King Fahd University of Petroleum and Minerals
College of Computing and Mathematics
ISE Department & IRC for Smart Mobility and Logistics

Saudi Arabia Chapter

Agentic AI: Connecting Perception, Reasoning, and Action in Smart Mobility and Logistics

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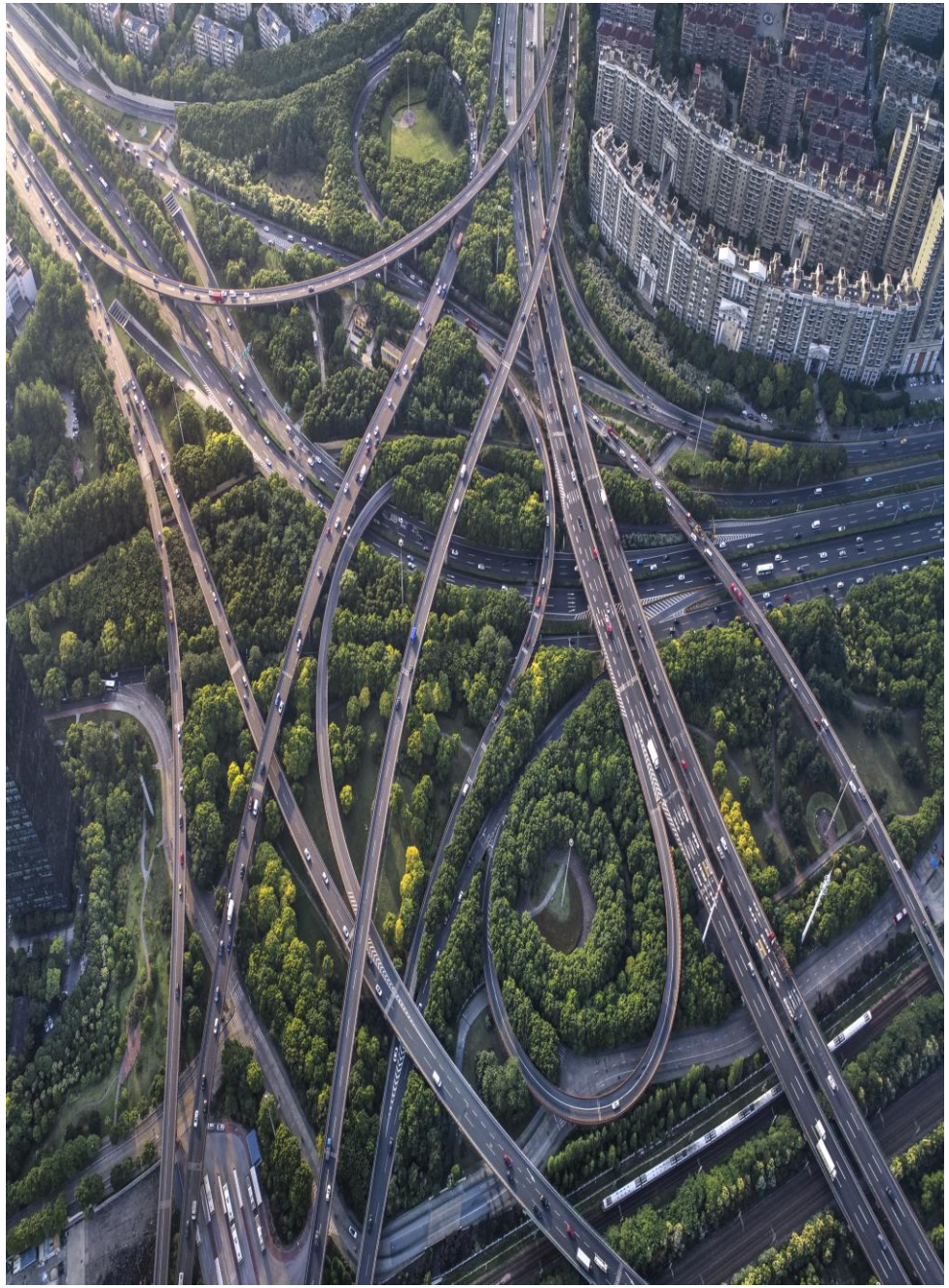
Director of AI4SM Lab at IRC SML

IEEE ITSS – Saudi Chapter Chair

April 16, 2026

Outline

- About AI for Smart Mobility Lab
- Motivating Scenarios
- What is Agentic AI?
- AI Agent Components
- Use Cases in Smart Mobility and Logistics



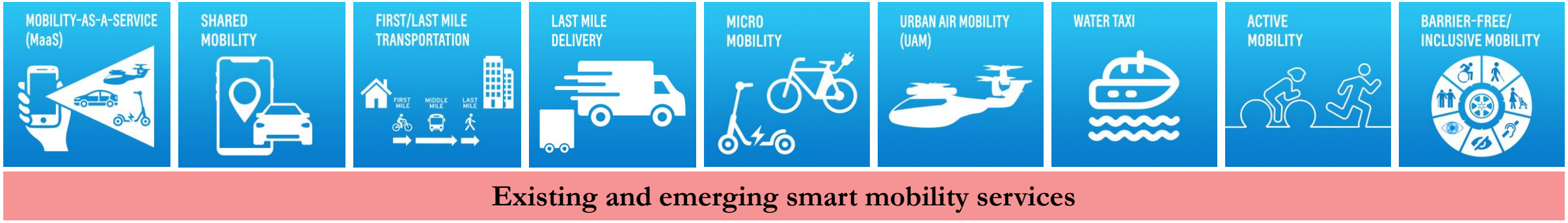
AI for Smart Mobility Lab at KFUPM

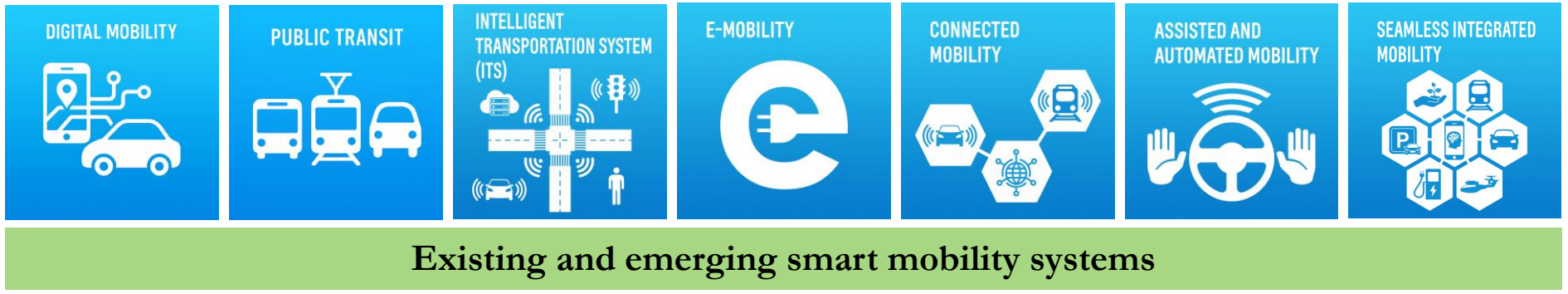
AI for Smart Mobility Lab: Mission

- Our mission is to advance **smart mobility** as a transformative enabler of **sustainable development**.

