendor   | Symbol    | Description              |
|----------|-----------|--------------------------|
| Vendor 1 | GTDEM10Y  | BUNDESREPUB. DEUTSCHLAND |
| Vendor 2 | DE10YT=RR | DEGV 2.900 02/15/36      |

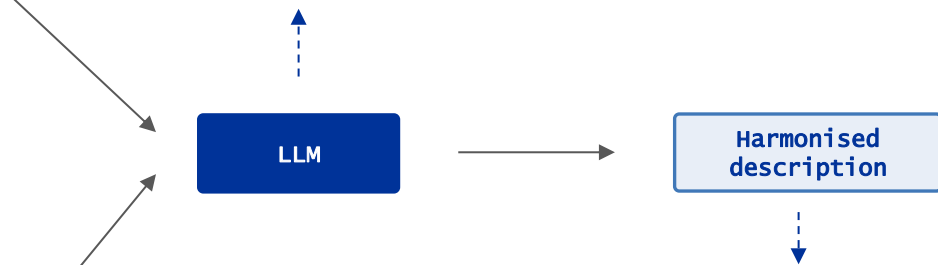
Problem: descriptions are not harmonised

# Building the data catalogue | LLM harmonisation

An LLM harmonises descriptions into one common, template-guided structure



LLM system prompt specifies **guidelines** based on *naming templates*.



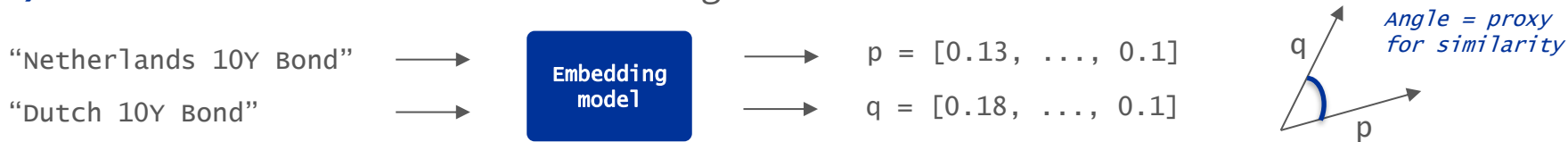
| Vendor   | Symbol    | Harmonised description                |
|----------|-----------|---------------------------------------|
| Vendor 1 | GTDEM10Y  | Germany 10Y Benchmark Government Bond |
| Vendor 2 | DE10YT=RR |                                       |

# Indexing the catalogue | Hybrid search

## 1) Traditional methods – treat text as *strings of characters*

|                       |                                                                      |                                                                         |                                                                                          |
|-----------------------|----------------------------------------------------------------------|-------------------------------------------------------------------------|------------------------------------------------------------------------------------------|
| <b>Exact matching</b> | Matches <b>exact terms</b> in metadata                               | Good for exact identifiers, such as <b>ticker/RIC, LEI, ISIN</b>        | <i>Netherlands 10Y Bond</i> <b>won't match</b><br><i>Netherlands 10-<u>Year</u> Bond</i> |
| <b>Lexical search</b> | Ranks by <b>lexical relevance</b> using token statistics (e.g. BM25) | Supports partial wording variations, but <b>doesn't capture meaning</b> | <i>Netherlands 10Y Bond</i> <b>won't closely match</b> <i>Dutch 10Y Bond</i>             |

## 2) Semantic search – considers *meaning* behind text



## 3) Hybrid search – fuses semantic and lexical ranks & matches against exact identifiers



# Indexing the catalogue | Fine-tuning semantic search

General-purpose models are suboptimal for financial information retrieval tasks

Different embedding models have different **notions of similarity**

Fine-tuning smaller models to minimise **triplet loss**

*LLMs can be used to efficiently generate training datasets.*

Search query: “oil future”

| Description        | Semantic rank | Lexical rank | Overall rank |
|--------------------|---------------|--------------|--------------|
| Soybean Oil Future | 1             | 1            | 1            |
| Brent Crude Future | 2             | 2            | 2            |
| WTI Future         | 3             | 2*           | 3            |

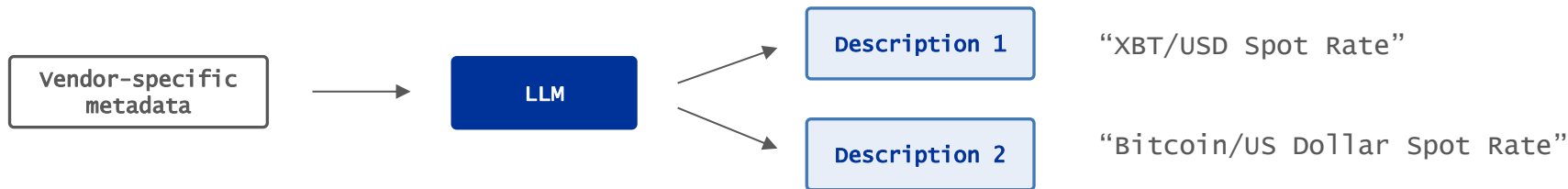
Problem: Whether “oil” refers to crude or soybean oil is context-dependent

| Anchor                     | Positive            | Negative            |
|----------------------------|---------------------|---------------------|
| Brent Crude Future         | Oil Future          | Soybean Oil Future  |
| Germany 10Y Benchmark Bond | German 10-Year Bond | German 11-year Bond |
| Germany 10Y Benchmark Bond | German 10Y Bond     | French 10Y Bond     |

\* Ranks tied; neither description contains “oil”

## Indexing the catalogue | Handling synonyms

To handle synonyms, we allow the LLM to (optionally) generate multiple *equivalent descriptions* instead of a single harmonised description



The semantic score of any given record equals the maximum semantic score among equivalent descriptions

Search query: **"bitcoin us dollar"**

|   | Description 1     | Similarity 1 | Description 2               | Similarity 2 | Max similarity |
|---|-------------------|--------------|-----------------------------|--------------|----------------|
| 1 | XBT/USD Spot Rate | 0.5          | Bitcoin/US Dollar Spot Rate | <b>0.9</b>   | <b>0.9</b>     |
| 2 | Bitcoin ETF       | <b>0.7</b>   | /                           |              | <b>0.7</b>     |

