

NEURO-SYMBOLIC CONVERSATIONAL AI FOR RELIABLE PRODUCTION SERVICE INTELLIGENCE

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Italiadomani
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SummerSoc
Service Oriented Computing

Hersonissos, Crete

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CYBER-PHYSICAL PRODUCTION SYSTEMS

Industry 4.0 and Internet-of-Things (IoT)

- Shop-floor assets are continuously monitored and controlled by a distributed ecosystem of components, reshaping manufacturing into Cyber-Physical Production Systems (CPPSs)
- Organizations want to **take advantage** of continuous data streams



Rossit, D.A., Tohmé, F., Frutos, M.: Production planning and scheduling in cyber-physical production systems: a review. *Int. J. Comp. Int. Manuf.* 32 (2019)

Agostinelli, S., Benvenuti, D., Casciani, A., De Luzi, F., Marinacci, M., Marrella, A., Rossi, J.: A Context-Aware Framework to Support Decision-Making in Production Planning. In: *CAiSE 2024*. (2024)

PRODUCTION SERVICE INTELLIGENCE (PSI)

Objectives

- Combine production data and digital models to enhance decision-making
- Foster human-production system collaboration

PSI tools as cloud-native microservices, accessed via standardized APIs

SIMULATION	MODEL CHECKING	PROCESS MINING
Predictive	Compliance	Descriptive

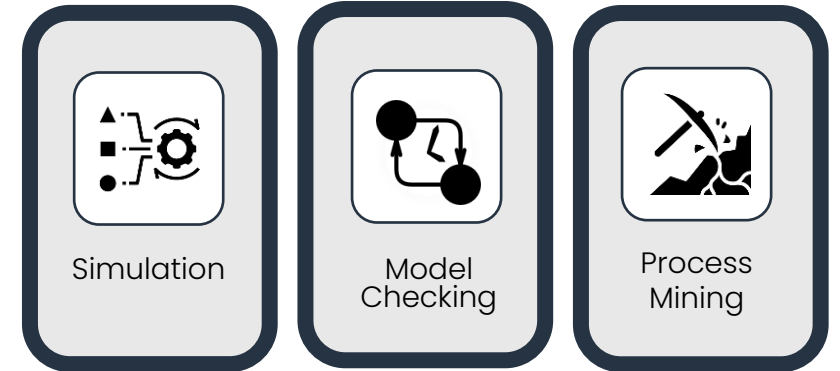
Agostinelli, S., Benvenuti, D., Casciani, A., De Luzi, F., Marinacci, M., Marrella, A., Rossi, J.: A Context-Aware Framework to Support Decision-Making in Production Planning. In: CAiSE 2024 (2024)
Keskin, Z., Joosten, D., Klasen, N., Huber, M., et al.: LLM Enhanced Human-Machine Interaction for Adaptive Decision-Making in Dynamic Manufacturing Process Environments, IEEE Access 13 (2025)

PPI: ARE WE REALLY OKAY WITH THIS?

The “Silo” Problem

- Fragmented interfaces
- Technical expertise required

➤ Each PSI tool: different technologies, formats, languages



Use Case

*“As a **plant manager**, I want to combine compliance checks with what-if analysis of the production so that I can accommodate a new order.”*

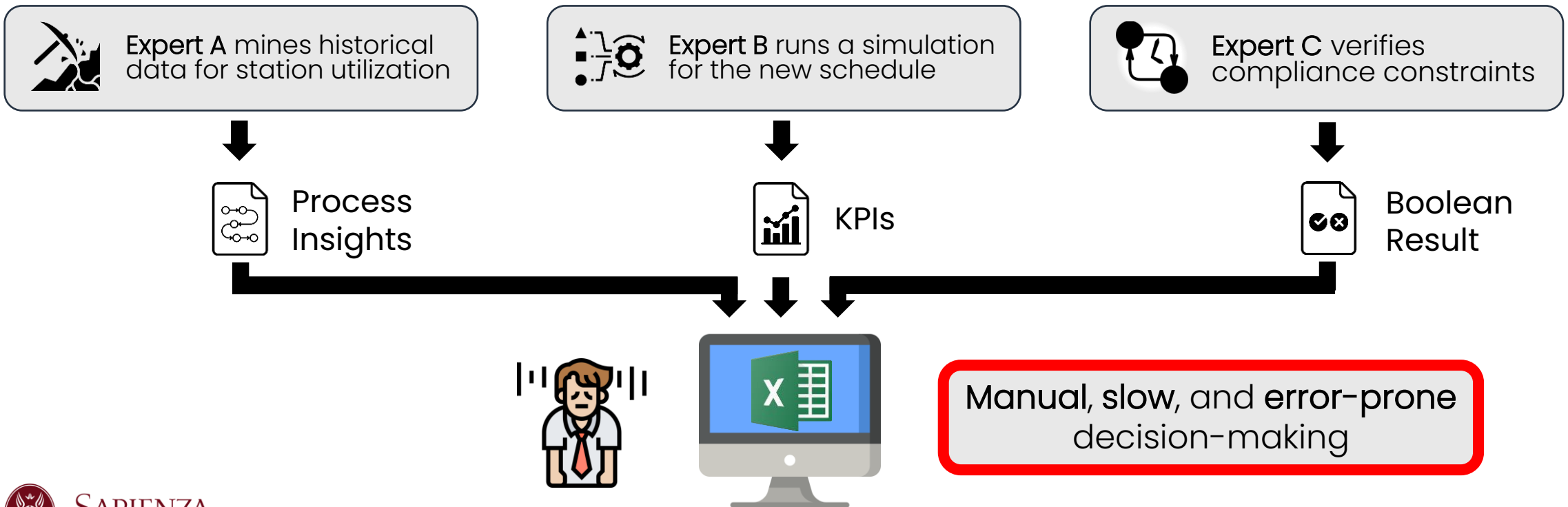
Keskin, Z., Joosten, D., Klasen, N., Huber, M., et al.: LLM Enhanced Human–Machine Interaction for Adaptive Decision-Making in Dynamic Manufacturing Process Environments, IEEE Access 13 (2025)
Frigerio, N., Tan, B., Matta, A.: Simultaneous control of multiple machines for energy efficiency: a simulation-based approach, Int. J. Prod. Res. 62 (3) (2024)
Agostinelli, S., Benvenuti, D., Casciani, A., De Luzi, F., Marinacci, M., Marrella, A., Rossi, J.: A Context-Aware Framework to Support Decision-Making in Production Planning. In: CAiSE 2024 (2024)

MULTI-PERSPECTIVE ANALYSIS

Manual Integration is required!