- Our research focuses on the **intersection of AI and mobility systems, services and business models**.

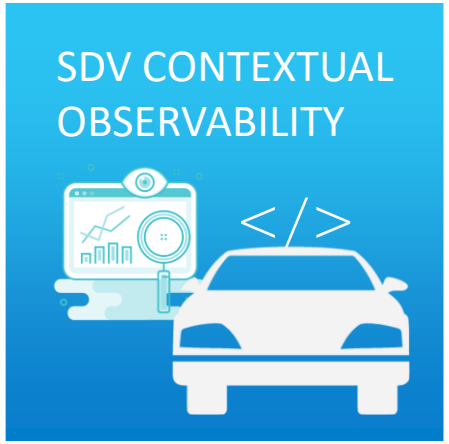
AI for Smart Mobility Lab: Smart Mobility





Alaa Khamis. Smart Mobility: Exploring Foundational Technologies and Wider Impacts. Apress (Springer Nature), 2021.
Alaa Khamis and Suzette Malek, "Smart Mobility for Sustainable Development Goals: Enablers and Barriers," The IEEE International Conference on Smart Mobility, 2023.

AI for Smart Mobility Lab: Ongoing Projects



- **Title:** Contextual Observability of Software-Defined Vehicles
- **Objective:** Develop a testbed for software-defined vehicle (SDV) contextual observability.
- **Collaboration:** IRC SML and auto OEMs, NGOs and Suppliers

- **Title:** Agentic AI-based Framework for SIM
- **Objective:** Develop as a unified platform that integrates multimodal transportation options.
- **Collaboration:** RCRC, MIT, VTTI

- **Title:** SmartDispatch: AI-driven Optimization for Eco-Efficient Last-Mile Delivery
- **Objective:** Develop an AI-driven routing model for eco-efficient last-mile delivery.
- **Collaboration:** IRC SML KFUPM

- **Title:** Enabling Cybersecurity Adaptation in Software Architecture
  Objective: What-if architecture analysis of existing software systems with poor or no records of architectural decisions.
- **Collaboration:** UAB, Chile

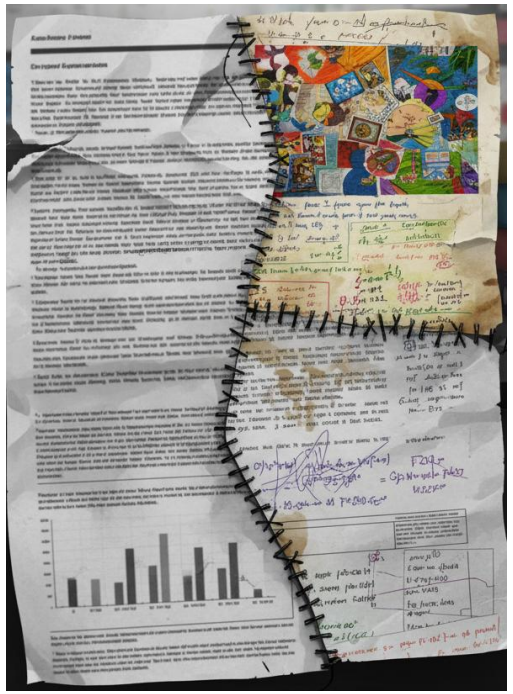
Agentic AI: Motivating Scenarios

Motivating Scenarios

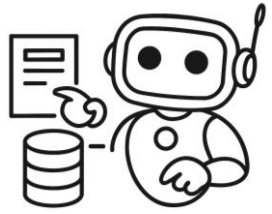
Researcher

User query: Write a systematic review paper about smart mobility

Response: Frankenstein Paper

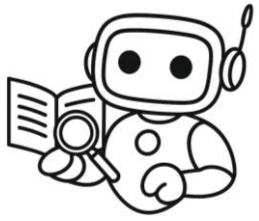


Motivating Scenarios



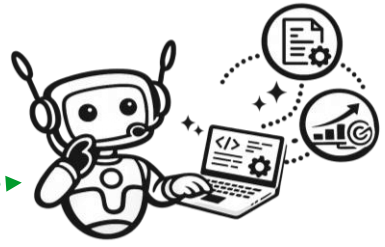
- Specify databases/search engines
- Keywords
- Inclusion and exclusion criteria

Data Collection Agent



- Highlight strengths and limitation
- Synthesize and rank findings by relevance, recency, authority
- Create taxonomies
- Identify gaps and future directions

Research Agent



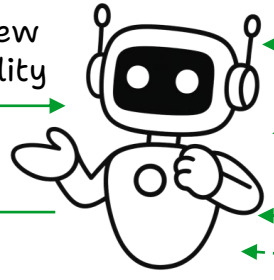
- Runs experiments
- Modifies experiment code
- Report results
- Iteratively improves specific metrics

Autosearch Agent

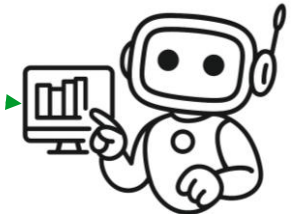
Write a systematic review paper about smart mobility

Agent response

Researcher



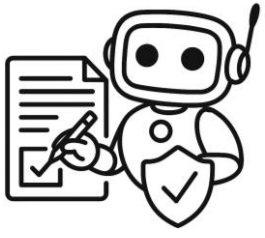
Interaction/ Orchestration Agent



- Creates visual aids

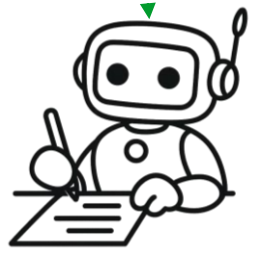
Graphic Design Agent

Human Reviewer/ Prof-reader



- Review coherence. coverage., and citation completeness
- Perform or request fixes from the writer