# Implementation notes & lessons learned

Consistency of LLM-generated descriptions was maintained mostly through guidelines provided in **system instructions**

**FAISS\*** was used as the semantic search backend; catalogue data was stored in an **SQLite database**

Open-source model *multilingual-e5-large-instruct*, obtained from **Hugging Face** and fine-tuned with **SentenceTransformers**, was used to produce embeddings

**Streamlit** – a lightweight Python framework for building full-stack data applications – was used to build the user interface

**Relevance** is not the same as **similarity**. For the query “Bitcoin USD”, “Bitcoin USD ETF” may rank as more similar, but “XBT/USD Spot Price” is the more relevant result

*Strict schema enforcement instead of soft guidance (a) requires defining the complete taxonomy upfront, (b) is inflexible and (c) only marginally improves consistency.*

*For moderately-sized catalogues (< 10 million records), more sophisticated solutions (such as OpenSearch) are often not warranted due to maintenance cost and complexity.*

*Small, open-source embedding models bring lower runtime latency, improved performance (when fine-tuned), and enhanced privacy.*

*The scalability benefit of complex architectures doesn't outweigh the maintenance cost, especially when the load is relatively small (< 100 concurrent users).*

*Fine-tuning helps, but for optimal performance one should use a specialised ranking model – a reranker – and possibly an additional relevance metric such as popularity.*

\* An open-source library for fast vector search



HONG KONG MONETARY AUTHORITY  
香港金融管理局



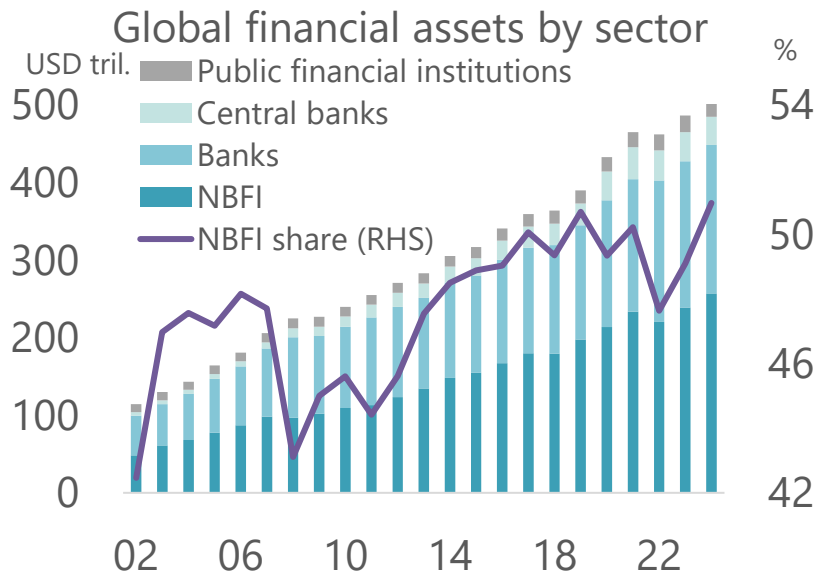
**NBFI Sentiment Analysis and Negative News Monitoring using Generative AI Technology**  
Henry Chan (Hong Kong Monetary Authority), Silvia Pezzini (Columbia University)

**13<sup>th</sup> IFC Biennial Conference, 20-21 August 2026**  
**“Filling information gaps in central banking: effectively leveraging data and innovative tools”**

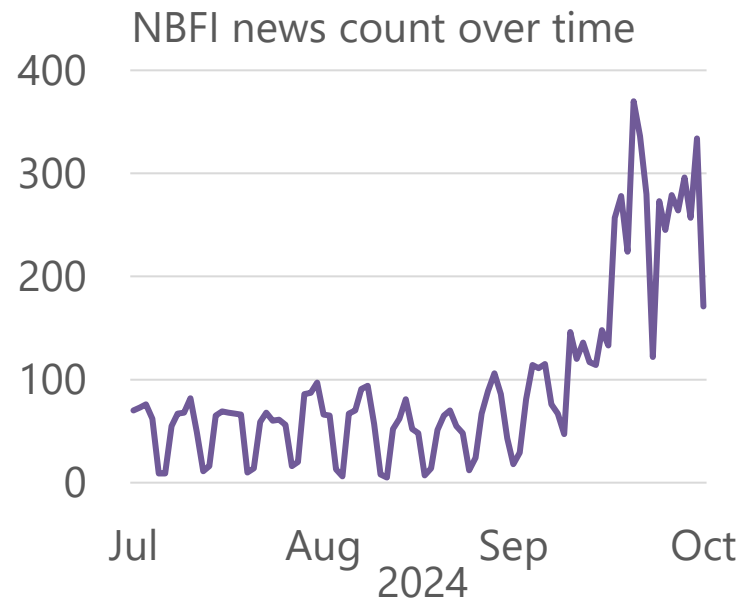
# Motivation of using AI-based tool: pain points in gathering MI about NBFIs

- NBFIs sector has been growing fast, accounting for **half of global financial assets**.
- However, **gathering trusted information** on potentially risky NBFIs is **difficult**:
  - They are **less regulated than banks**, limiting access to regulatory information.
  - Most of them such as hedge funds are **privately held** with limited public disclosure.
- AI-based news analytics can help identify **NBFI risk and sentiment signals**.