➤ User → Manual interaction with multiple tools → Manual integration of the results

Example: A massive new order arrives.



WHY NOT JUST USE LLMS?

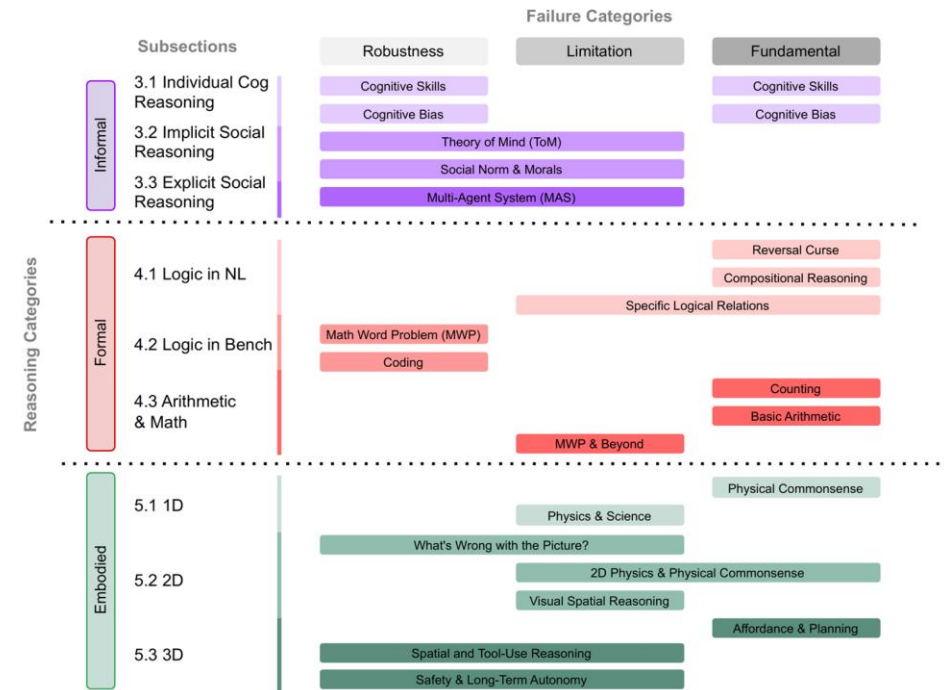
LLMs are probabilistic retrievers, not inference engines

- Models do not “plan” but perform approximate retrieval of plan heuristics
- Effectiveness **declines** when questions are **paraphrased**
- **Chain-of-Thought** traces are learned structural patterns. Answers may follow flawed/incorrect “reasoning” traces
- LLMs **lack self-verification** mechanisms

Hallucinated downtime or safety property in CPPSs



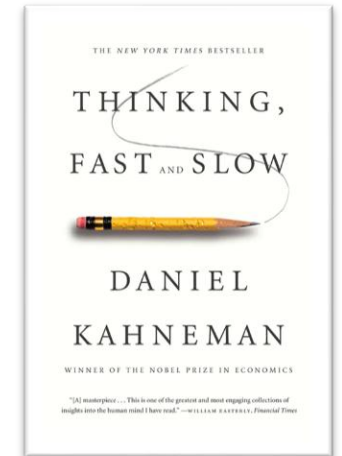
Unacceptable!



Kambhampati, S., Valmeekam, K., Guan, L., Verma, M., et al.: Position: LLMs Can't Plan, But Can Help Planning in LLM-Modulo Frameworks, ICML 2024 (2024)
Lunardi, R., Mea, V. D., Mizzaro, S., Roitero, K.: On Robustness and Reliability of Benchmark-based Evaluation of LLMs. ECAI 2025 (2025)
Stechly, K., Valmeekam, K., Kambhampati, S.: On the Self-Verification Limitations of Large Language Models on Reasoning and Planning Tasks, ICLR 2025 (2025)
Song, P., Han, P., Goodman, N.: Large Language Model Reasoning Failures, Trans. Mach. Learn. Res. (2026)

NEURO-SYMBOLIC INTELLIGENCE

SYSTEM 1	SYSTEM 2
<i>Fast, intuitive, data-driven</i>	<i>Slow, deliberative, reason-based</i>
• Good at learning, poor at reasoning • Data-hungry • Uninterpretable • Prone to hallucinations • Scalable • Grounded in language use	• Good at reasoning, poor at learning • Data-efficient • Interpretable • Hallucination-free • Hand-crafted • Grounded in facts
Generative AI	Symbolic AI