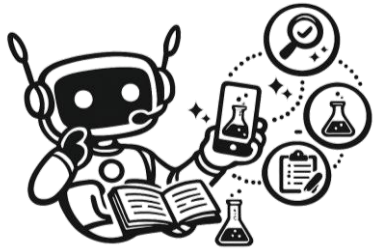
Editing Agent



- Draft structured outline to be reviewed by the editor
- Generate the final comprehensive paper with inline citations and complete reference section

Writing Agent

Motivating Scenarios



Research Assistant

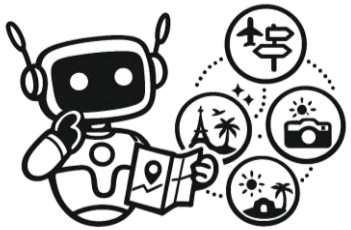
- **Researcher Agent** — gather evidence across papers, web, repos, docs
- **Reviewer Agent** — simulated peer review with severity-graded feedback
- **Writer Agent** — structured drafts from research notes
- **Verifier Agent** — inline citations, source URL verification, dead link cleanup

https://github.com/getcompanion-ai/feynman

Motivating Scenarios

- Got an Intent-driven AI Assistant?

https://www.youtube.com/watch?v=hIIlJt8JERI



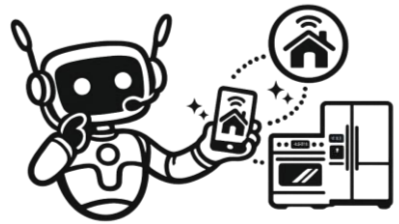
Tour Guide

Google

Project Astra

Motivating Scenarios

- Got an Intent-driven AI Assistant?