**NBFIs account for half of global financial assets**



**Daily news coverage of HK-active NBFIs**

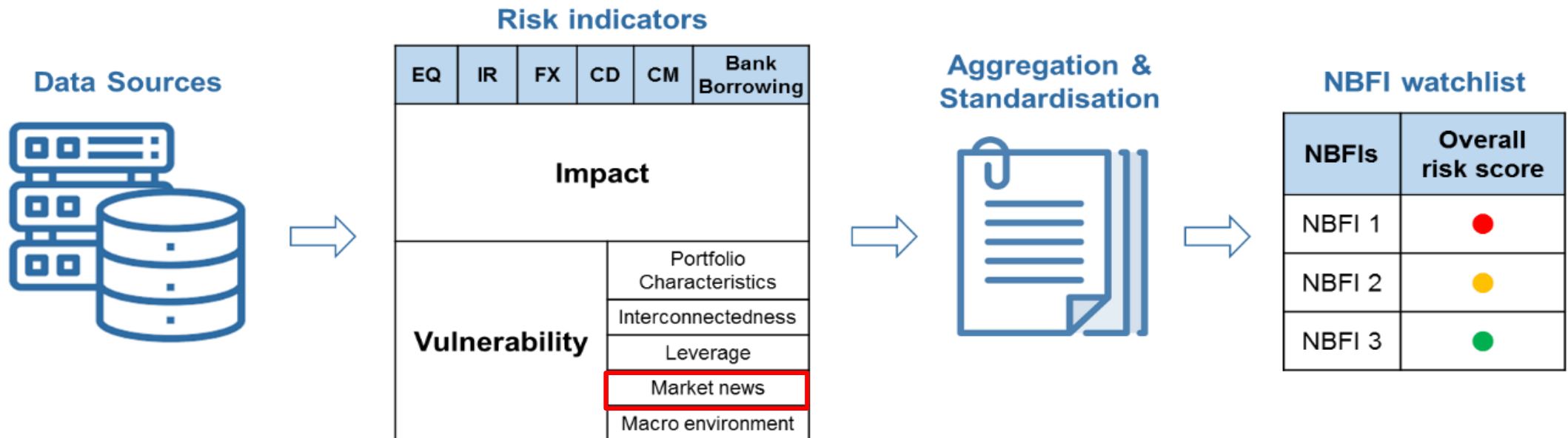


**Turn news into Market Intelligence (MI)**

Speculation Margin Call  
Banned Bill Hwang Disclosure  
Archegos Total return swap Risky  
Equity derivatives Losses Hedging  
Risk management Family office NBFI

# Non-bank financial institutions (NBFI) surveillance framework

- Following Archegos' default which unexpectedly created USD 10 bn losses to the financial system, the HKMA developed an NBFI framework to identify potentially destabilizing NBFIs.
- It **combines diverse datasets** from TR data on **OTC derivatives to banking data to news**, to generate **risk indicators** to quantify potential impact and vulnerability of an NBFI.
- Risk indicators are standardised & aggregated into **impact** and **vulnerability scores** for each NBFI.
- Output is a **watchlist** ranking top NBFIs with NBFIs' risk level as **red-amber-green** (high-med-low).



## Four-step process for NBFIs sentiment analysis using GenAI

- The market news indicator is built through **sentiment analysis** in four steps, namely:
  1. sourcing relevant news via web scraping
  2. assessing market sentiment in news headlines using GenAI tool
  3. converting sentiment into a score
  4. assigning a rating to each NBFIs
- Through these four steps, each NBFIs is given a sentiment rating which serves as an input for the risk assessment of that NBFIs in our surveillance framework.
- In addition to sentiment analysis, GenAI is useful to **identify negative news** articles about NBFIs **for deep-dive and assessment** as to whether they may pose financial stability concern.

Eg: if found a headline "Prime brokers suspend equity trading with hedge fund X on block trade concerns", it merits deep-dive look into what happened and why.



# Sourcing relevant NBF1 news via web scraping

- **Aim: Gather market intelligence**
  - Web scraping of NBF1 news via Google News (with plan to expand into other sources).

## Identify a list of NBFIs active in the jurisdiction

(Based on OTC derivatives data reported to the Hong Kong Trade Repository HKTR)



## Search and download relevant news using script

|      | date       | title                                             |
|------|------------|---------------------------------------------------|
| 0    | 09/07/2024 | 3D Investment Partners offers to take Japanese... |
| 1    | 09/07/2024 | 3D Investment Partners Issues Open Letter and ... |
| 2    | 09/07/2024 | Japan??s Tohokushinsha, Co-Producer of ???L...    |
| 3    | 09/07/2024 | Shareholder Offer From 3D Investment Partners ... |
| 4    | 09/07/2024 | KKR Secures About a Third of Fuji Soft, Dousin... |
| ...  | ...        | ...                                               |
| 8743 | 07/10/2024 | Archegos Founder Hwang Guilty in Massive Fraud... |
| 8744 | 07/10/2024 | Why was Archegos worse than the Fed??s five-...   |
| 8745 | 07/10/2024 | DOJ said to beef up scrutiny of banks hit by A... |
| 8746 | 07/10/2024 | Archegos founder Bill Hwang convicted at crimi... |
| 8747 | 07/10/2024 | Jury begins deliberating at Archegos founder's... |

8748 rows x 6 columns

## Connect with GenAI tool via API Load the news for GenAI's assessment

A screenshot of a Jupyter Notebook interface. The notebook has two tabs: 'E:main.py' and 'E:generateSentimentAnalysis.py'. The 'E:main.py' tab is active, showing a Python script. The script imports 'json' and defines a function 'generate\_sentiment\_scores\_genai(df)'. It configures a 'sara\_cred' object with 'sara\_cred.get("sara\_cred")', 'sara\_cred.get("account")', and 'sara\_cred.get("password")'. It then iterates over 'df.iterrows()', using 'sara\_client.login(sara\_cred["sara\_cred"], sara\_cred["password"])' and 'news = df["title"] + " " + df["summary"]'. A 'sentiment\_prompt' is defined, and a 'sentiment' is generated using 'sara\_client.chat\_sml(sentiment\_prompt)'. The script also includes a 'try: except Exception as e:' block and a 'df.loc[:, "Sentiment"] = sentiment' line. The 'E:generateSentimentAnalysis.py' tab is also visible, showing a similar script. The bottom of the notebook shows a status bar with 'Simple', 'Python', and '10.54 GB RAM'.

AI tool via API and asks the tool to assess

# Assessing market sentiment in public news using GenAI

- **Conduct sentiment analysis using GenAI:** Leverage HKMA GenAI tool trained on internal knowledge base to interpret the news and quantify sentiment based on language and context.
- **Benefits:** Previously we used Natural Language Processing (NLP) for sentiment analysis. GenAI offers more accurate sentiment interpretation with deeper understanding of context and nuance.

