



A Step Towards Cognitive Automation

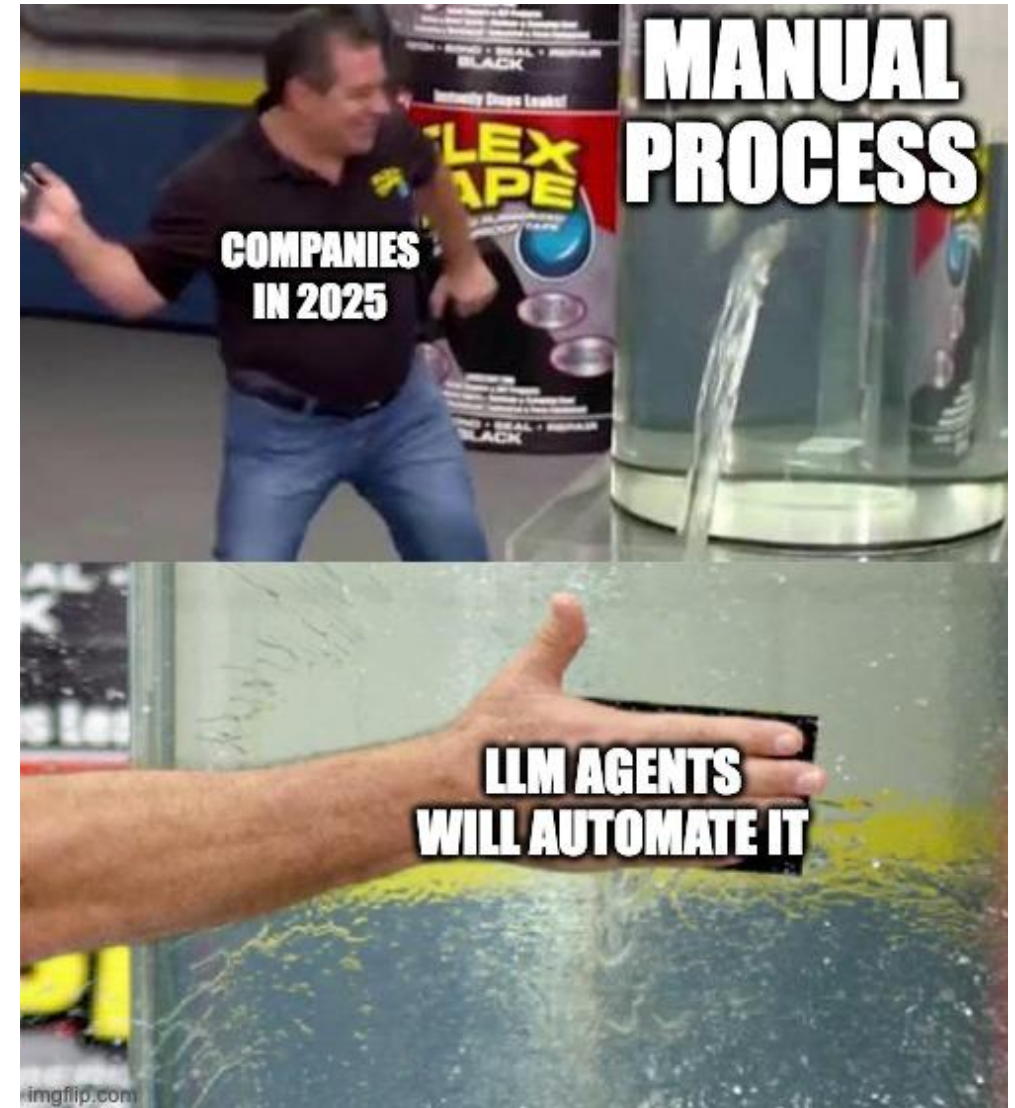
Integrating LLM Agents with Process Rules

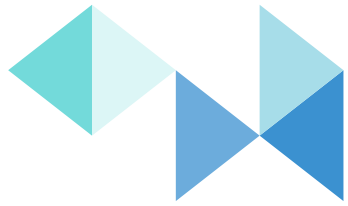
Sascha Kaltenpoth, Alexander Skolik, Oliver Müller and Daniel Beverungen



Motivation

1. Business Process Automation in 2025

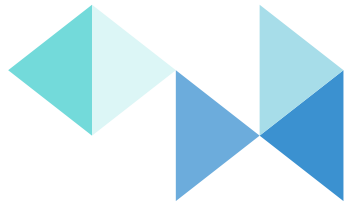




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2. The Goal of “Cognitive Automation”

- Traditional business process automation:
 - ✚ An important BPM core element^[27, 30]



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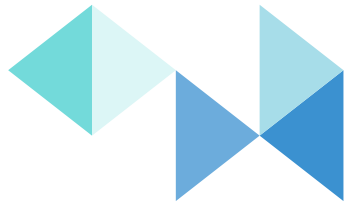
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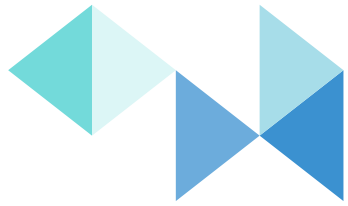
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 - ✚ Enables automation of less standardized and mid-frequently occurring processes^[24, 29]



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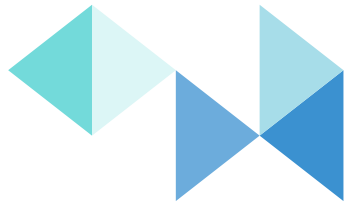
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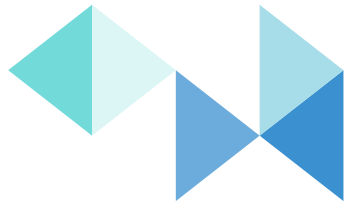
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 - ✚ Show advanced "cognitive" capabilities (e.g., reasoning, synthesis, summarization)^[11, 16, 22]



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 - ✚ Are multi-task or -process learners^[11, 16, 22]
- LLM agents are promising for automating complex processes with unstructured data: “cognitive automation”^[7]



Motivation

3. LLM agents and their stochastic nature

- LLM agents:
 - ✚ Support multi-process automation of “cognitive” processes (e.g., reasoning, synthesis)^[11, 16, 22]





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 - ✚ Their stochastic nature possibly leads to deviations from the predefined process^[11,16,33]





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→ LLM agents need to align with the process and **additionally support repeatability** like RPA





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- LLM agents need to **still support adaptability** to novel, unexpected user requests





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Therefore:

- LLM agents need to align with the process and **additionally support repeatability** like RPA
- LLM agents need to **still support adaptability** to novel, unexpected user requests
- LLM agents need to **also integrate existing automation** approaches (e.g., RPA, low-/no-code)



Motivation

„RPA is the body and AI is the brain“^[22]



Related Work

LLM agent-based automation approaches

- Support UI and API operations like RPA^[10, 13, 16, 37]

Framework	Input	Approach	Process Re- presentation	UI / Input operators	API / Service operators	Cognition / Reasoning	Goal	Source
LLMPA	Text Description	Prompting, Object Detection	Instruction Chain	X		X	RPA	[10]
SmartFlow	Text Description	Prompting, OCR	Workflow	X			RPA	[13]
ProAgent	Text Description	ReAct, Code Generation	Workflow, Dataflow	X	X	X	BPA	[37]
NL2ProcessOps	Text Description	RAG, Code Generation	Mermaid.js, Code	X	X	X	BPA	[16]
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- Support UI and API operations like RPA^[10, 13, 16, 37]
- „Cognitive“ decision making^[10, 16, 37]
- Approaches to align with the process^[10, 13, 16, 37]
- Structured process representations to improve process alignment^[10, 13, 16, 37]





Related Work

LLM agent-based automation approaches

- No comparison of structured and unstructured process representations

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- No comparison of structured and unstructured process representations
- No experimental analysis regarding:
 - Repeatability support against the stochastic nature of LLMs
 while simultaneously ensuring
 - Adaptability support for novel, unexpected requests



Research Question

How can LLM agents be leveraged to effectively **adapt to novel processes** and simultaneously **align with existing, repetitive processes** as a **step towards cognitive automation?**



Research Design

A 2x2 Evaluation of LLM agent-based automation

1. Generate process descriptions:
 - Unstructured descriptions: text descriptions
 - Structured process descriptions: „Process Rules“





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2x2 Evaluation	Repeatability (repetitive, known processes)	Adaptability (novel, unexpected processes)
	Handling SAP errors with text input	Fulfilling user requests with text inputs
Text descriptions (unstructured descriptions)		
Process Rules (structured descriptions)	Handling SAP errors with process rules	Fulfilling user requests with process rules



Research Design

0.1 The Repeatability Use Cases – Handling SAP IDoc Errors

- An energy grid provider with mid-frequently occurring SAP IDoc^{*1}-errors sent from an external storage system