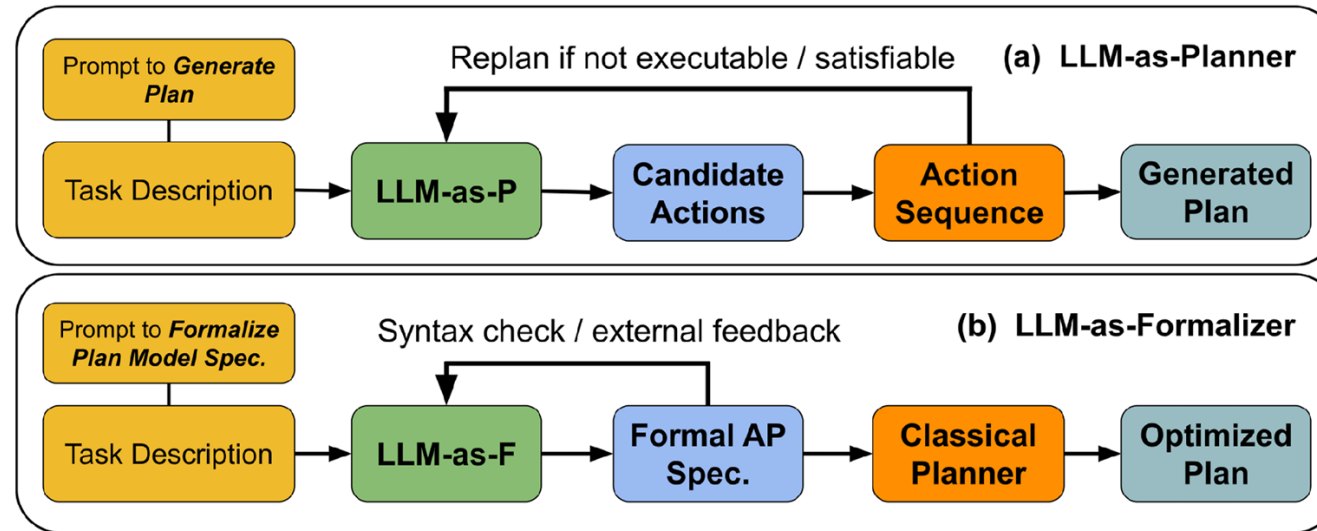


Kahneman, D.: Thinking, fast and slow. Penguin (2012)

The human mind combines **both**.

If we can figure out how to combine the best of both worlds, we can create a conversational system that is **interpretable, verifiable**, yet **responsive to shop-floor data streams**.

LLM SHIFT: FROM SOLVER TO FORMALIZER

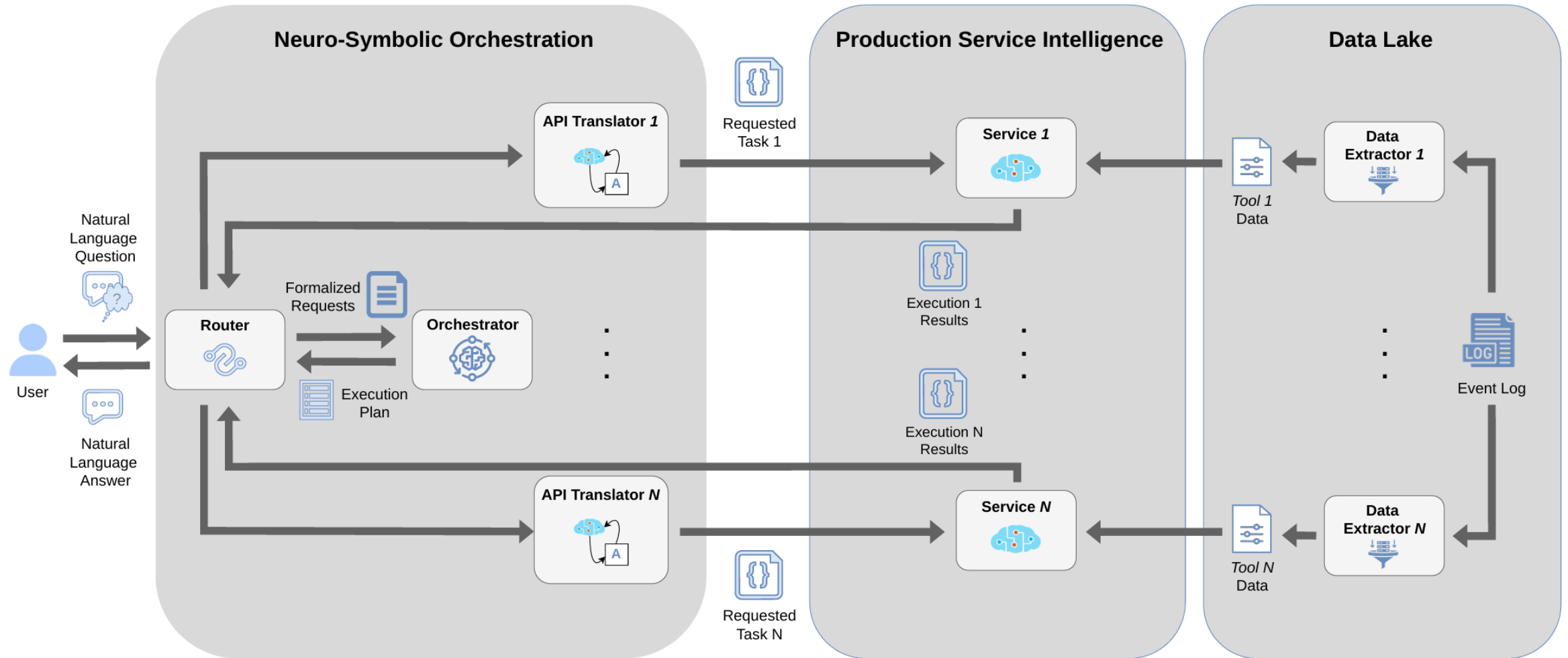


APPROACH	LLM-AS-PLANNER	LLM-AS-FORMALIZER
<i>Role</i>	Generates plan	Translates to PDDL
<i>Execution</i>	Direct	Delegated to symbolic planner
<i>Reliability</i>	Struggles	Sound



Tantakoun, M., Muise, C., Zhu, X.: LLMs as Planning Formalizers: A survey for leveraging Large Language Models to construct automated planning models. In: Findings of the ACL 2025. (2025)
 Stechly, K., Valmeekam, K., Kambhampati, S.: On the self-verification limitations of Large Language Models on reasoning and planning tasks. In: ICLR 2025 (2025)