## Load the news for GenAI's assessment

**Prompt:** You are a financial market expert with extensive experience in sentiment analysis. Your task is to analyse the sentiment of the news headline.

*"Archegos founder Bill Hwang convicted at fraud trial over fund's collapse."*

**Please assign a sentiment based on the following categories:**

- (Very/Slightly) Positive
- Neutral
- (Very/Slightly) Negative



SARA

**Negative**



HKMA

## Output sentiment of each news

NBFI-related news articles

Date: 16 Sep 2024    Sentiment: **Negative**  
"NBFI B" Slumped 5% in August Market Turmoil

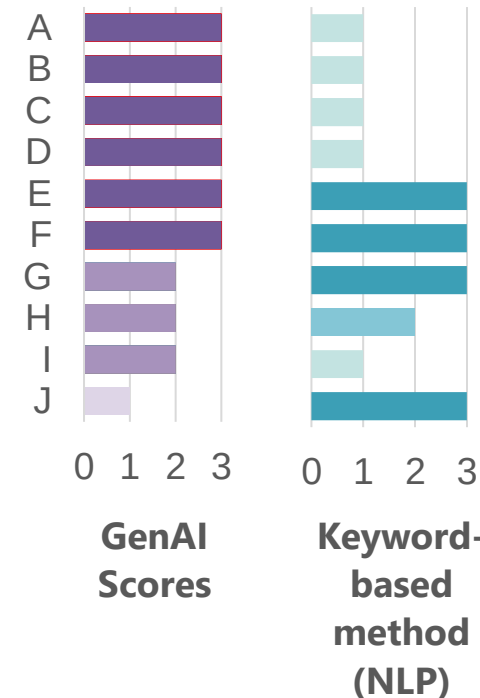
Date: 25 Oct 2024    Sentiment: **Negative**  
"NBFI C" Among Hedge Funds Losing Money Over Failed China Deal

Date: 15 May 2024    Sentiment: **Slightly Negative**  
Ex-traders of "NBFI D" Cite Pay Upset in Secrets Countersuit

Source: Google News

## Comparison of approaches

NBFI



Note: In the initial stage, only news heading, not whole article, is fed into GenAI for analysis due to technical limitations.

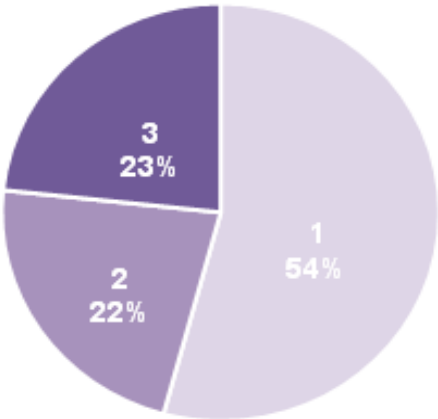
# How the pool of news articles of an NBFIs is converted to a sentiment rating

1. Assign a sentiment score to each news heading based on GenAI assessment.
2. Sum up **negative** news scores to derive an overall NBFIs sentiment score. (Focus on -ve news to avoid potential dilution of -ve sentiment by +ve news.)
3. Rank NBFIs by sentiment score and assign sentiment ratings, helping assess NBFIs vulnerability.

| Sentiment         | Sentiment score [-1;+1] |
|-------------------|-------------------------|
| Very positive     | 1.0                     |
| Positive          | 0.7                     |
| Slightly positive | 0.5                     |
| Neutral           | 0.0                     |
| Slightly negative | -0.5                    |
| Negative          | -0.7                    |
| Very negative     | -1.0                    |

| NBFIs                   | Date   | News heading                                          | Sentiment         | Score |
|-------------------------|--------|-------------------------------------------------------|-------------------|-------|
| Hedge Fund A            | 18 Sep | Hedge fund A experienced losses for 2 quarters        | Negative          | -0.7  |
|                         | 2 Oct  | Hedge fund A made a wrong bet on US interest rate cut | Slightly negative | -0.5  |
| Overall sentiment score |        |                                                       |                   | -1.2  |

| Rating | Sentiment scores           |
|--------|----------------------------|
| 1      | -x ≤ median                |
| 2      | median < -x ≤ 3rd quartile |
| 3      | -x > 3rd quartile          |



Note: x represents the sentiment score of an NBFIs. -x is the absolute value. A rating of 3 means a very negative sentiment for an NBFIs. The rating distribution was based on relevant NBFIs news articles on Google News from 9 Jul to 7 Oct 2024.