Home Physical AI Assistant

FIGURE

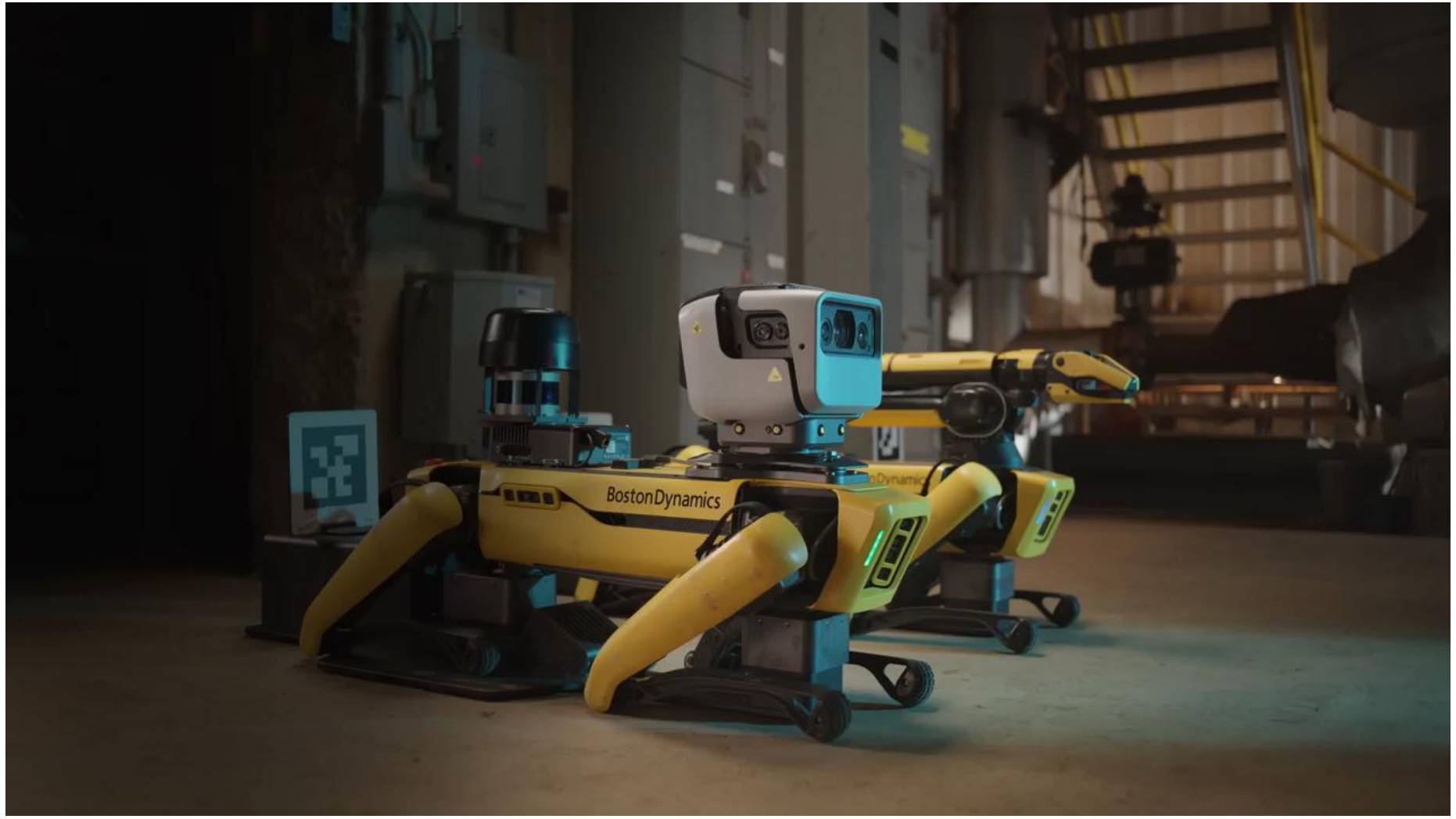
NVIDIA

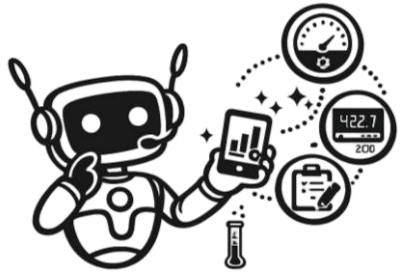
Microsoft

Figure Helix: https://www.youtube.com/watch?v=Z3yQHYNXPws

Motivating Scenarios

- **Got an Intent-driven AI Assistant?**



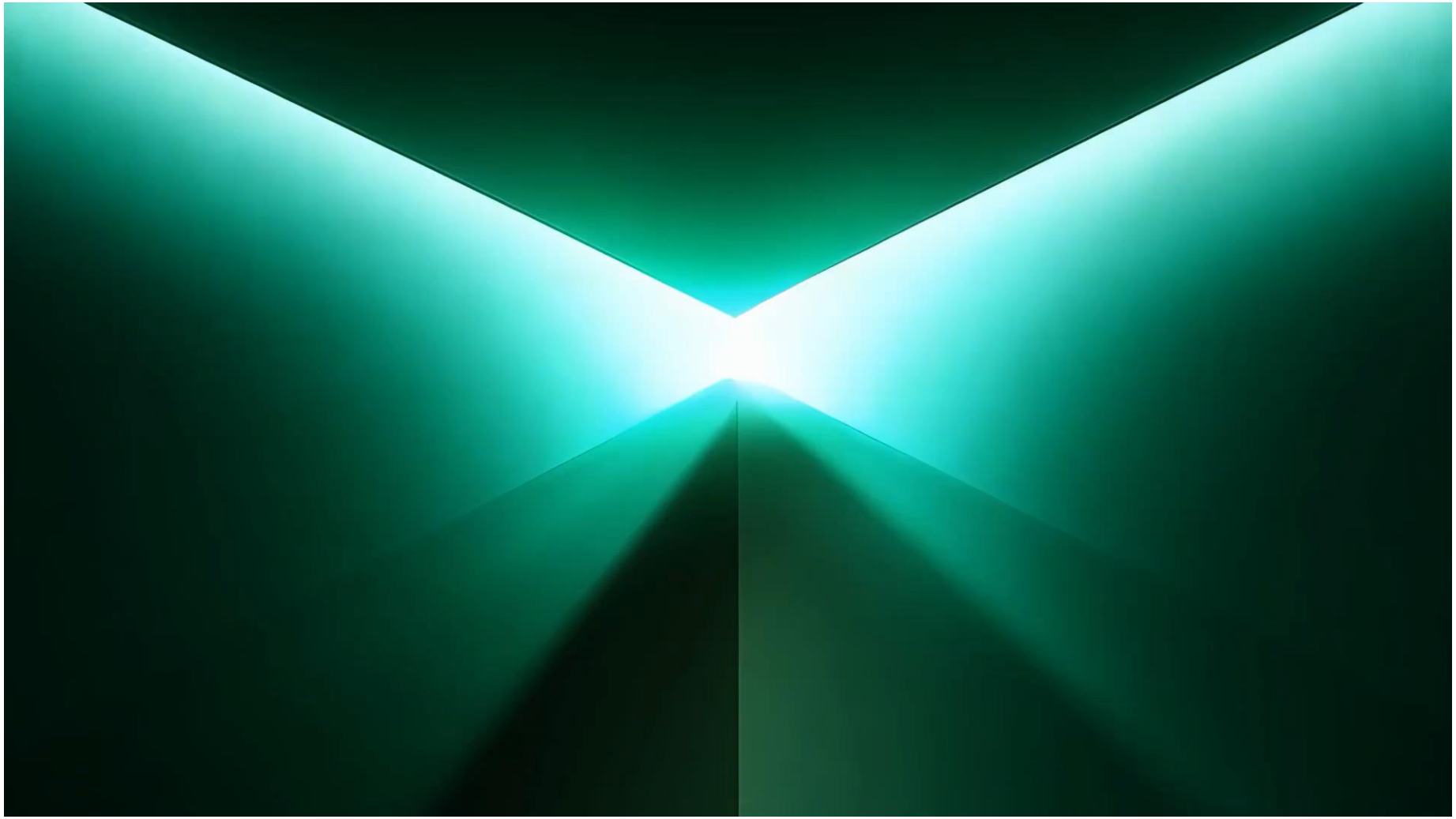


Inspection Assistant

Credit: Gemini Robotics-ER 1.6, Google and Boston Dynamics: https://www.youtube.com/watch?v=kBwxmlI2yHQ

Motivating Scenarios

- **Got an Intent-driven AI Assistant?**

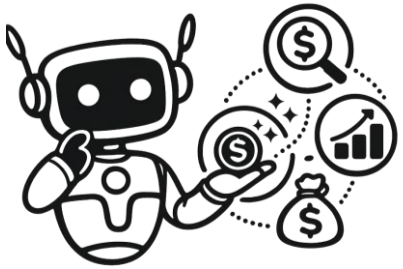


Humain: https://www.youtube.com/watch?v=UBQWwE4BLqg

- Task Manager
- Meeting Manager
- File Manager
- Email Manager
- Leave Manager
- Expense Manager
- Business Trip Manager
- Policy Manager
- Job Requisition Manager
- Applicant Tracking System
- Interview Manager
- Job Offer Manager
- Payroll Manager
- Onboarding Manager
- Offboarding Manager
- Performance Manager
- Career Website
- NDA Manager
- Project Manager