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→ RPA may be inefficient (complex to automate, automation for every error)
- After handling the first error, the solution of this error is known
→ An LLM agent needs support repeatability of same (error solving) process

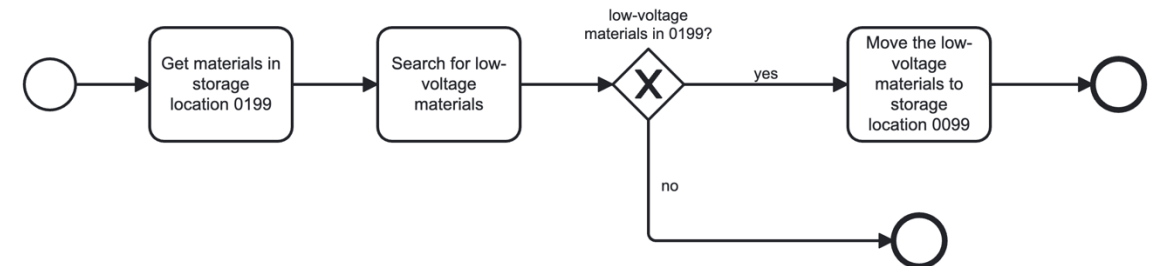




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0.2 The Adaptability Use Case – Fulfilling User Requests

- Same energy grid provider has other “cognitive” processes such as inventory audit

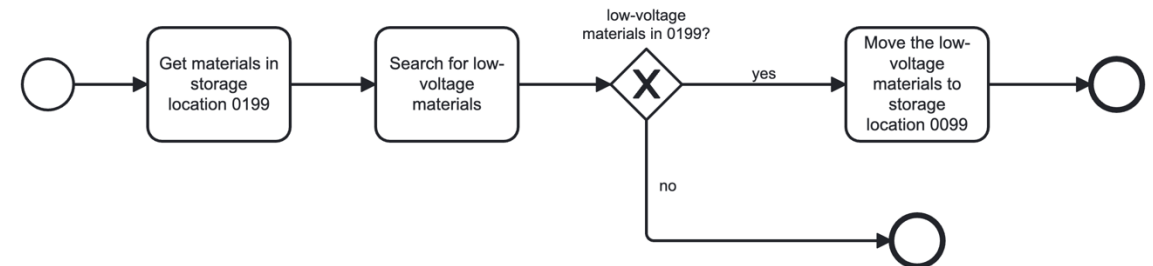




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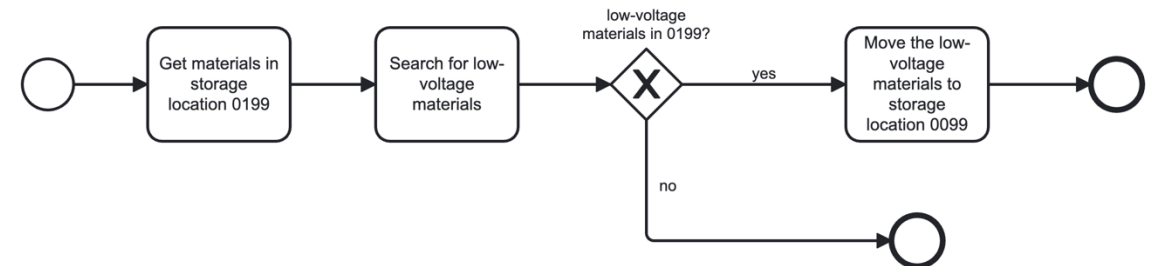
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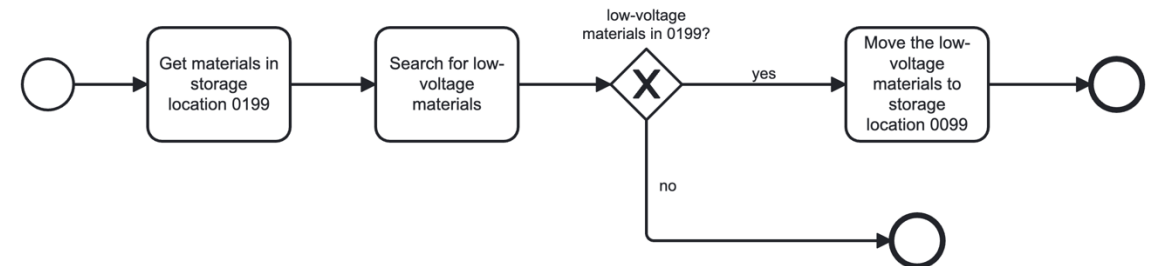
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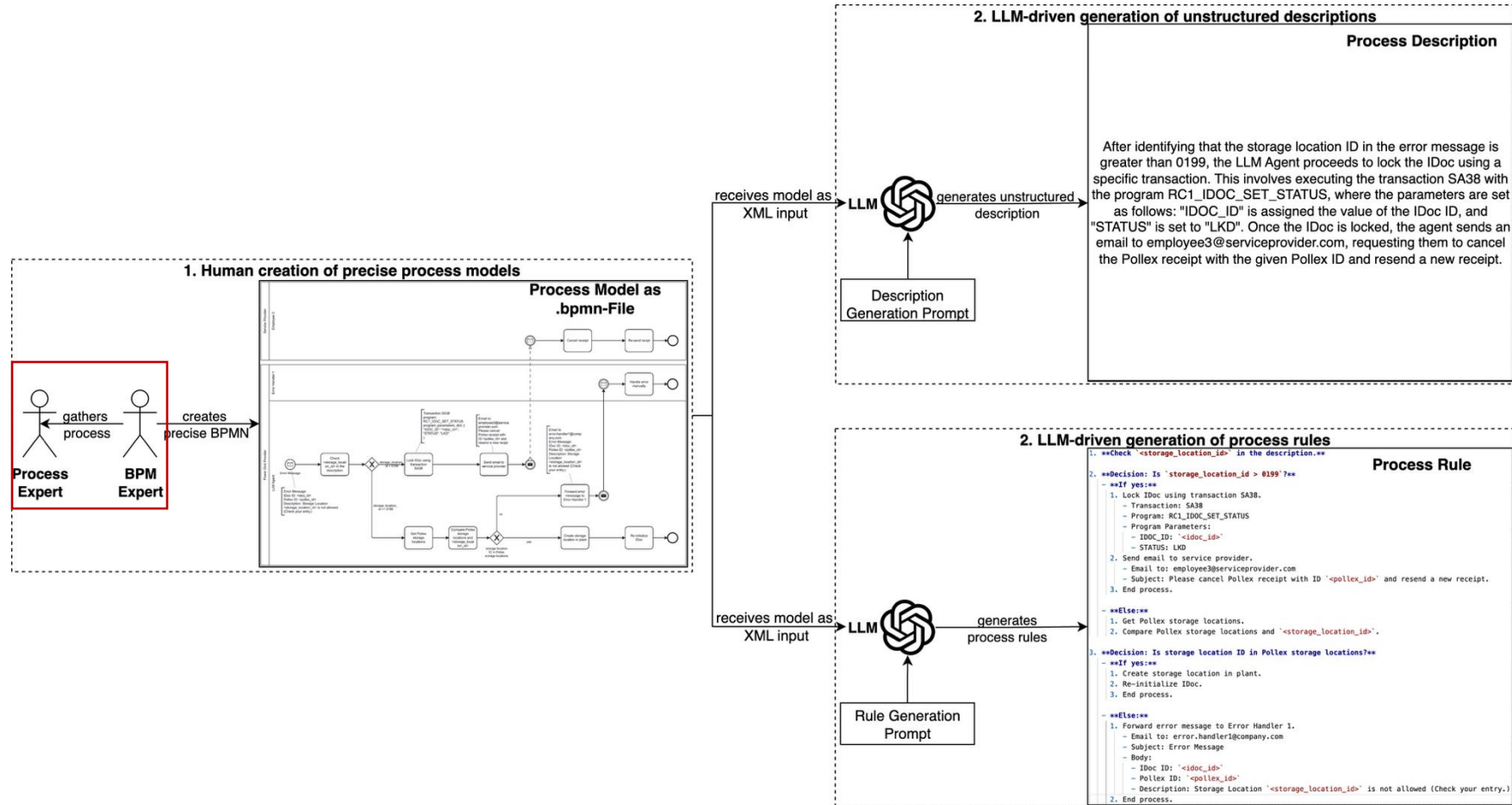
- These processes are not repetitive but novel and unexpected
- The LLM agent needs to be adaptive to completely novel, unknown requests