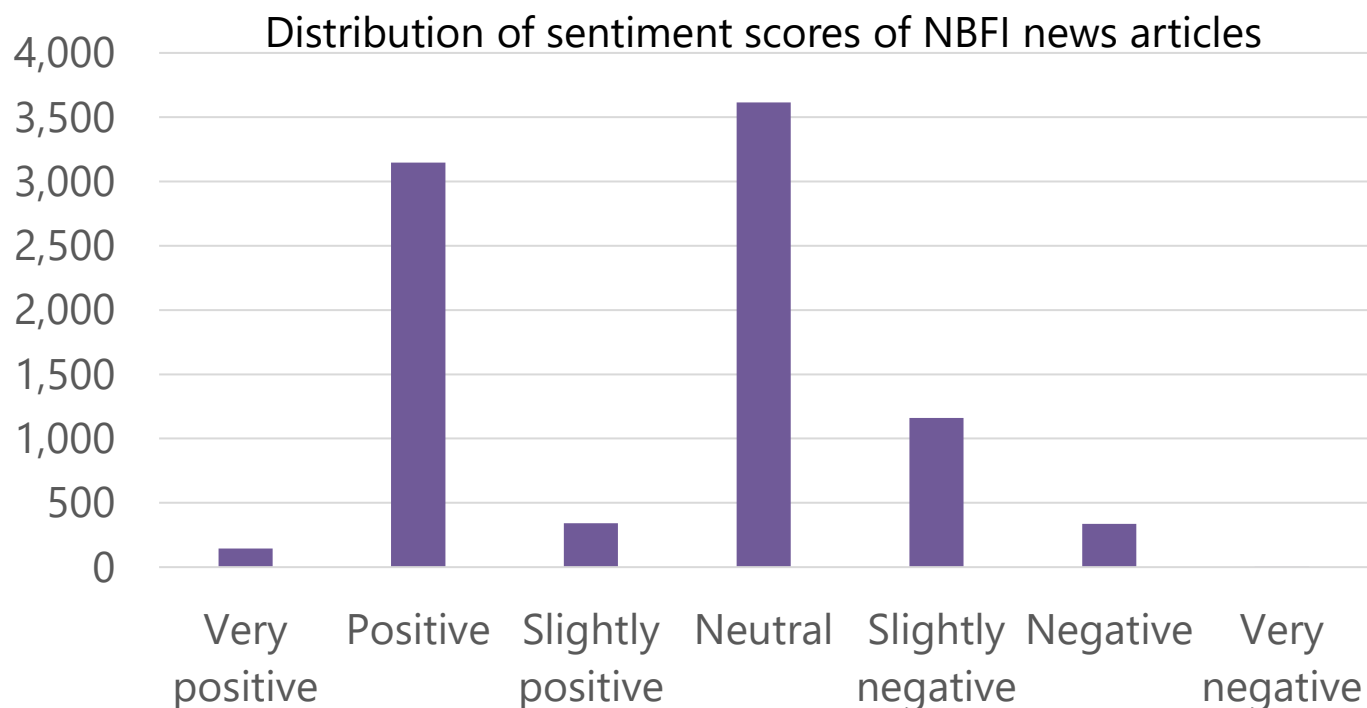
# Challenges and way forward for AI-based financial stability monitoring

- One challenge is **demand for computing power** and **time needed to process** numerous articles.
  - E.g. sentiment analysis of news articles related to 1,000+ NBFIs in the last 3 months took half-day.
- A high frequency or volume of web scraping requests may lead to **websites blocking access**.
- Despite the challenges, the benefits of using GenAI encourage us to further develop the tool.
  - Expanding the analysis to include **entire news articles** instead of just headlines.
  - Connecting to more **commercial news databases** for diverse sourcing.
  - Exploring **other use cases** outside the NBFI space, such as sentiment analysis on currency stability.



## Annex 1: NBFIs negative news monitoring

- The market sentiment indicator supplements market intelligence gathered in more qualitative way.
- Possible to run extensive search on thousands of NBFIs and thousands of articles with limited manual effort and time, and to **focus on a smaller group of NBFIs** with potential risk of market disruption.
- The search sometimes uncovers relevant news that merit further **deep-dive analysis**.



Source: Author calculation based on a sample of 8,748 news from 09 Jul 2024 to 07 Oct 2024.

### Example

#### Headline

"Prime brokers suspend equity trading with hedge fund X on block trade concerns"

#### Sentiment

GenAI tool assigns a very negative sentiment

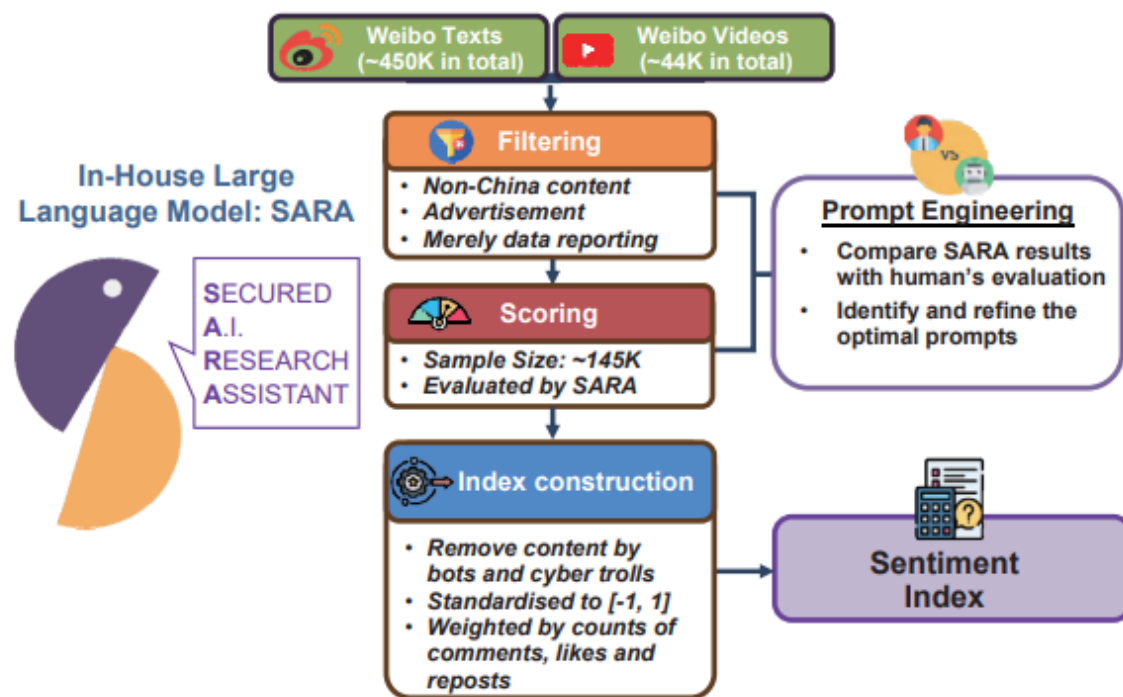
#### Surveillance

Take a deeper look at hedge fund X's potential impact and vulnerability according to HKMA's NBFIs surveillance framework.

## Annex 2: Other use cases of GenAI tool

- Tracking Mainland China's housing market sentiment using social media big data and GenAI.