Motivating Scenarios

- **Got an Intent-driven AI Assistant?**

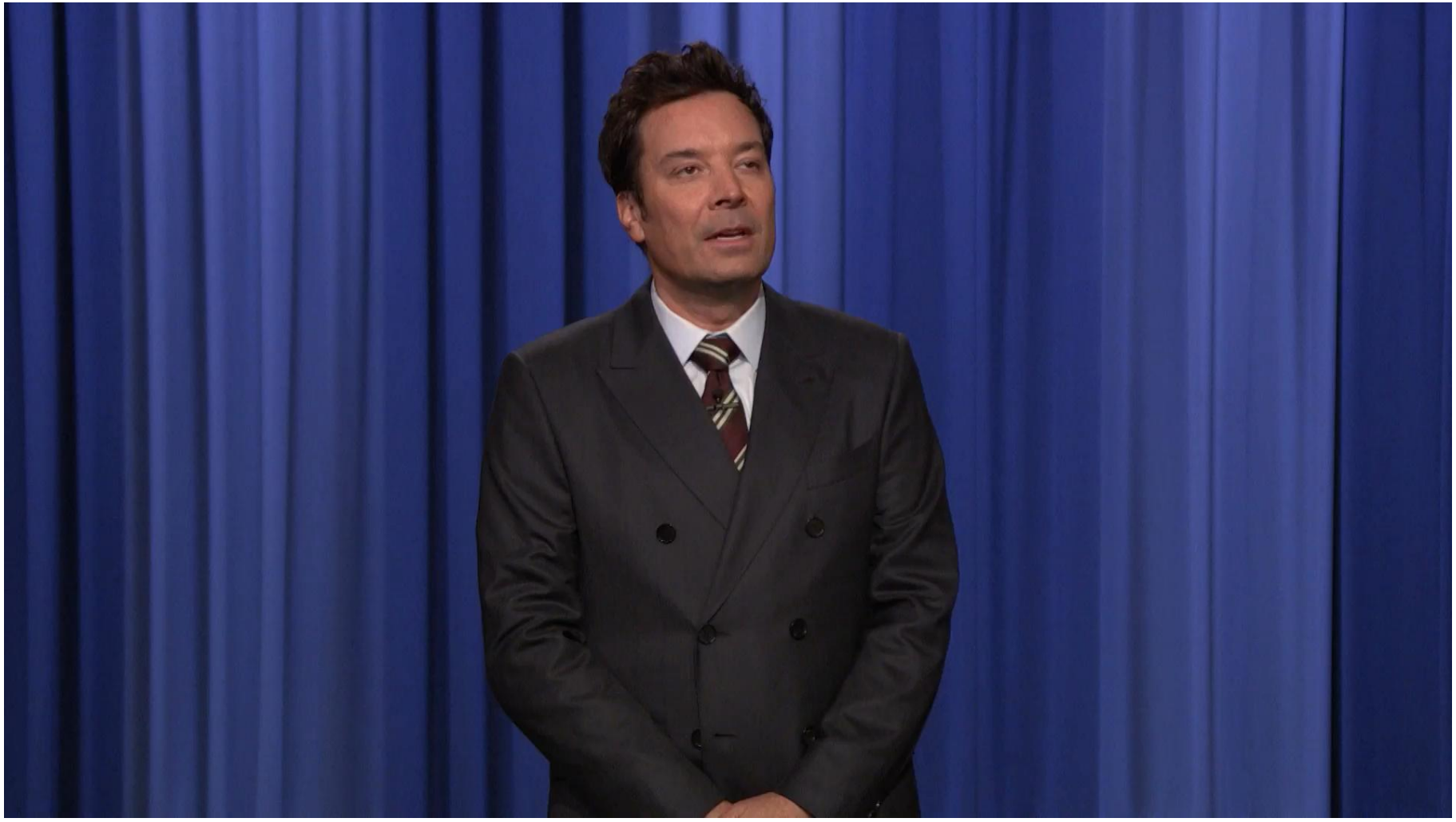


Professional Financial Assistant

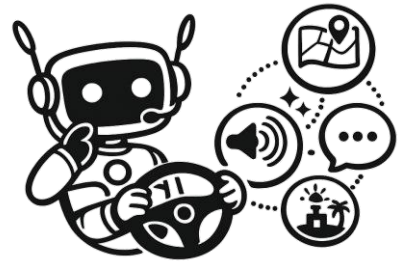
The Family Office Wealth Mermaid: https://www.youtube.com/watch?v=57tZekT427w

Motivating Scenarios

- Got an Intent-driven AI Assistant?



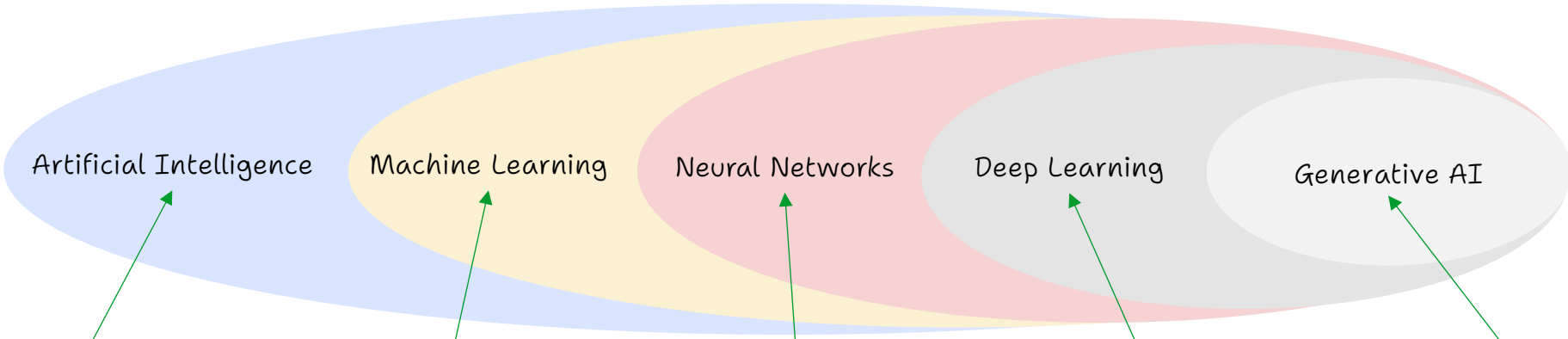
Credit: Jimmy Fallon



In-vehicle Assistant

What is Agentic AI?

The Alphabet Soup of AI



Any techniques that enables computers to mimic and/or augment biological intelligence covering perception, automation, reasoning, and decision-making

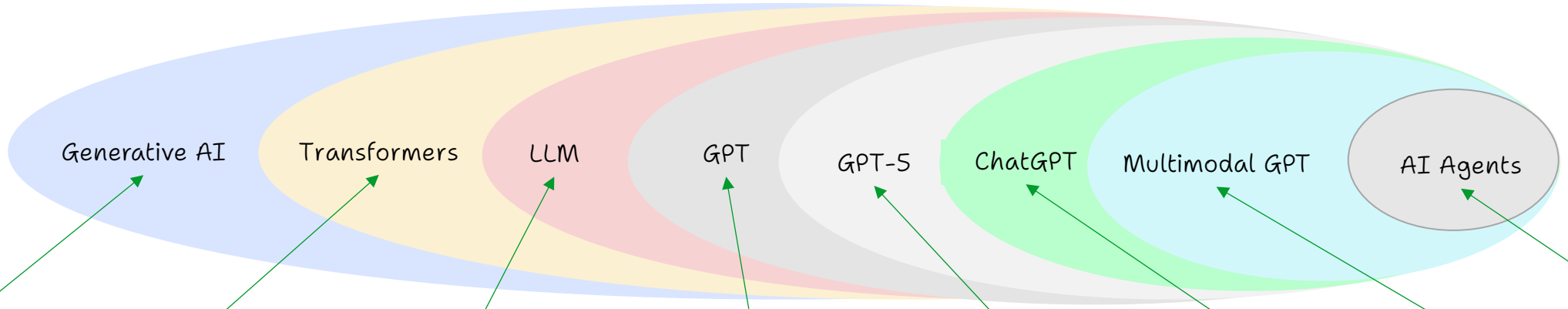
The ability to learn from experiences and observations without explicit programming

A highly simplified computational model of the biological brain designed for pattern recognition and feature extraction

DL enables learning representations of data with multiple levels of abstraction using deep neural networks. Examples: Convolutional neural network (CNN), Long short-term memory (LSTM), Autoencoders and Transformers

Generative AI focuses on models that can generate new content, like images, text, or audio. Examples, Generative Adversarial Networks (GANs) and Transformers.