NEURO-SYMBOLIC ARCHITECTURE FOR SERVICE ORCHESTRATION

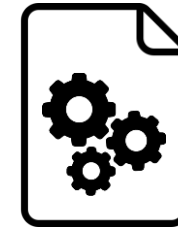


SIMULATION AS A SERVICE

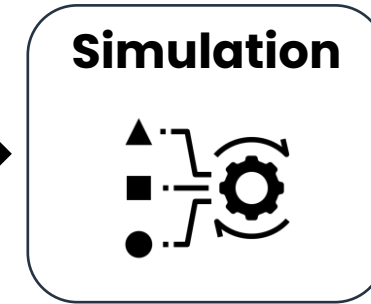
- *What-if* analysis without disrupting operations
- Implementation: SimPy

Matloff, N.: Introduction to Discrete-Event Simulation and the SimPy Language, University of California at Davis. 2 (2009)
Zhang, L., Zhou, L., Ren, L., Laili, Y.: Modeling and simulation in intelligent manufacturing. Computers in Industry 112, (2019)

Digital Twin



Scenario



KPIs

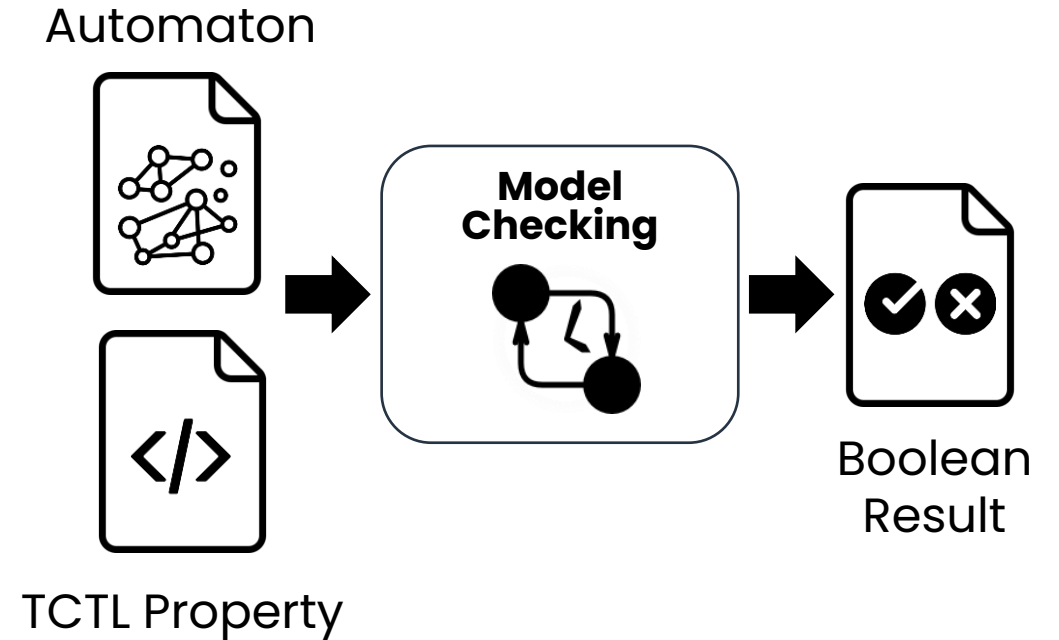
Use Case

*"As a **production manager**, I want to establish a performance baseline and assess the impact of a machine breakdown so that I can plan the production."*

MODEL CHECKING AS A SERVICE

- Safety guarantees via model checking
- Implementation: UPPAAL

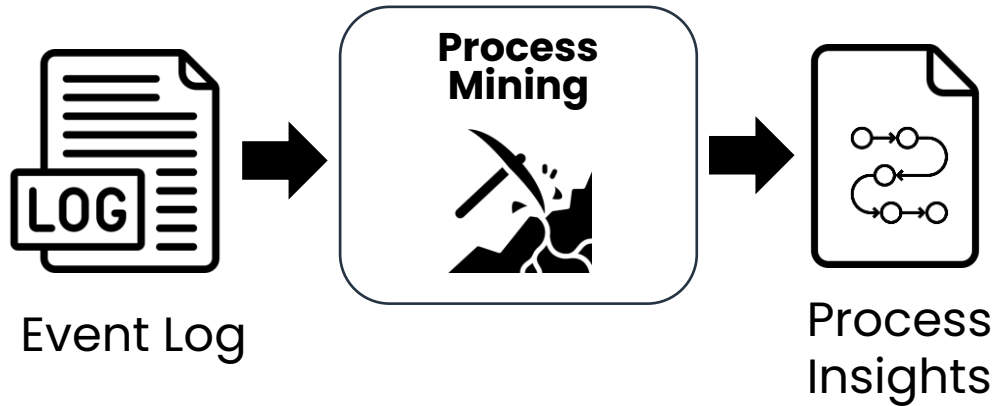
Larsen, K.G., Pettersson, P., Yi, W.: UPPAAL in a nutshell. Int. J. Softw. Tools Technol. Transf. 1 (1997)



Use Case

*“As a **safety engineer**, I want to understand the automaton semantics, verify global safety, and check temporal behaviors so that I can audit the production system.”*

PROCESS MINING AS A SERVICE



Process Intelligence Solutions. [PM4Py](#). Web. Jun, 2026

- Operates on **event logs** from shop floor
- Implementation: PM4Py

Tasks:

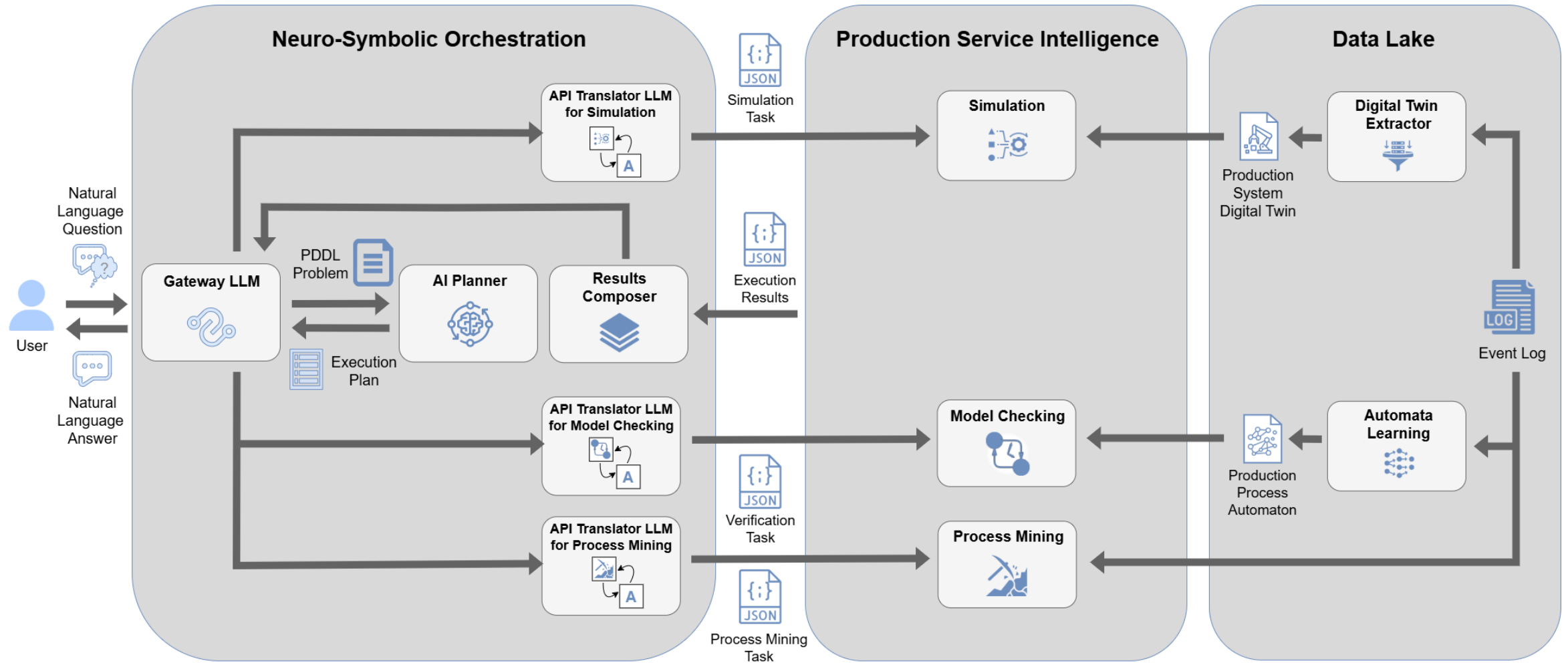
- Process Discovery → Petri Net
- Conformance Checking → Deviations
- Time Filtering → Filtered Event Log
- Performance Analysis → KPIs, Variants

Use Case

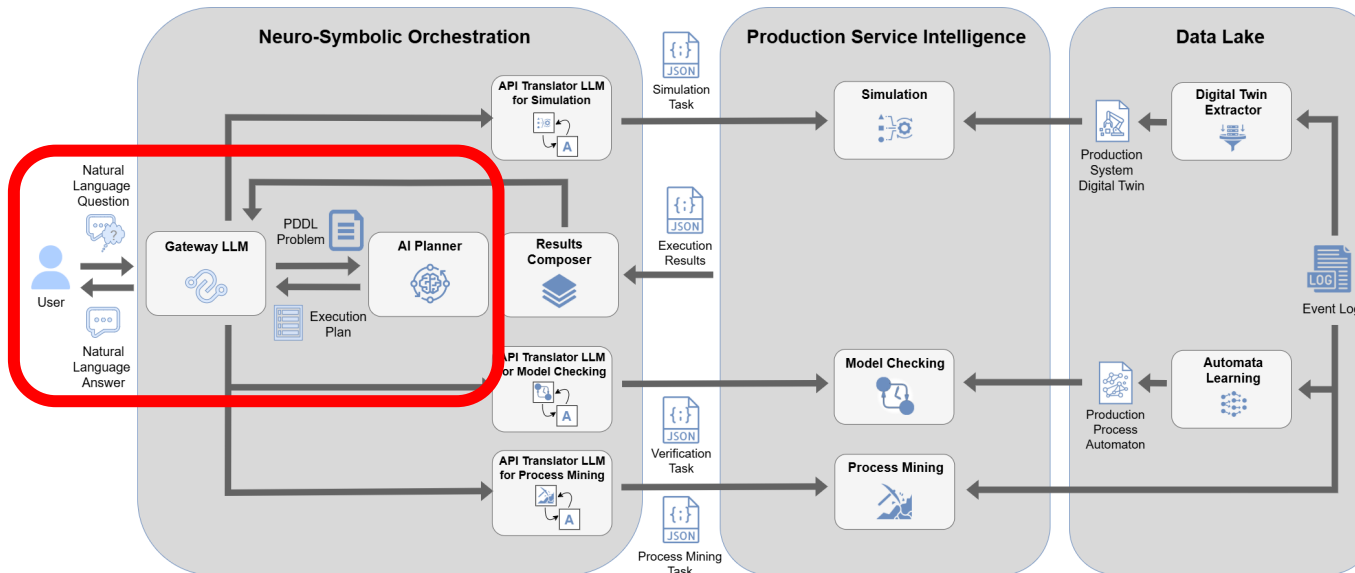
*“As a **process analyst**, I want to discover the Petri net from the event log and check if reality matches the model so that I can analyze historical executions.”*

INSTANTIATION

GitHub



INTENT ROUTING AND SERVICE COMPOSITION VIA PLANNING



Intent Routing:

- Analyzes textual query → identifies intents

Routing logic:

- Single-service → Direct to Translator
- Multi-perspective → Forward to Orchestrator