Research Design

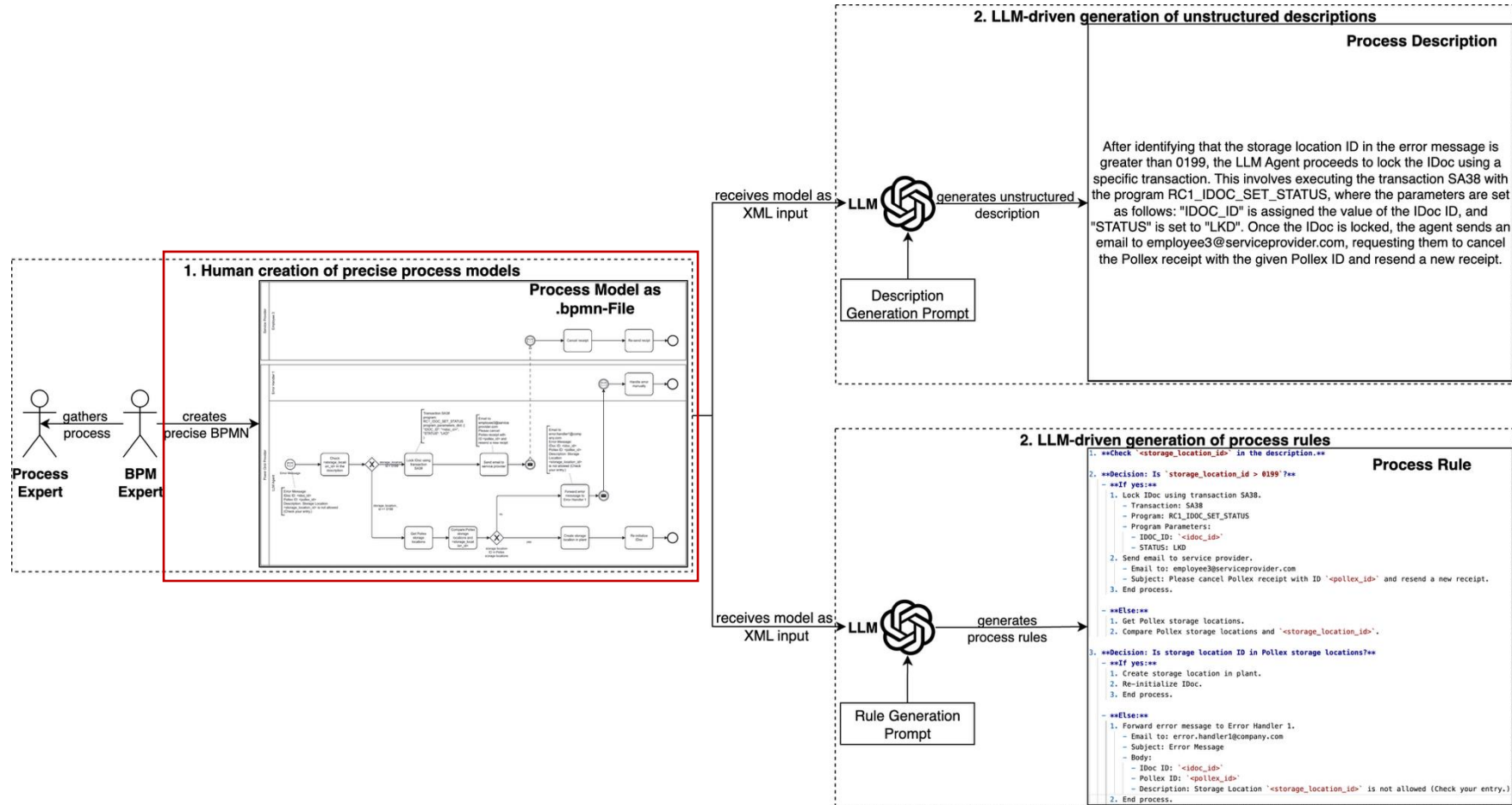
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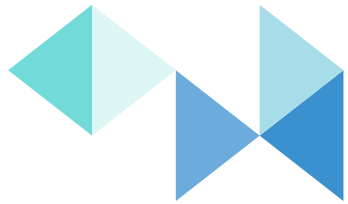




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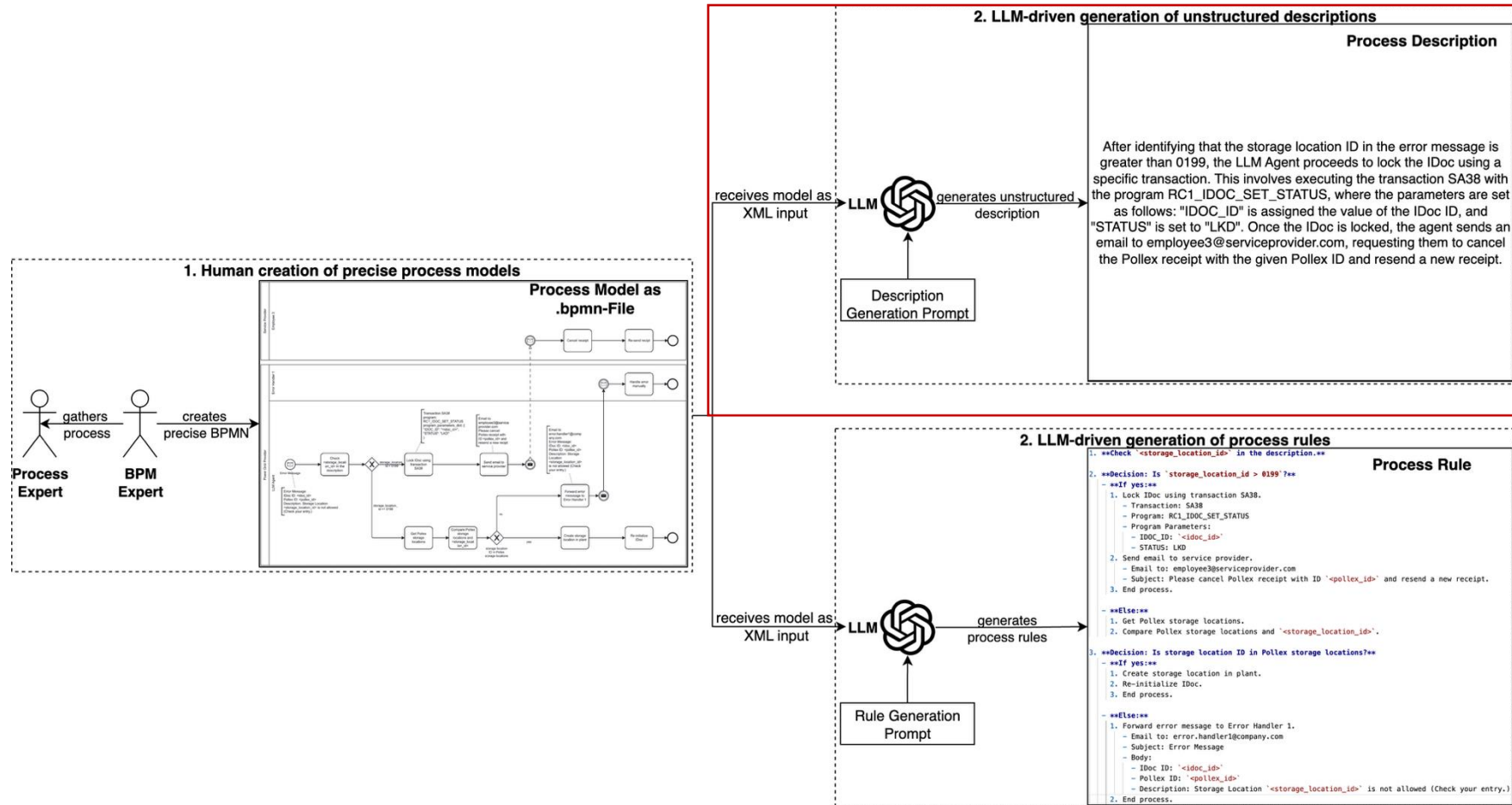
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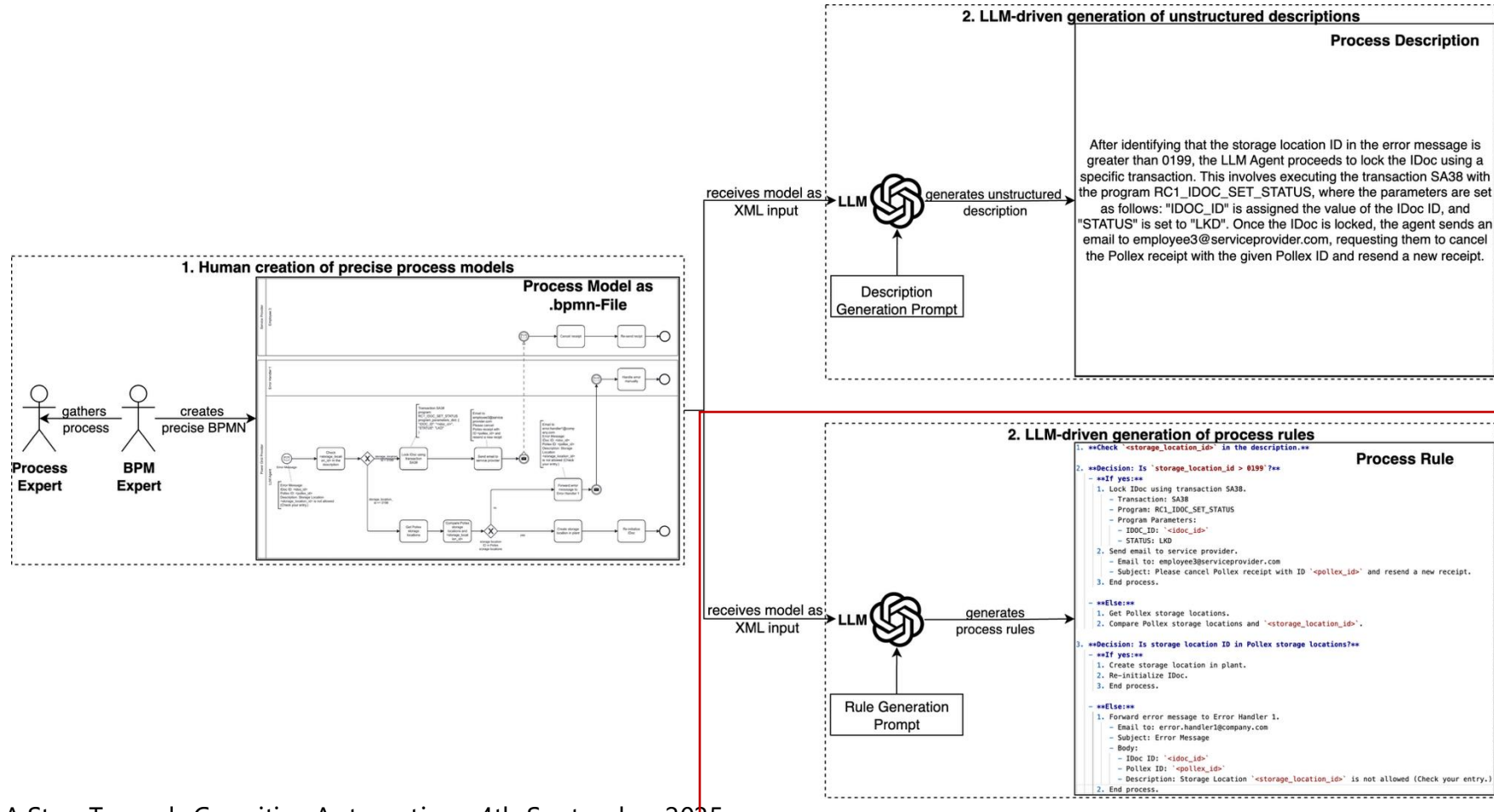
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Research Design