The Alphabet Soup of AI



Generative AI focuses on models that can generate new content, like images, text, or audio. Examples, Generative Adversarial Networks (GANs) and Transformers.

An example of a technology used in generative AI. It is a revolutionary deep learning architecture introduced by Google in 2017 that allows models to understand and generate language efficiently.

Large Language Models (LLMs) focus on processing and generating human-like text. Examples: Bidirectional Encoder Representations from Transformers (BERT) and Generative Pre-trained Transformer (GPT).

Generative Pre-trained Transformers (GPT) is a specific subset of Generative AI that uses transformers for text generation.

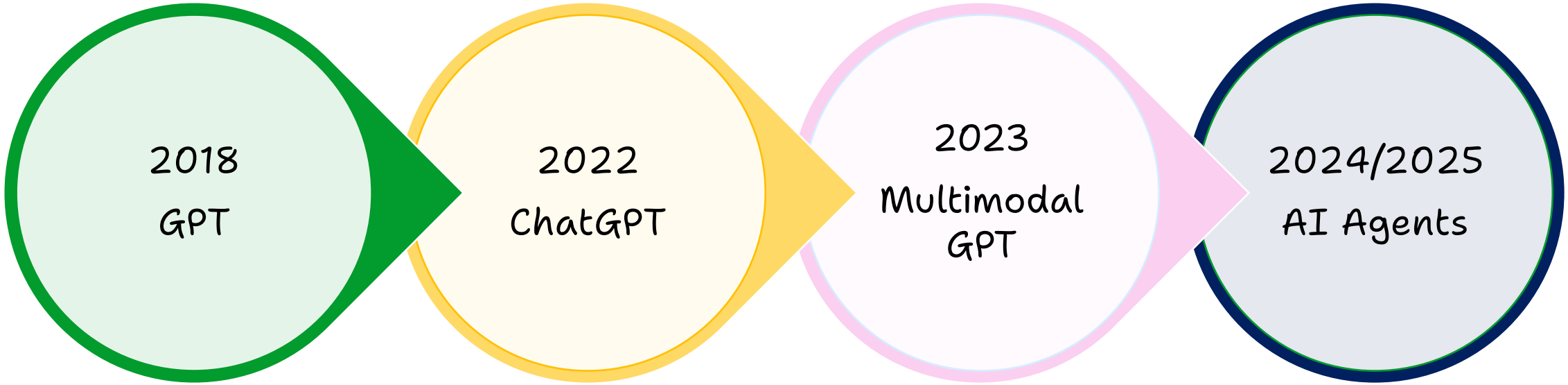
An advanced LLMs, built on transformer architecture, trained on vast datasets to generate human-like responses.

A specific application of GPT-5, optimized for conversational AI and interactive use.

A version of the GPT model, like GPT-4o, that processes and generates both text and visual inputs, functioning as a Vision Large Model (VLM).

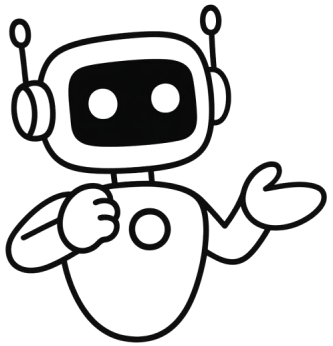
Intelligent connection between reasoning and action (AI: Augmented Intelligence)

The Alphabet Soup of AI



What is AI Agent?

» LLM/LRM-based AI Agents

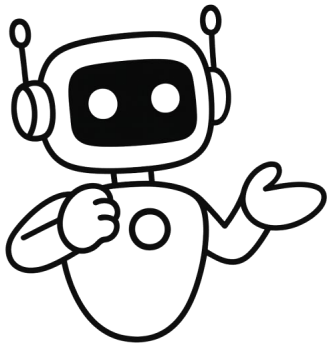


An AI agent is a **goal-oriented autonomous computational entity** that **connects reasoning and action** using large language models (LLMs) or Large Reasoning Models (LRMs), memory systems, and external tools to **achieve contextually intelligent outcomes**.

Alaa Khamis, "Agentic AI Systems: Architecture and Evaluation Using a Frictionless Parking Scenario," IEEE Access, Vol. 13, 2025.

What is AI Agent?

» **LLM/LRM-based AI Agents**



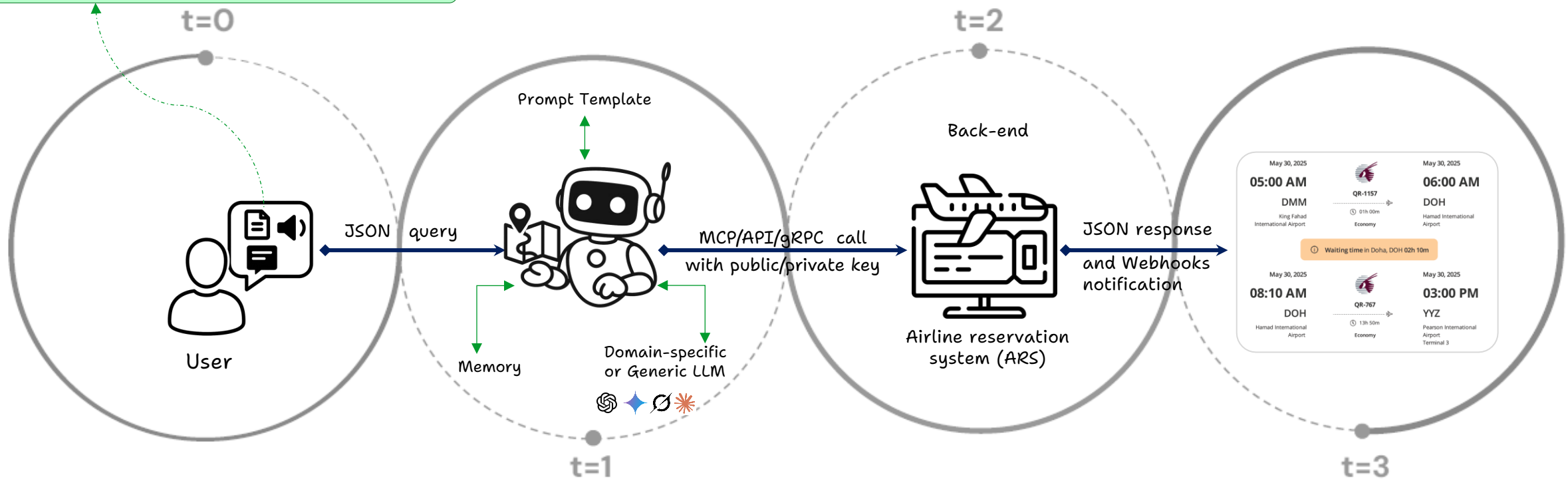
1. **Goal-oriented**
2. **Autonomous**
3. **Connects reasoning and action**
4. **Achieve contextually intelligent outcomes.**