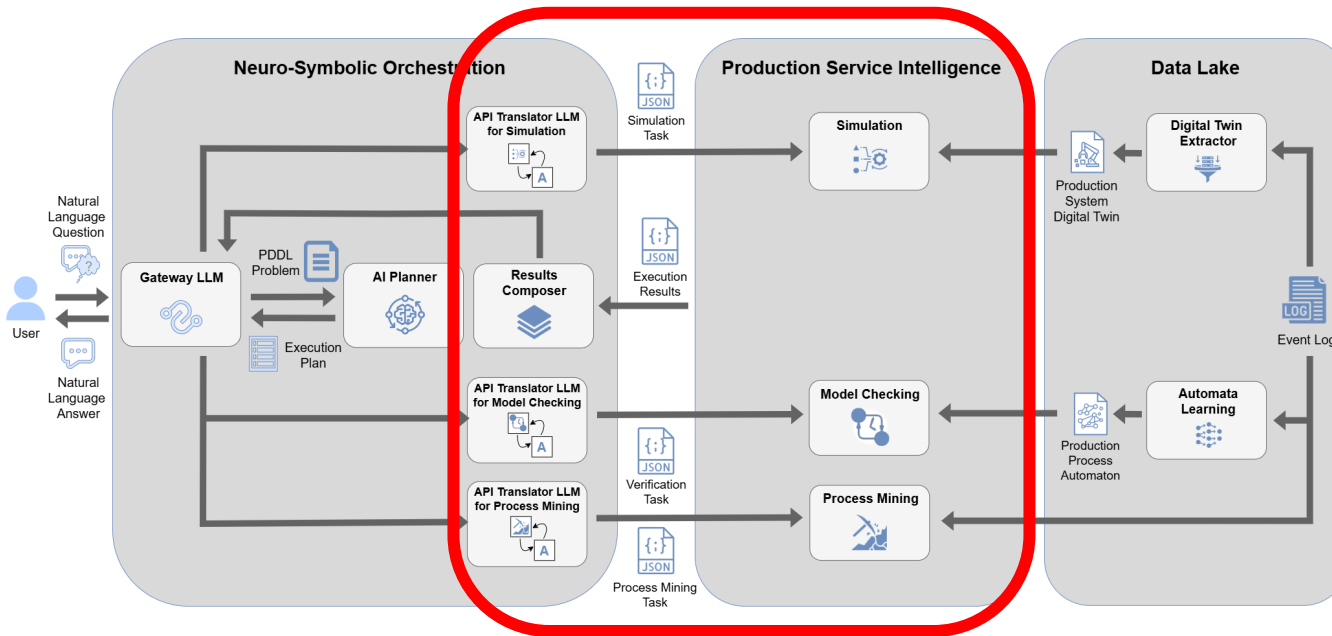
Orchestration:

- LLM translates intents in PDDL goals
- Planner (Fast Downward) → sound plan

Why not let LLM plan?

- Prevent hallucinations in service composition

API TRANSLATION & RESPONSE



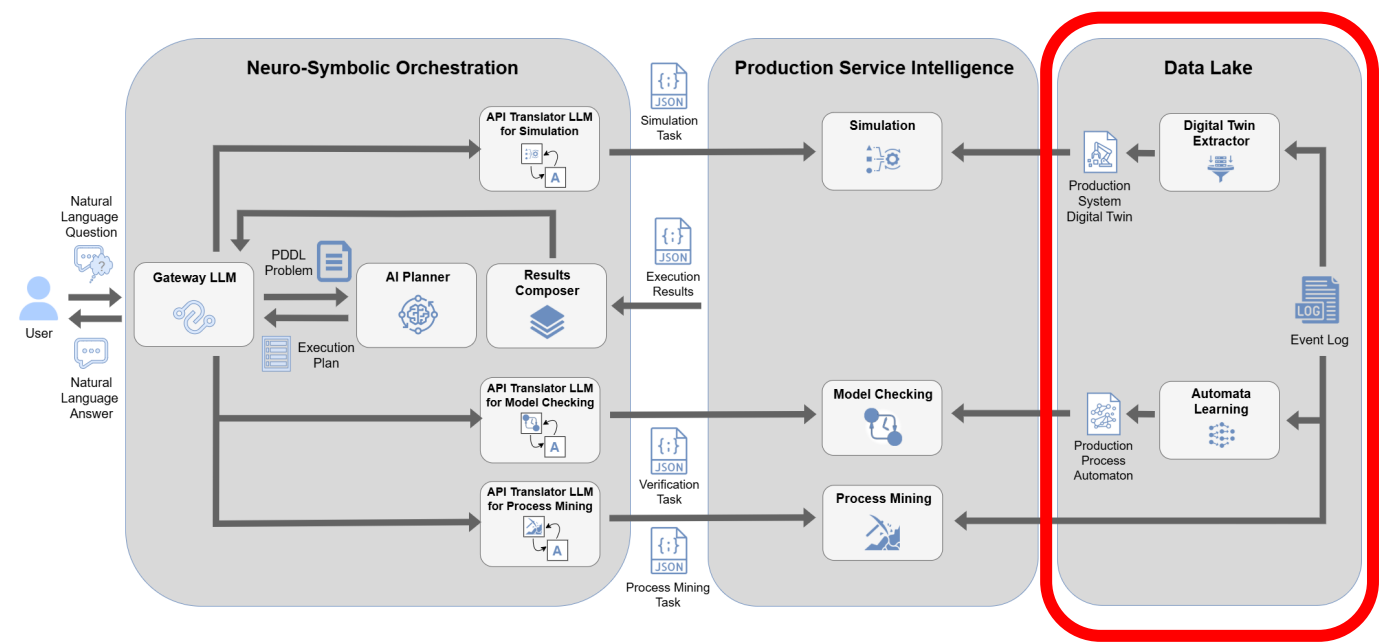
- Specialized translator LLM for each PSI tool (avoids interference)
- Planned actions → Encoded JSON payload → Service execution → Result

Soundness Guarantee

- Computation occurs outside LLMs
→ Reliable results

Gupta, A., Sheth, I., Raina, V., Gales, M.J.F., Fritz, M.: LLM task interference: An initial study on the impact of task-switch in conversational history. In: Proc. of the Conf. on Empirical Methods in NLP, EMNLP 2024. ACL (2024)