1. Generating Process Descriptions – Unstructured vs Structured Descriptions



Research Design

1. Generating Process

```

1. **Check `<storage_location_id>` in the description.**

2. **Decision: Is `storage_location_id` > 0199? **
  - **If yes:**
    1. Lock IDoc using transaction SA38.
      - Transaction: SA38
      - Program: RC1_IDOC_SET_STATUS
      - Program Parameters:
        - IDOC_ID: ``
        - STATUS: LKD
    2. Send email to service provider.
      - Email to: employee3@serviceprovider.com
      - Subject: Please cancel Pollex receipt with ID `` and resend a new receipt.
    3. End process.

  - **Else:**
    1. Get Pollex storage locations.
    2. Compare Pollex storage locations and ``.

3. **Decision: Is storage location ID in Pollex storage locations? **
  - **If yes:**
    1. Create storage location in plant.
    2. Re-initialize IDoc.
    3. End process.

  - **Else:**
    1. Forward error message to Error Handler 1.
      - Email to: error.handler1@company.com
      - Subject: Error Message
      - Body:
        - IDoc ID: ``
        - Pollex ID: ``
        - Description: Storage Location `` is not allowed (Check your entry.)
    2. End process.
  
```

Process
Expert

Rule Generation
Prompt

```

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      - Description: Storage Location `` is not allowed (Check your entry.)
  2. End process.
  
```

Structured descriptions

Process Description

The storage location ID in the error message is the LLM Agent proceeds to lock the IDoc using a transaction SA38 with the program RC1_IDOC_SET_STATUS, where the parameters are set ID" is assigned the value of the IDoc ID, and ID". Once the IDoc is locked, the agent sends an email to employee3@serviceprovider.com, requesting them to cancel the given Pollex ID and resend a new receipt.

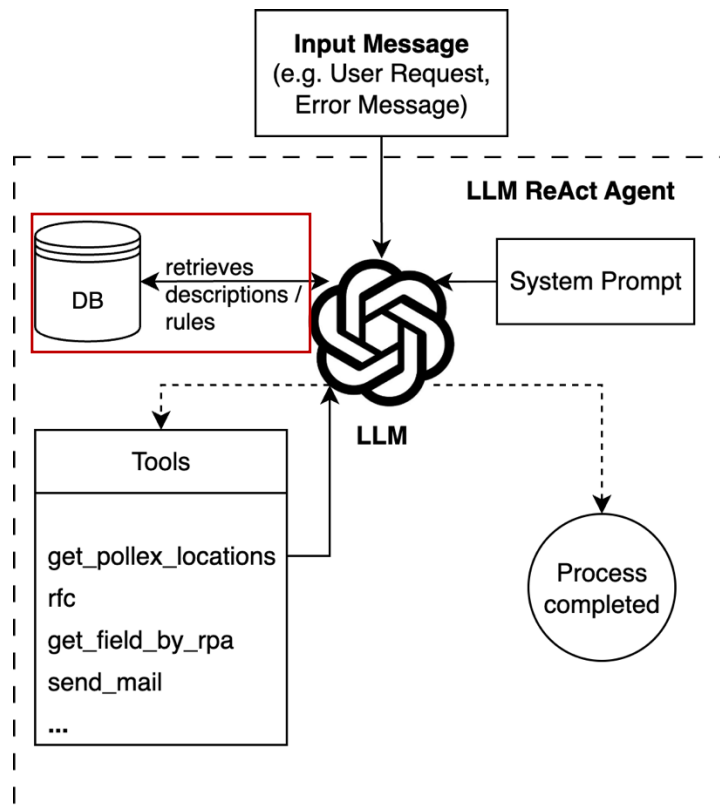
Process Rule

serviceprovider.com
Pollex receipt with ID `` and resend a new receipt.
locations and ``.
Is ID in Pollex storage locations? **
in plant.



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2. Implementing the LLM Agent – A Reason-and-Act Approach



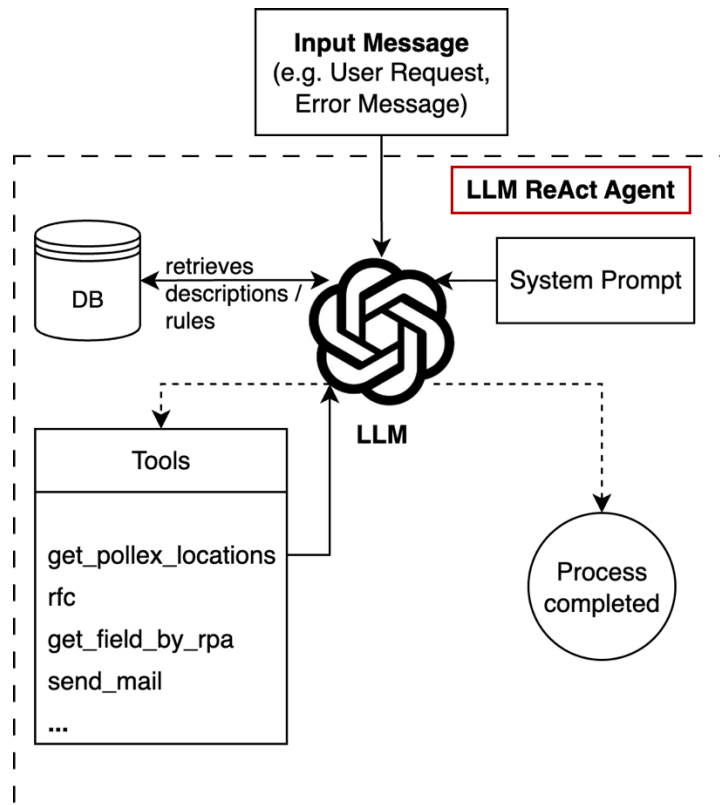
- **DB:** Database, returns the solution to the most similar error message when called (repeatability)