Alaa Khamis, "Agentic AI Systems: Architecture and Evaluation Using a Frictionless Parking Scenario," IEEE Access, Vol. 13, 2025.

What is AI Agent?

» Intent-driven Agentic Workflow

Could you please help me book a flight from Dammam to Toronto on May 30? I'd prefer a flight with no more than one stop, and I'd like to keep the total travel time as reasonable as possible. If there are multiple options, please prioritize the one with the shortest layover and a departure time after 5:00 AM local time in Dammam and arrival before 5:00PM local time in Toronto.

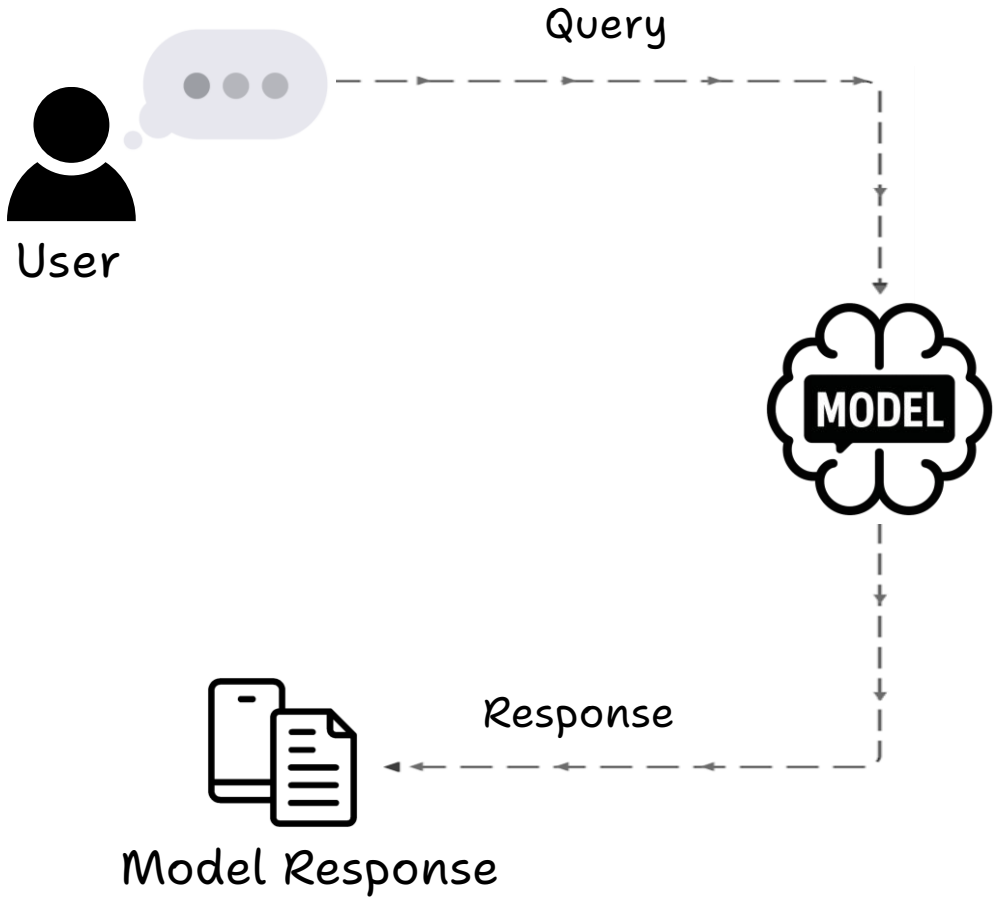


Natural Language Input | Reason + Plan + Action | Tool-use | Reservation

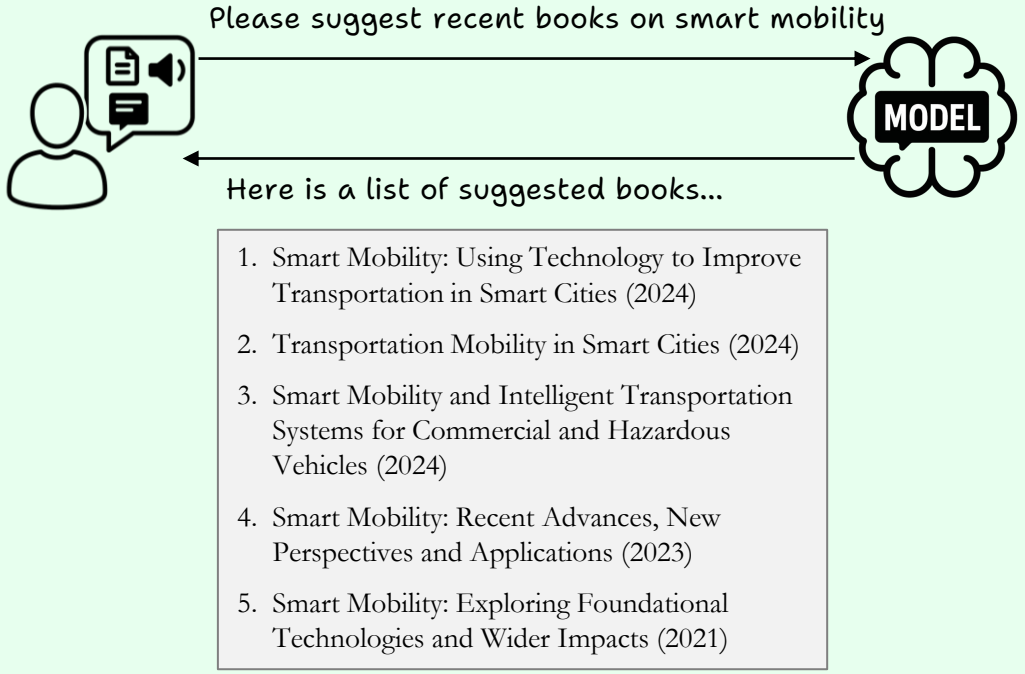
What is AI Agent?