DATA LAKE

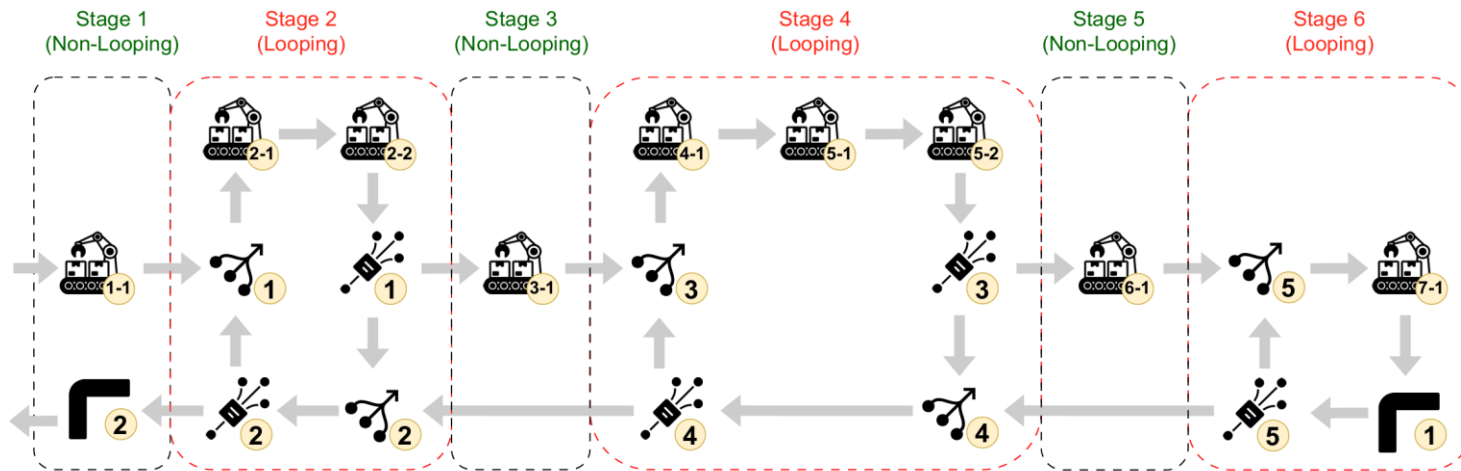
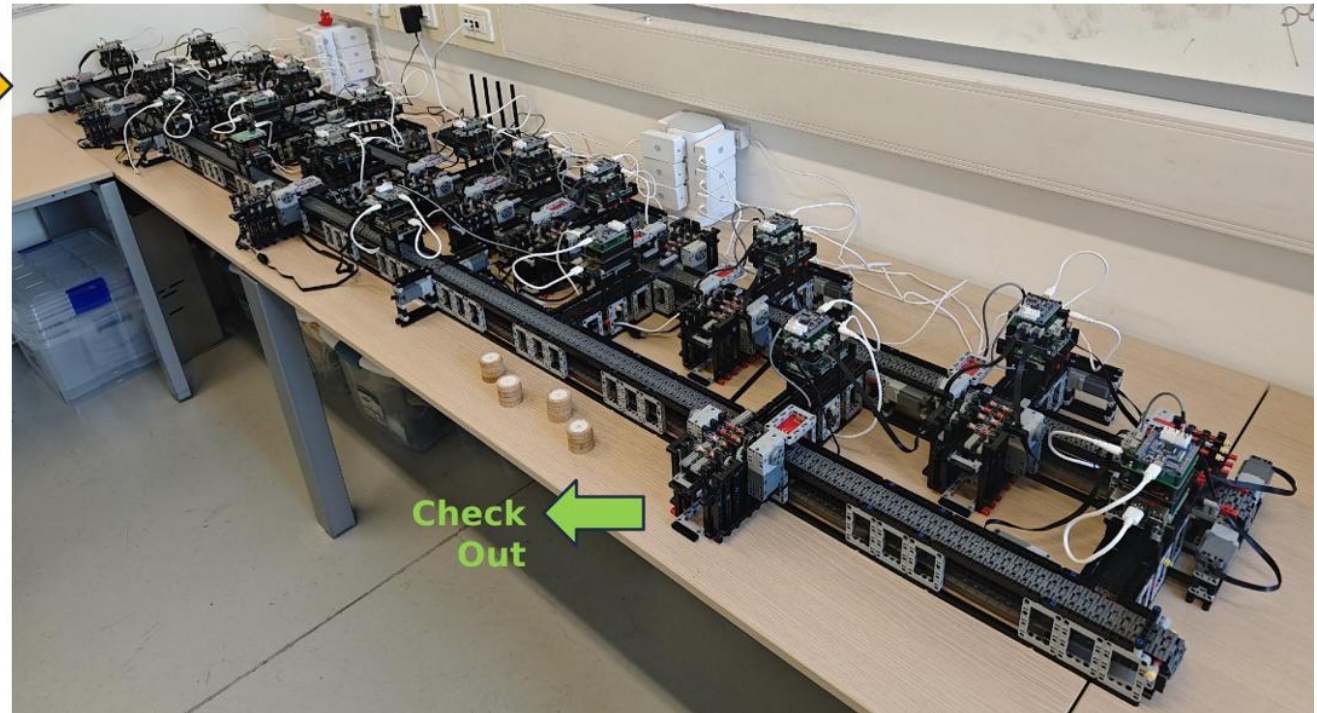


- Event log from shop-floor sensors
- Automated models extraction (no manual modeling)

EXTRACTOR	OUTPUT	USED BY
Digital Twin	Scenario Parameters	Simulation
Automata Learning	Probabilistic Timed Automaton	Model Checking
-	Raw Event Log	Process Mining