Research Design

2. Implementing the LLM Agent – A Reason-and-Act Approach

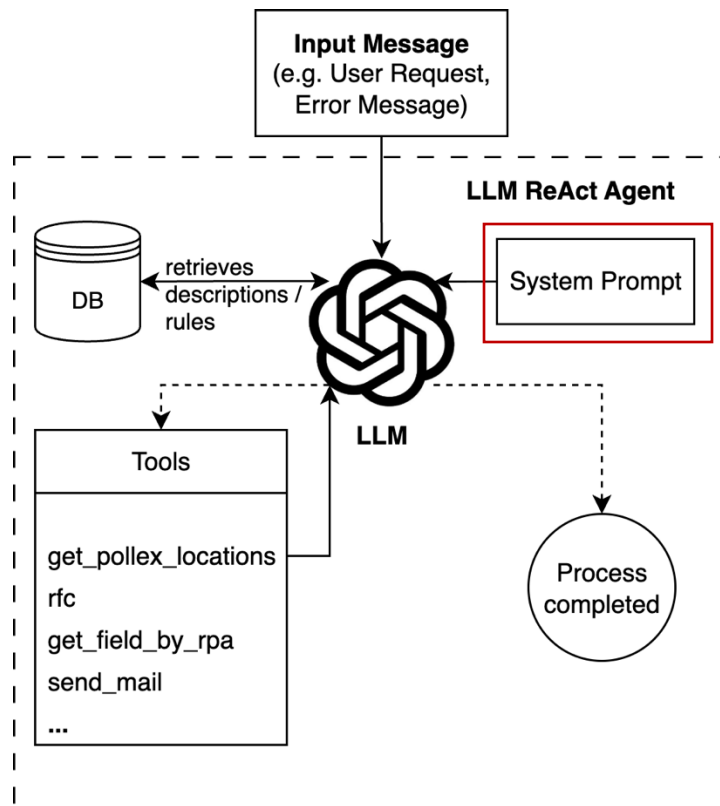


- **DB:** Database, returns the solution to the most similar error message when called (repeatability)
- **ReAct:** Agent receives input and iteratively thinks, acts, and observes using tools (adaptability)
- **Tool:** Function callable by LLM agent using a text command, returns response in text form



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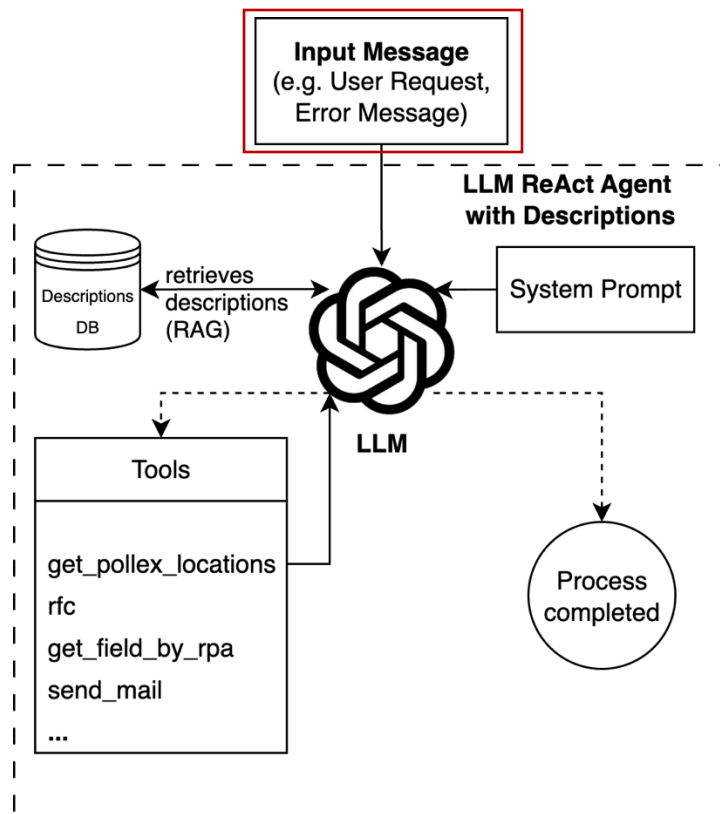
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- **Tool:** Function callable by LLM agent using a text command, returns response in text form
- **System prompt:** Description of agent's behavior



Research Design

2. Implementing the LLM Agent – The System Prompt – Unstructured Descriptions

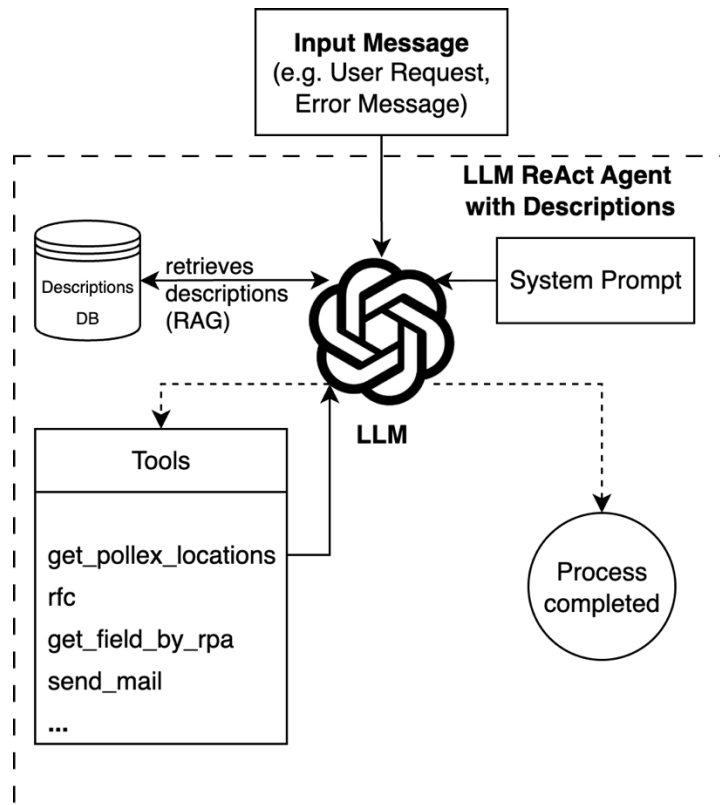
1. Agent receives error message or user request





Research Design

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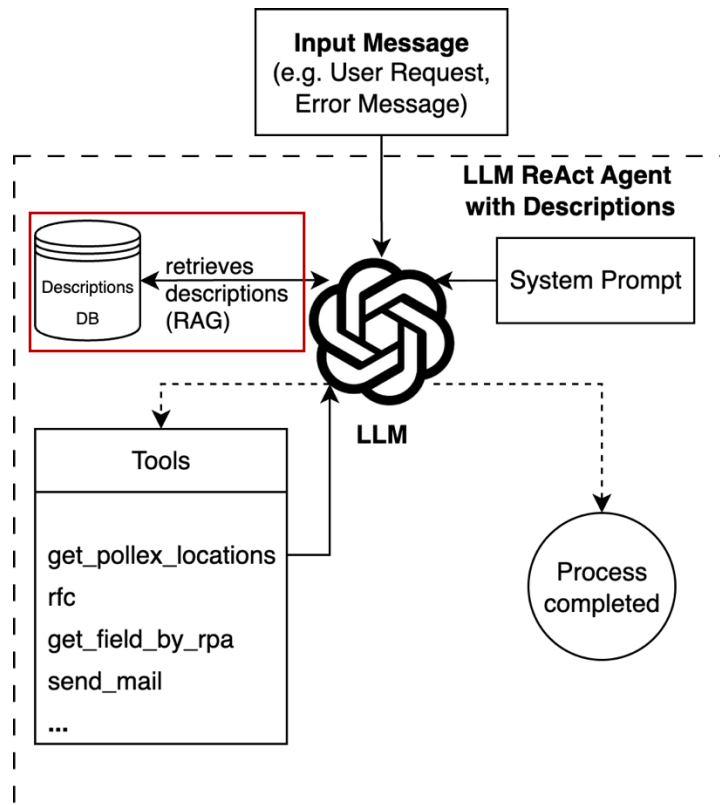
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2. Decision:





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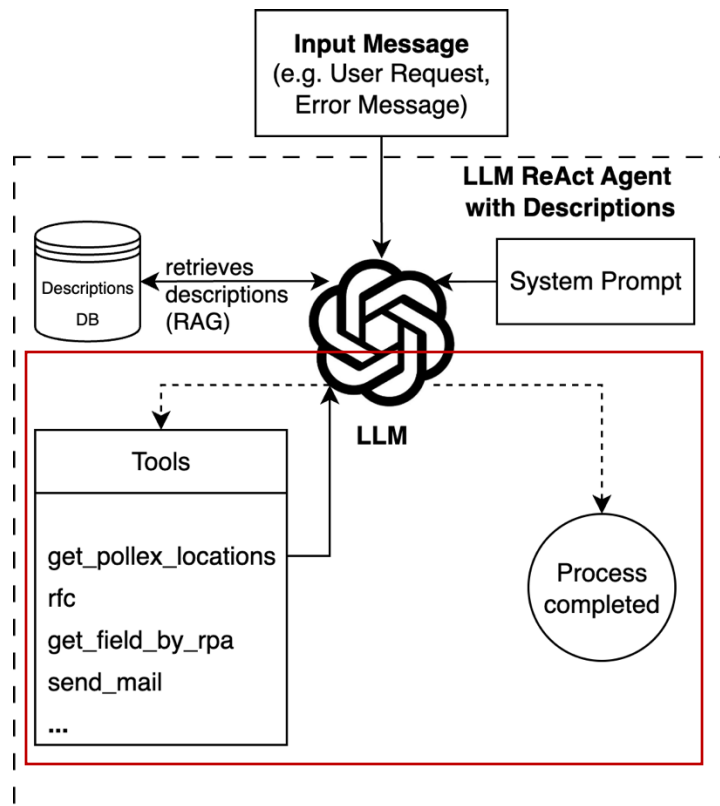
1. Agent receives error message or user request
2. Decision:
 - If error message
 - Agent retrieves the most similar description to the input message
 - Agent follows the description





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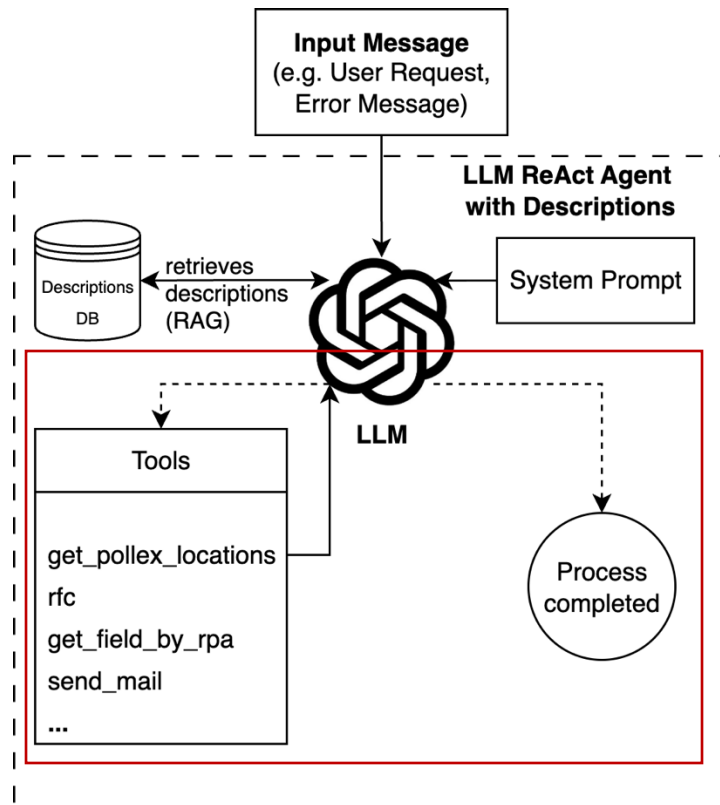
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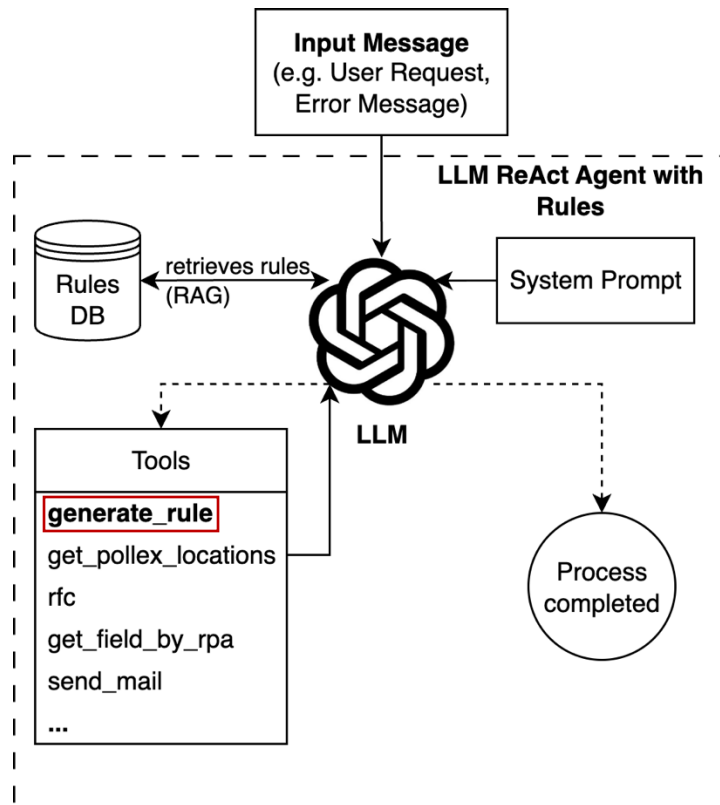
1. Agent receives error message or user request
2. Decision:
 - If error message
 - Agent retrieves the most similar description to the input message
 - Agent follows the description
 - Else (user request)
 - **Agent handles the request directly**





Research Design

2. Implementing the LLM Agent – The System Prompt – Process Rules



1. Agent receives error message or user request
2. Decision:
 - If error message
 - Agent retrieves the most similar rule to the input message
 - Agent follows the rule
 - Else (user request)
 - **Agent generates a rule ("generate_rule"-tool)**
 - **Agent follows the rule**



Research Design

3. Evaluating the LLM Agents' Repeatability vs Adaptability

Repeatability:

- Automatic evaluation of 119 Instances of 8 real-world processes with diverse characteristics
- Repeated 5 times with different seeds (robustness of repeatability)
- Calculation of economic outcomes (based on human work saved)

Adaptability:

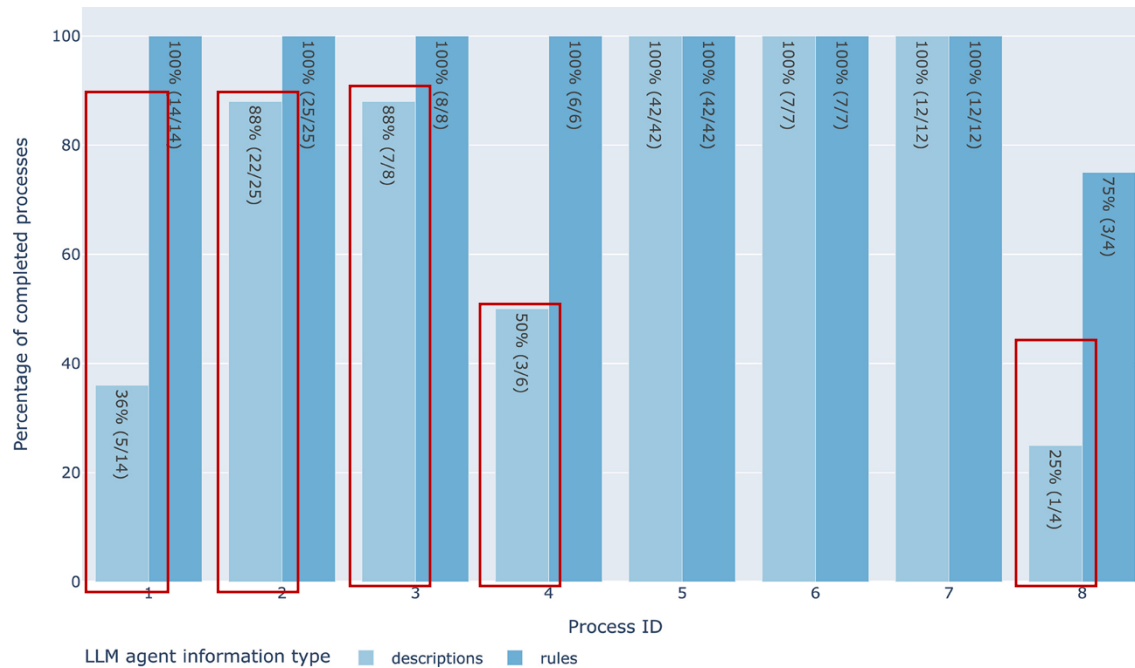
- Manual evaluation of 54 instances of 24 different synthetic processes
- Evaluated once (due to manual effort and existing work)
- 1-3 paths and 1-15 tasks (increasing complexity)