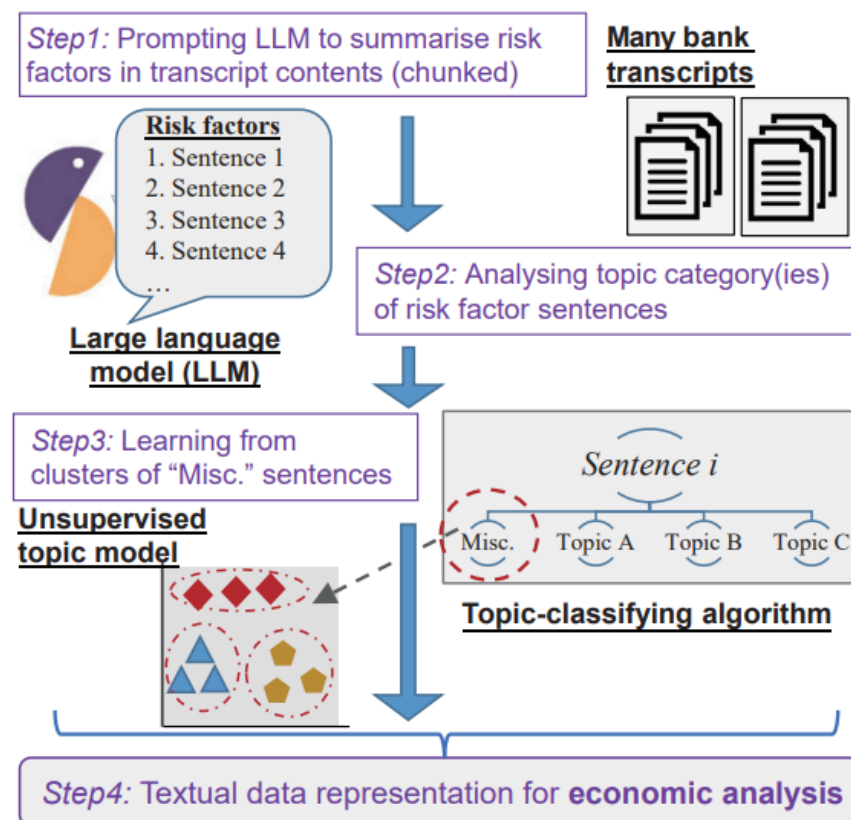
### The development process of the GenA.I.-driven housing market sentiment index



Source: HKMA staff illustration.

- Monitor systemic risks in global banking using earnings call transcript data

### Schematic diagram of the GenA.I.-powered monitoring framework



Note: "Misc." indicates the group of summarised risk sentences that the topic-classifying algorithm assigns as 'miscellaneous'.

# Malaysia's Experience in Assessing Currency Exchange Data as an Indicator of Cash Travel Spending

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**IFC 13<sup>th</sup> Biennial Conference**

Basel, Switzerland

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*The views expressed in this presentation are those of the authors and not necessarily those of Bank Negara Malaysia.*



# Presentation Outline

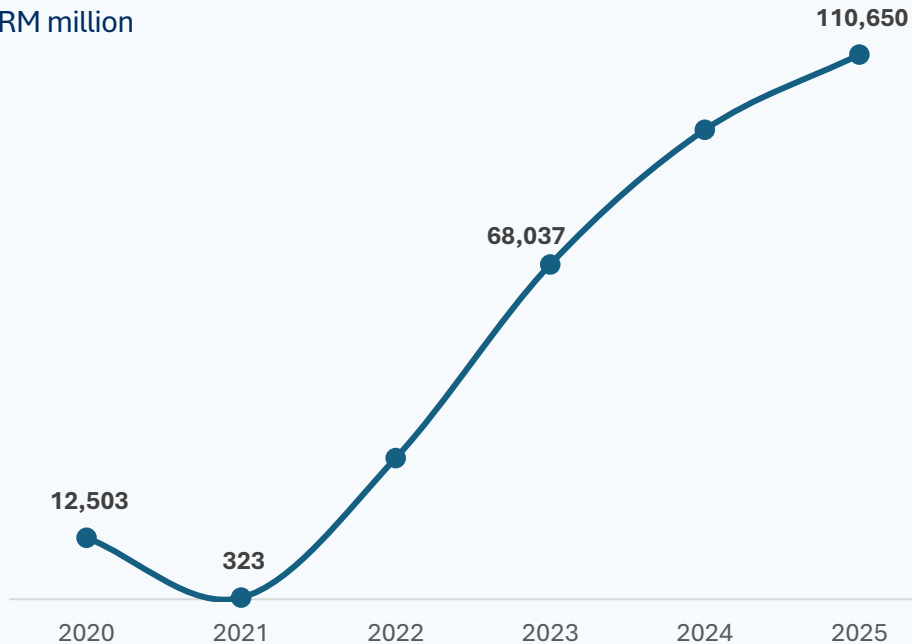
- 1 Introduction
- 2 Data Construction and Empirical Framework
- 3 Findings and Interpretations
- 4 Challenges and Limitations
- 5 Conclusion

# Cash travel spending remains a persistent measurement challenge in balance of payments statistics

Malaysia's BOP Travel receipts highlight the importance of timely supplementary indicators for analysis and policy assessment. While digital payments are increasingly observable, cash-based travel spending remains less visible in conventional data sources.

## Malaysia BOP Travel receipts

RM million



Source: Department of Statistics Malaysia (DOSM)

Note: The estimates are derived from a data model developed by DOSM primarily using information from Annual Departing Visitors' Survey conducted by the Tourism Malaysia, ITRS and administrative records from various government agencies including the Immigration Department and Malaysia Healthcare Travel Council.

### Why it matters

Travel is an important BOP services component, but cash-based transactions are not fully observable through payment and banking systems.

### What remains less visible

Cash physically carried into Malaysia may be spent domestically without passing through formal payment channels, especially when below declaration thresholds.

### Why currency exchange (CE) data

Foreign currency converted into ringgit by non-residents can provide a supplementary signal on cash-intensive travel spending.

Measurement gap

Supplementary data

Empirical test

The key question

Does currency exchange data add a useful cash-spending signal beyond payment-based travel indicators?