CASE STUDY: LEGO FACTORY

Check In →



MOTOWN: http://www.open.diag.uniroma1.it/project_detail/28097.
Web. Jul, 2026

PRELIMINARY EVALUATION SETUP

Dataset Composition



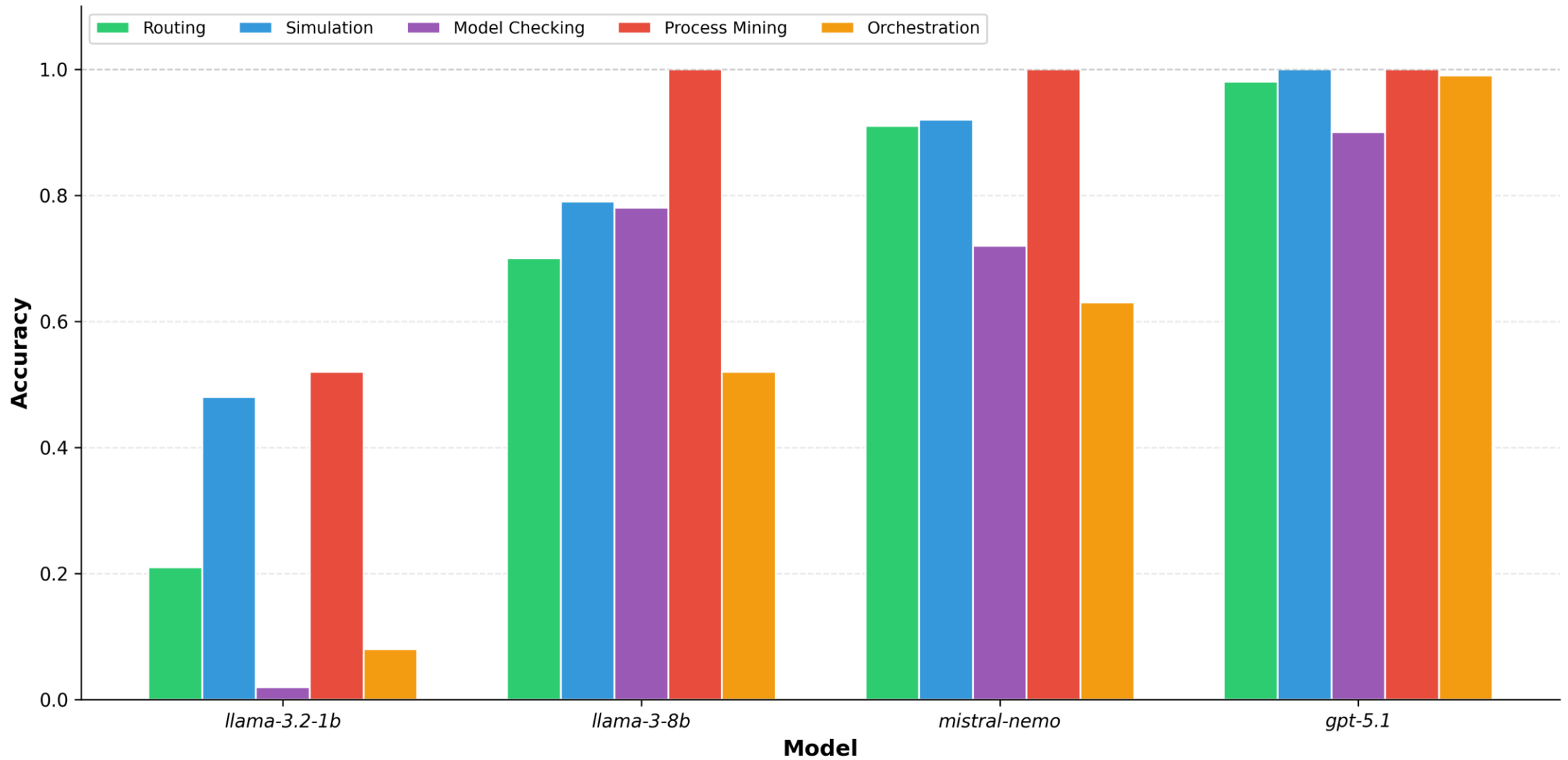
- 1.5k <natural-language request, expected answer> pairs (300 samples/task)
- Five tasks:
 - *routing* of a request; and
 - *API translation* for *simulation*, *model checking*, *process mining*, and *multi-perspective orchestration*.

Performance Metric



- We measured **accuracy** ($\text{\#correct LLM-generated outputs} / \text{\#questions}$)
 - For routing: **correct** if answer includes expected service label
 - For API translations: **correct** if answer is a valid JSON that matches syntax and parameters for the target service

RESULTS



THREATS TO VALIDITY



Internal Validity

LLM Stochasticity

- *Temperature = 0*
- *Performed 5 runs/test*

Prompt Quality

- *In-context learning*
- *Few-shot prompting*



External Validity

Domain Bias

- Domain-independent architecture

Model Diversity

- Benchmarked 4 LLMs to avoid single-provider bias

Reproducibility

- Documented model versions against risks of commercial API updates/deprecation



Construct Validity

Metric Focus

- Accuracy used to validate encoding and orchestration

System Boundaries

- Utility is bounded by the capabilities of PSI layer

Data Grounding

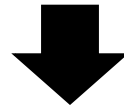
- Logical consistency is guaranteed
- Reliability of PSI results depends on data quality

CONCLUSION

A Conversational Methodology for Production Service Intelligence



- Introduced a domain-agnostic neuro-symbolic conversational AI framework for reliable, multi-perspective PSI on CPPSs.
- Transitioned LLMs from flawed PSI executors to flexible formalizers:
 - the LLM encodes and redirect;
 - the symbolic AI planner handle orchestration and services perform computations.



Future Work



- Fine-tuning to mitigate encoding hallucinations and streamline the modeling effort
- Evaluation with industrial practitioners
- Real-time IoT stream processing and state-aware service composition



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July 2nd, 2026

THANK YOU

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GitHub



About Me



SAPIENZA
UNIVERSITÀ DI ROMA