Results

The Repeatability Evaluation – Handling SAP IDoc Errors



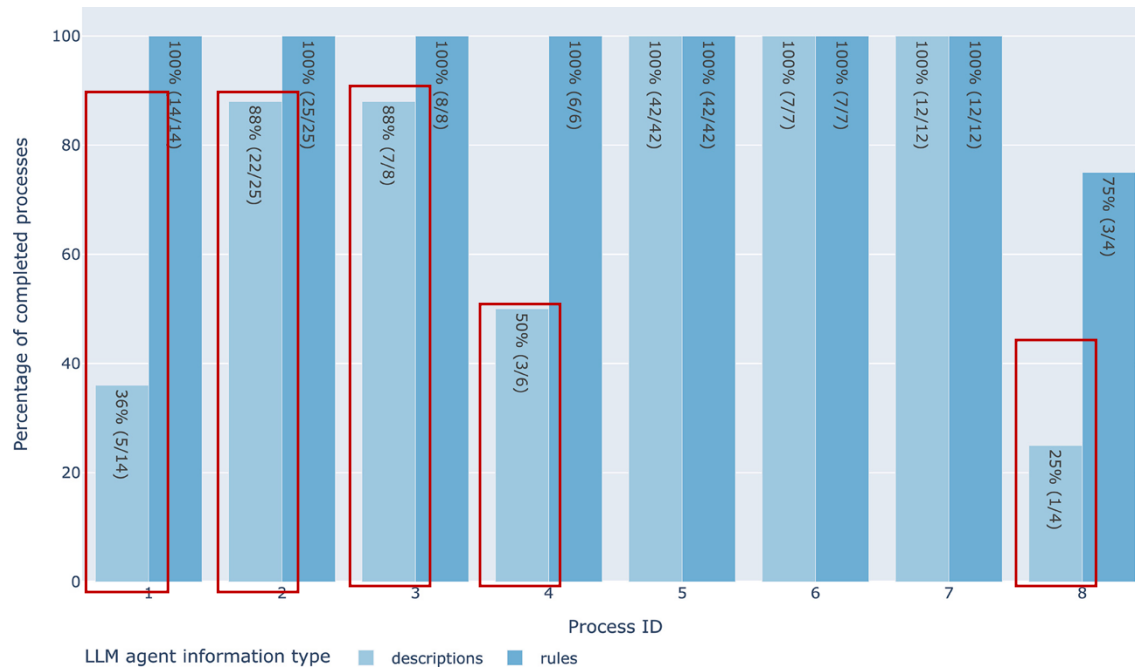
- LLM agent with descriptions cannot successfully complete all instances of processes 1, 2, 3, 4, and 8





Results

The Repeatability Evaluation – Handling SAP IDoc Errors



- LLM agent with descriptions cannot successfully complete all instances of processes 1, 2, 3, 4, and 8

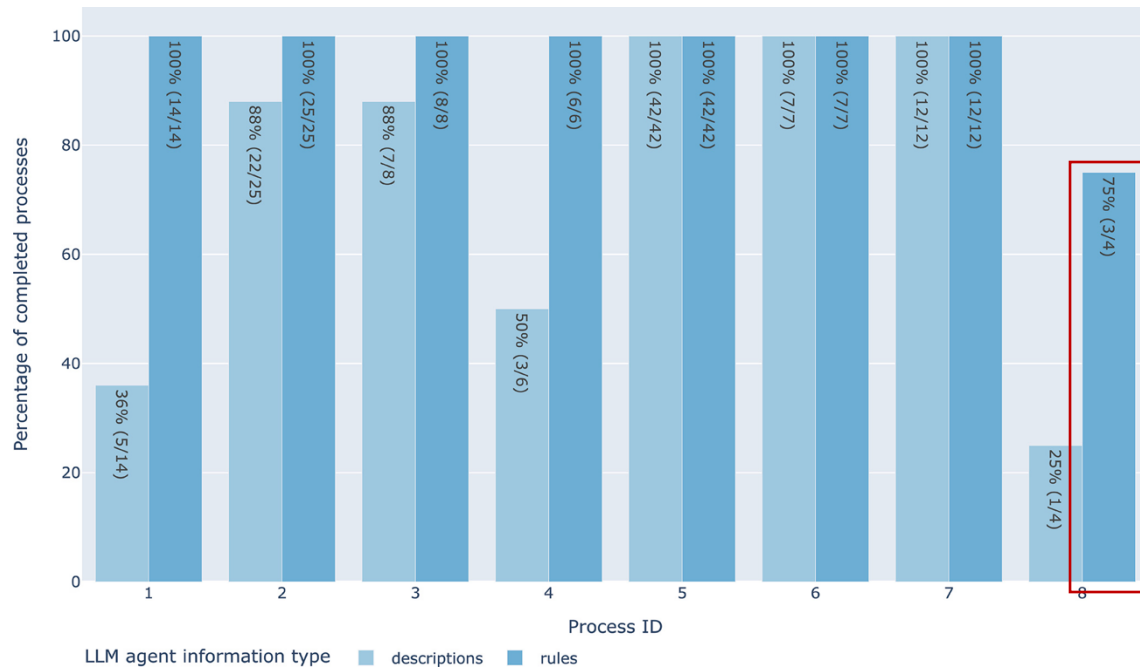
→ LLM agent with descriptions „forgets“ or skips steps and overlooks decision-relevant information





Results

The Repeatability Evaluation – Handling SAP IDoc Errors



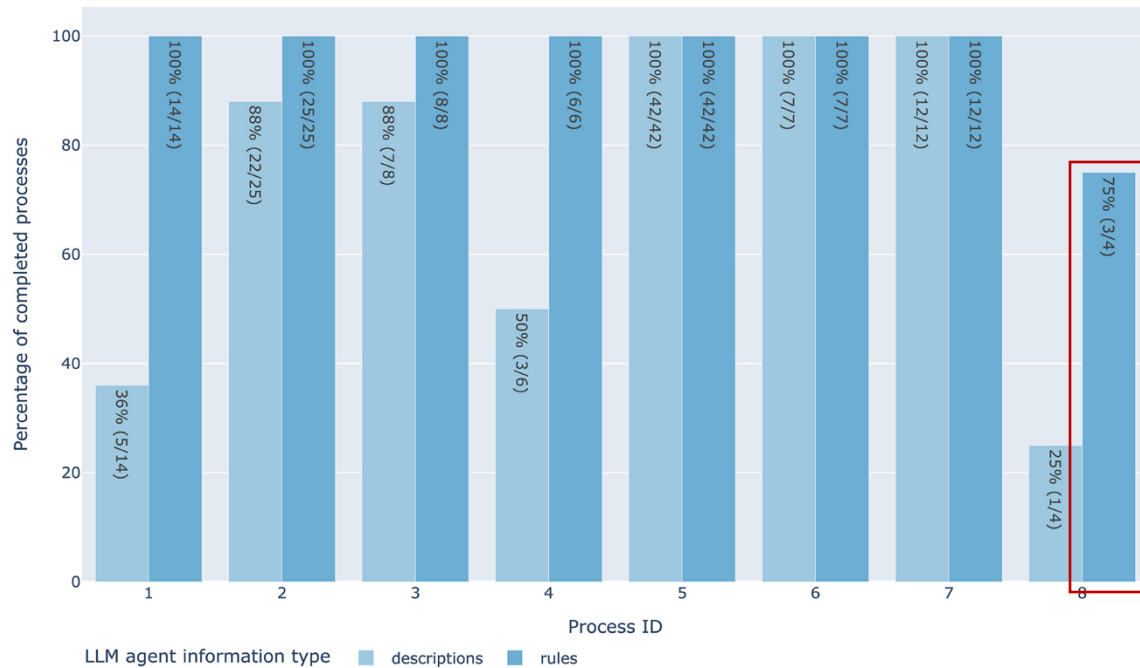
- LLM agent with descriptions cannot successfully complete all instances of processes 1, 2, 3, 4, and 8
- LLM agent with descriptions „forgets“ or skips steps and overlooks decision-relevant information
- LLM agent with process rules only fails to complete one instance of process 8