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# From data construction to empirical testing

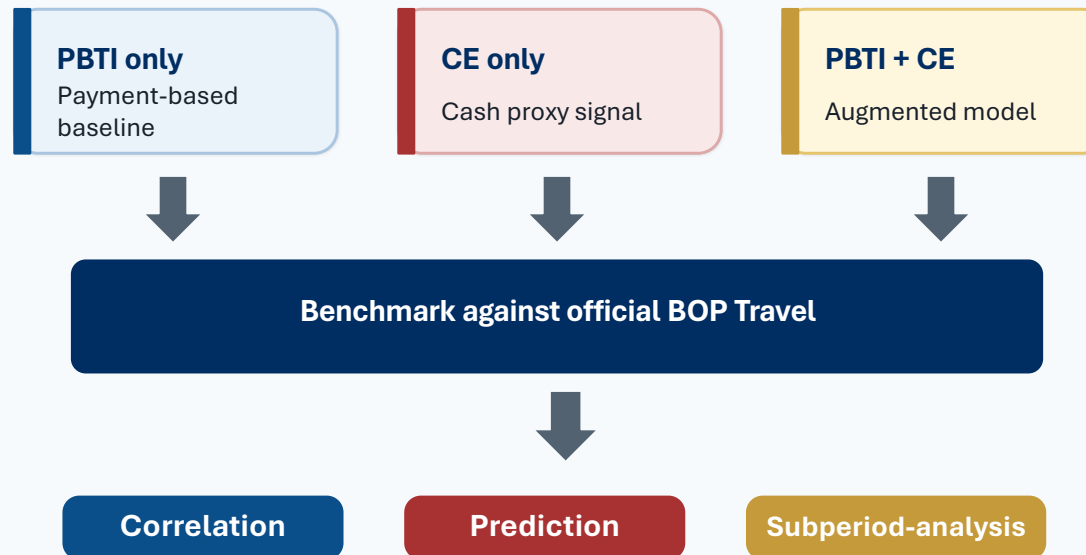
Build a payment-visible baseline and test whether currency exchange adds an incremental cash-spending signal against official BOP Travel.

## 1. Data construction: build the indicators

| Indicator                                     | What it captures                                                                                              | Role                 |
|-----------------------------------------------|---------------------------------------------------------------------------------------------------------------|----------------------|
| <b>Payment-based Travel Indicators (PBTI)</b> | Payments Statistics + ITRS<br><i>Payment-visible travel spending e.g. card, e-wallet, ATM cash withdrawal</i> | Baseline indicator   |
| <b>Currency Exchange (CE)</b>                 | Net foreign currency purchases<br><i>Cash proxy for domestic spending</i>                                     | Supplementary signal |
| <b>BOP Travel</b>                             | Official travel receipts                                                                                      | Target benchmark     |

Logic: PBTI is the baseline, CE is the cash proxy, and BOP Travel is the benchmark.

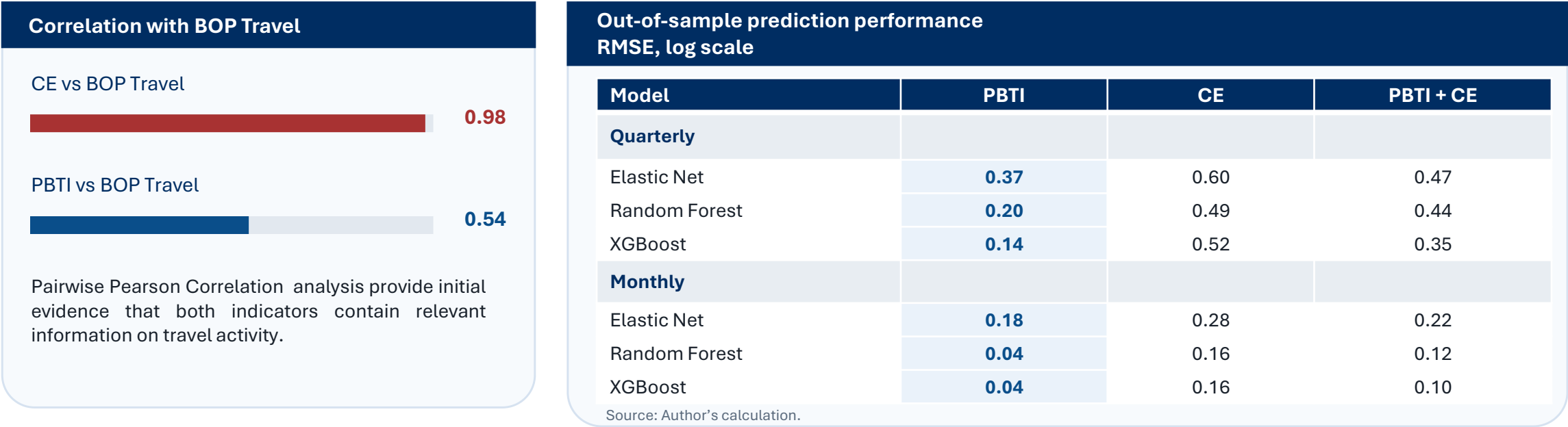
## 2. Empirical framework: test added value



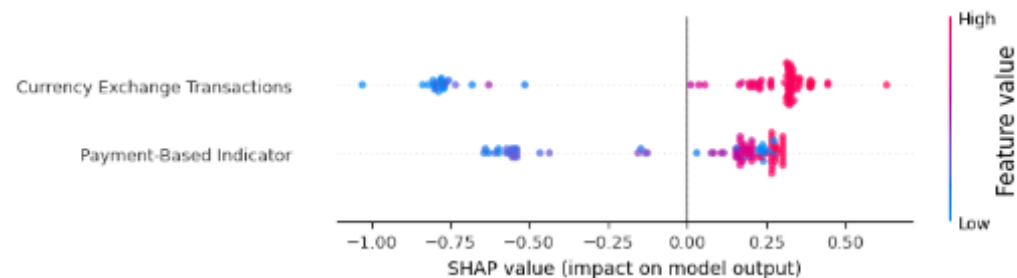
Assess whether CE improves tracking of BOP Travel beyond PBTI.

# Currency exchange transactions move closely with BOP Travel, but do not improve predictive performance beyond PBTi

Across specifications, models based on **PBTi produce lower out-of-sample prediction errors** than those relying solely on currency exchange transactions. This suggests that **PBTi provides more stable predictive signals**, likely reflecting its broader coverage of travel-related transactions observable within the banking system.