Results

The Repeatability Evaluation – Handling SAP IDoc Errors



	Descriptions	Rules
Completions	84 %	99 %

→ 15 % Improvement using process rules

→ Leading to a cost reduction of 89 %*

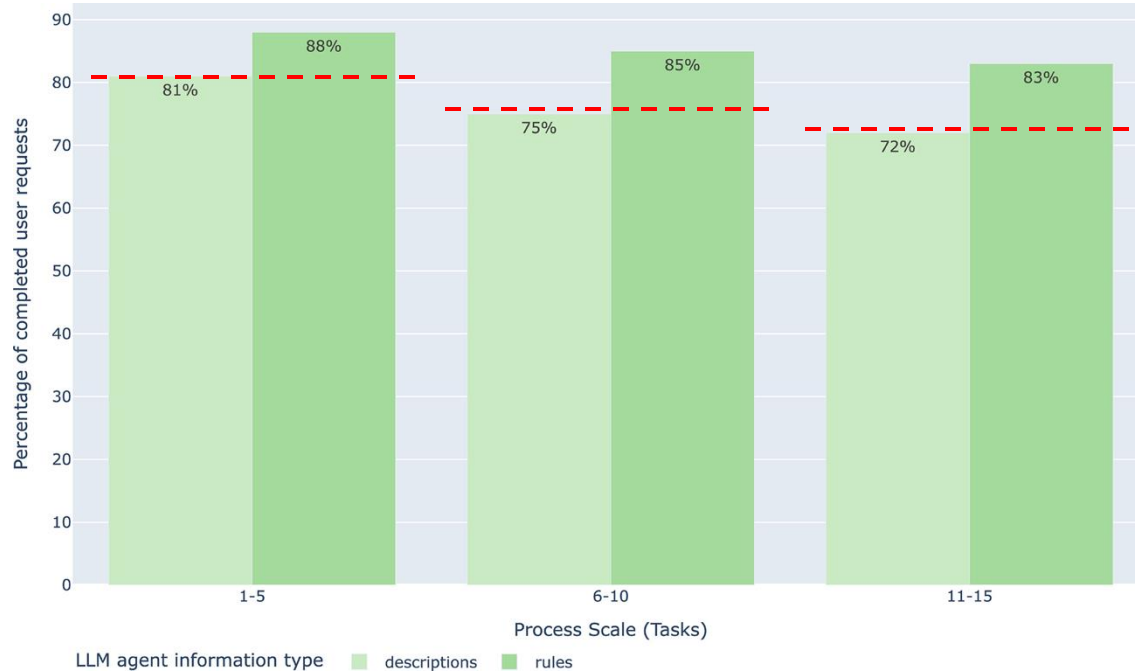
*10 instances included human work even if automation „works“





Results

The Adaptability Use Case – Fulfilling User Requests



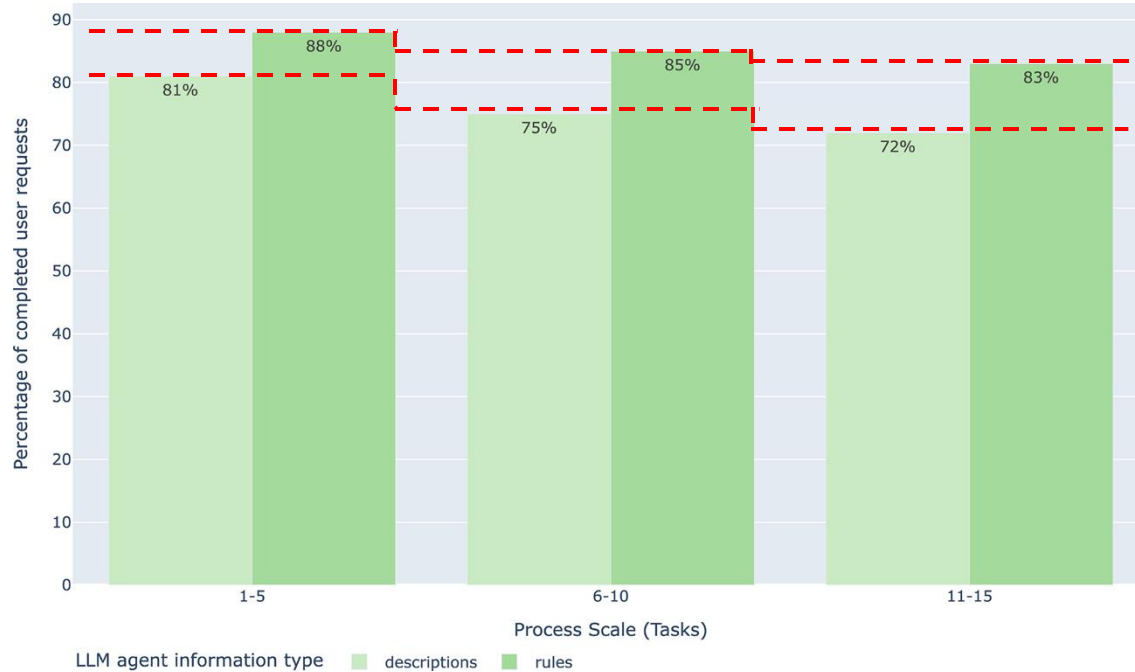
- LLM agent with process rules completes more processes successfully





Results

The Adaptability Use Case – Fulfilling User Requests



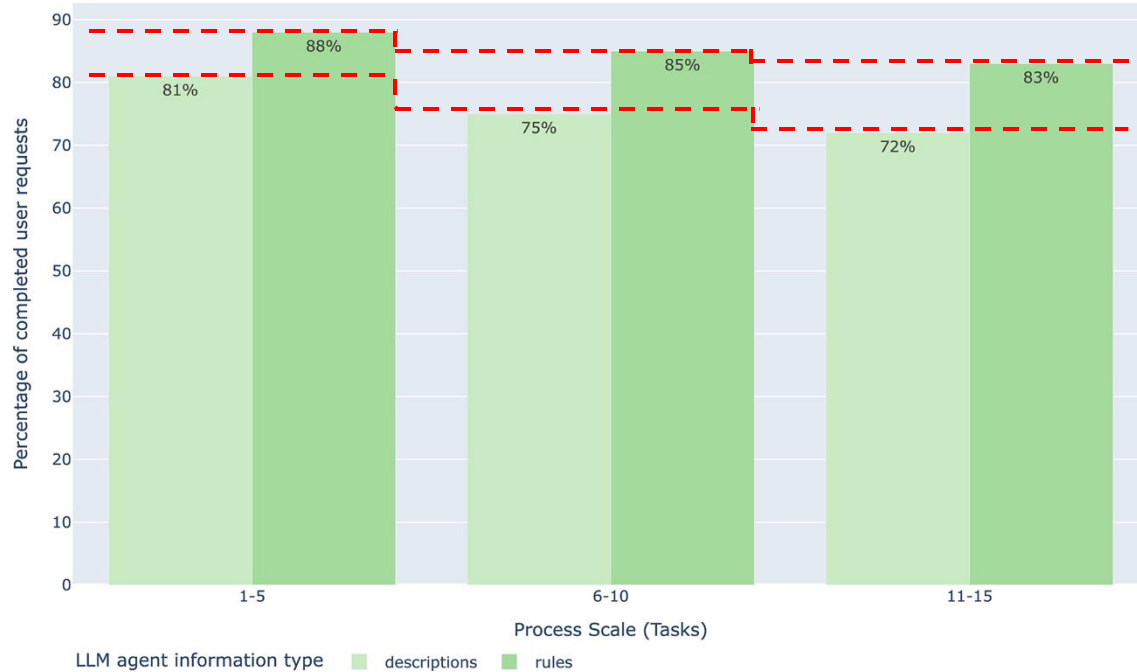
- LLM agent with process rules completes more processes successfully
- LLM agents' automation capabilities decline with increasing process length





Results

The Adaptability Use Case – Fulfilling User Requests



	Descriptions	Rules
Completions	76 %	85 %

→ 9 % Improvement using process rules





Contributions and Implications

Theory

Insights into structured and unstructured process representations:





Contributions and Implications

Theory

Insights into structured and unstructured process representations:

- Structured process representations improve process alignment of LLM agents





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Practice

An LLM automation agent blueprint:





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An LLM automation agent blueprint:

- Capable of “cognitive” processes





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An LLM automation agent blueprint:

- Capable of “cognitive” processes
- Highly repeatable (rules database)





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An LLM automation agent blueprint:

- Capable of “cognitive” processes
- Highly repeatable (rules database)
- Simultaneously adaptable (“rule generation”-tool)





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An LLM automation agent blueprint:

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- Integrates other automation methods (e.g., RPA)





Contributions and Implications

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An LLM automation agent blueprint:

- Capable of “cognitive” processes
- Highly repeatable (rules database)
- Simultaneously adaptable (“rule generation”-tool)
- Integrates other automation methods (e.g., RPA)

→ A step towards “cognitive automation”





Limitations and Future Research

Limitations

- Processes are naturally not evenly distributed (real-world use case)





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Future Research

1. Extend the LLM agent design by:
 - a) A rule storage for successfully automated processes
→ self-adaptive learning





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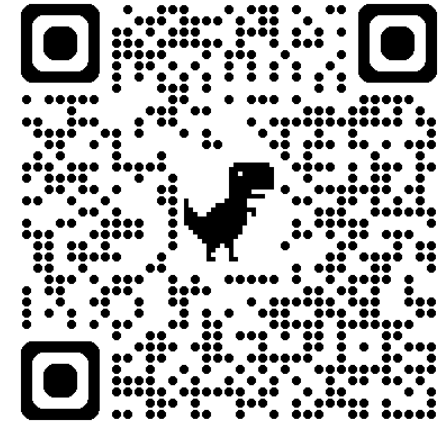
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→ self-adaptive learning
 - b) Model Context Protocol (MCP) for adaptive tool integration
2. Evaluate the LLM agent design in a second use case to strengthen the results
3. Evaluate the LLM agent design in the actual real-world environment (energy grid provider)



Thank you for your attention!

Ask many questions, please!

Check out the online-appendix:



https://github.com/skaltenp/llm_agents_with_process_rules