## SHAP Analysis



SHAP analysis indicates that both indicators contribute to predictions, while the **payment-based indicator has the stronger influence**.

# Subperiod-analysis

Models were re-estimated separately for the pre-COVID, pandemic, and recovery periods to account for structural shifts associated with COVID-19.

## Pairwise Pearson Correlation Coefficients by Subperiod

The relationship with BOP Travel strengthened over time, from weaker pre-COVID correlations, particularly for PBTI, to stronger post-COVID co-movement.

| Correlation Measure      | Pre-Covid<br>(2018-2019) | Covid<br>(2020-2021) | Recovery<br>(2022-2026) |
|--------------------------|--------------------------|----------------------|-------------------------|
| PBTI vs BOP              | 0.33                     | 0.97                 | 0.93                    |
| CE vs BOP                | 0.56                     | 0.89                 | 0.98                    |
| PBTI vs Tourist Arrivals | 0.06                     | 0.92                 | 1.00                    |
| CE vs Tourist Arrivals   | 0.26                     | 0.92                 | 0.83                    |
| CE vs PBTI               | 0.43                     | 0.85                 | 0.86                    |

Source: Author’s calculation.

The increasing co-movement between PBTI and currency exchange over time suggests increasing overlap in the travel-related information captured by the two indicators.

## What changes across regimes?

**Pre-COVID**      **CE performs best**

**COVID**      **Shock dominates**

**Recovery**      **PBTI regains lead**

Out-of-Sample Prediction Performance by Subperiod  
(XGBoost, RMSE)

| Subperiod | PBTI         | CE           | PBTI + CE |
|-----------|--------------|--------------|-----------|
| Pre-COVID | 0.061        | <b>0.039</b> | 0.051     |
| COVID     | <b>0.207</b> | 0.209        | 0.210     |
| Recovery  | <b>0.047</b> | 0.179        | 0.091     |

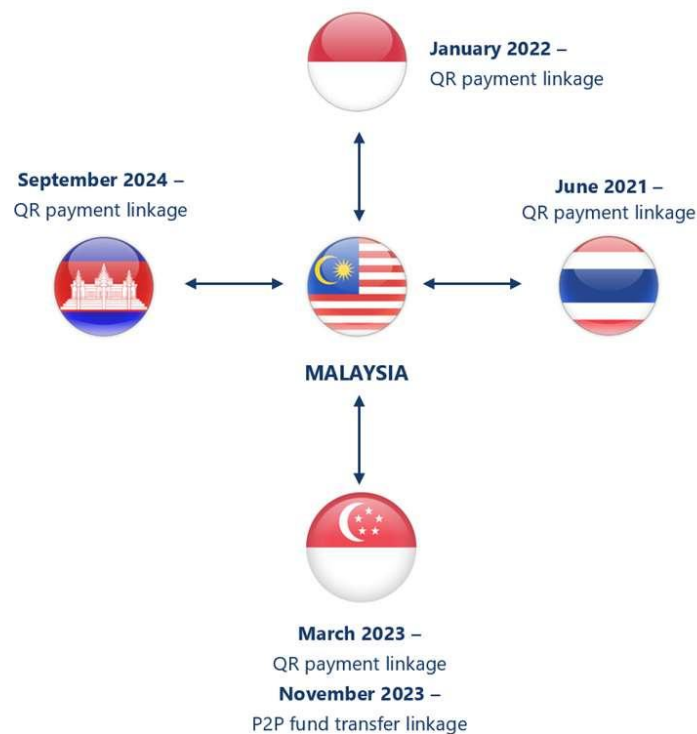
Source: Author’s calculation.

**Contribution of currency exchange transactions is more pronounced when cash behaviour captures distinct information, but becomes less incremental as PBTI expands in coverage and increasingly reflects travel-related activity.**



# Interpretations and Linkages with Malaysia's Payment Landscape

## Cross-Border Payment Linkages between Malaysia and ASEAN Countries



Source: Bank Negara Malaysia Annual Reports 2024 and 2025

## Digitalisation Increases the Coverage of Payment-Based Indicators

### 01 Malaysia is becoming increasingly cashless

Travel-related spending is **shifting away from cash spending** and towards digital payment channels.

### 02 More travel activity is captured in PBTi

**QR-based payments, card transactions and ATM withdrawals increase** the share of spending observable through payment-based indicators

### 03 CE reflects only part of tourists' cash behaviour

Some tourists exchange currency, while others obtain ringgit through ATM withdrawals or spend directly using cards and QR payments. As these activities are already captured in PBTi, CE adds limited new information for prediction.

# Challenges and Limitations

| Limitation                                                                                        | Implication                                                                                                                                                                                         |
|---------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <b>A</b> <b>Residency cannot be identified directly from transaction data.</b>                    | Differences between the BOP residency concept and transaction-based classifications may introduce measurement noise and weaken the observed contribution of currency exchange data.                 |
| <b>B</b> <b>Structural disruptions and limited data may affect the stability of the findings.</b> | Pandemic-related disruptions and a relatively small quarterly sample may influence the stability of the results, warranting reassessment as additional post-pandemic observations become available. |
| <b>C</b> <b>The modelling framework excludes broader travel-spending determinants.</b>            | Incorporating traveller characteristics and tourism-related factors may improve explanatory power and help better isolate the contribution of currency exchange transactions.                       |

## Conclusion: CE serves as a complementary indicator, rather than a direct measure of cash travel spending



### What the evidence shows

- ✓ Both PBTI and CE contain information on travel activity.
- ✓ PBTI provides more consistent predictive signals, while the incremental value of currency exchange transactions remains limited and context-dependent.



### Where CE adds value

- ✓ Currency exchange data are most useful as a supplementary input in periods of structural change or where cash usage is expected to capture distinct behaviour.
- ✓ In more stable conditions with broad digital payment coverage, payment-based indicators are generally sufficient as a primary measure.



### How to operationalise

- ✓ Adopt a layered approach, using PBTI as the core indicator and currency exchange data as a supplementary signal.
- ✓ **Future work:** Improve residency identification and explore tourist behaviour across countries and spending patterns.

**Thank you!**

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