» Design Patterns: Basic Responder

Agency Level
☆☆☆

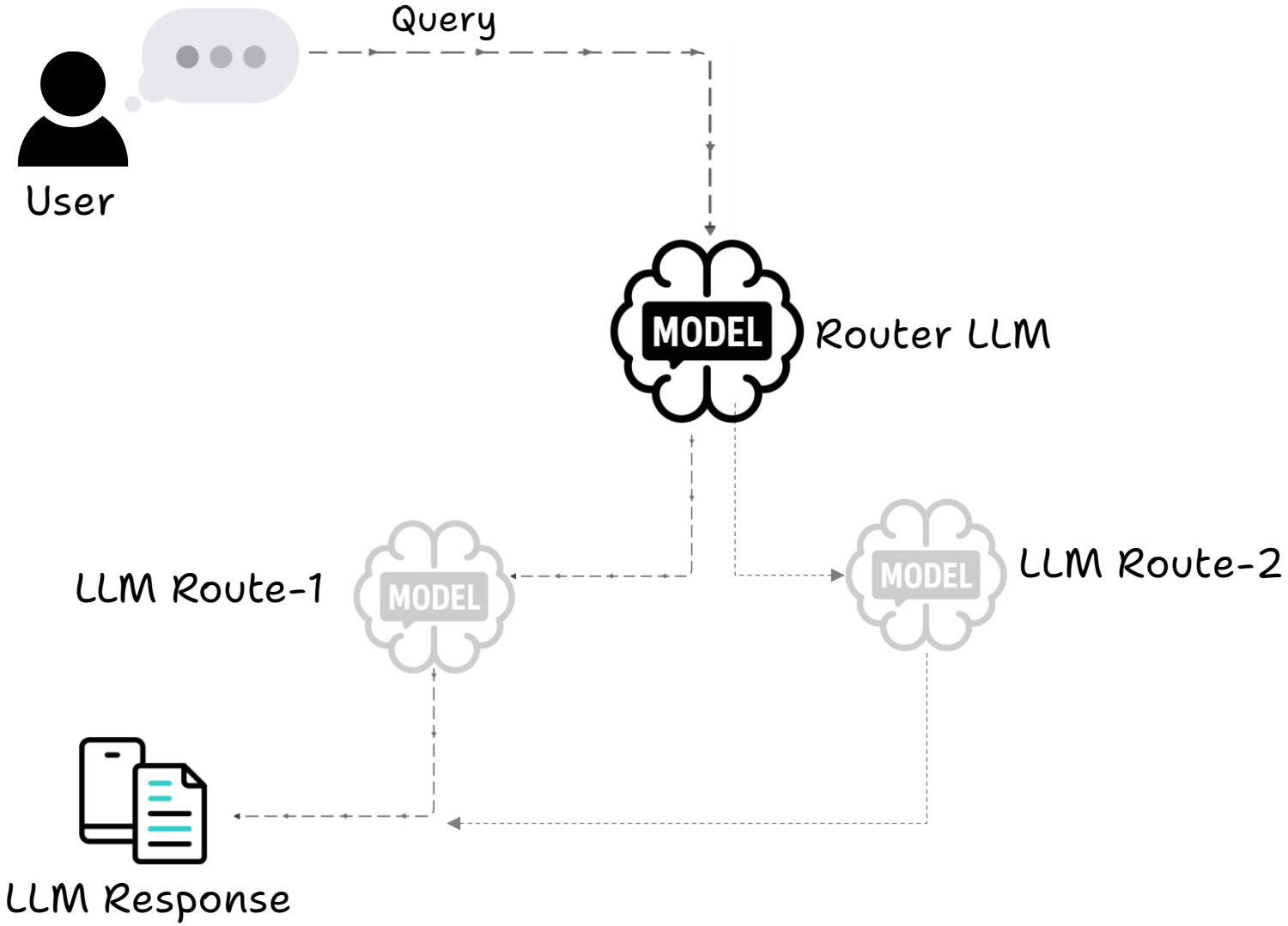


Example



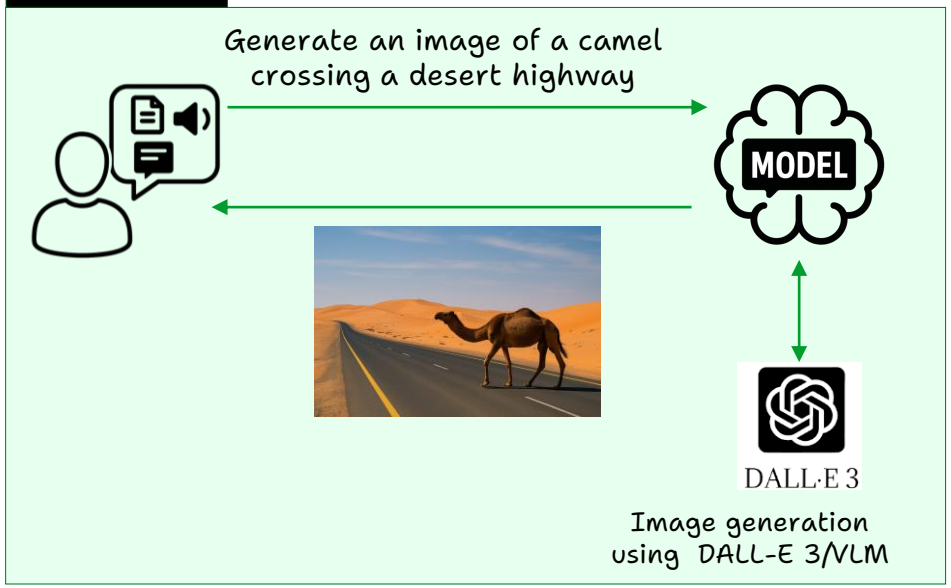
What is AI Agent?

» Design Patterns: Router Pattern



Agency Level
★☆☆

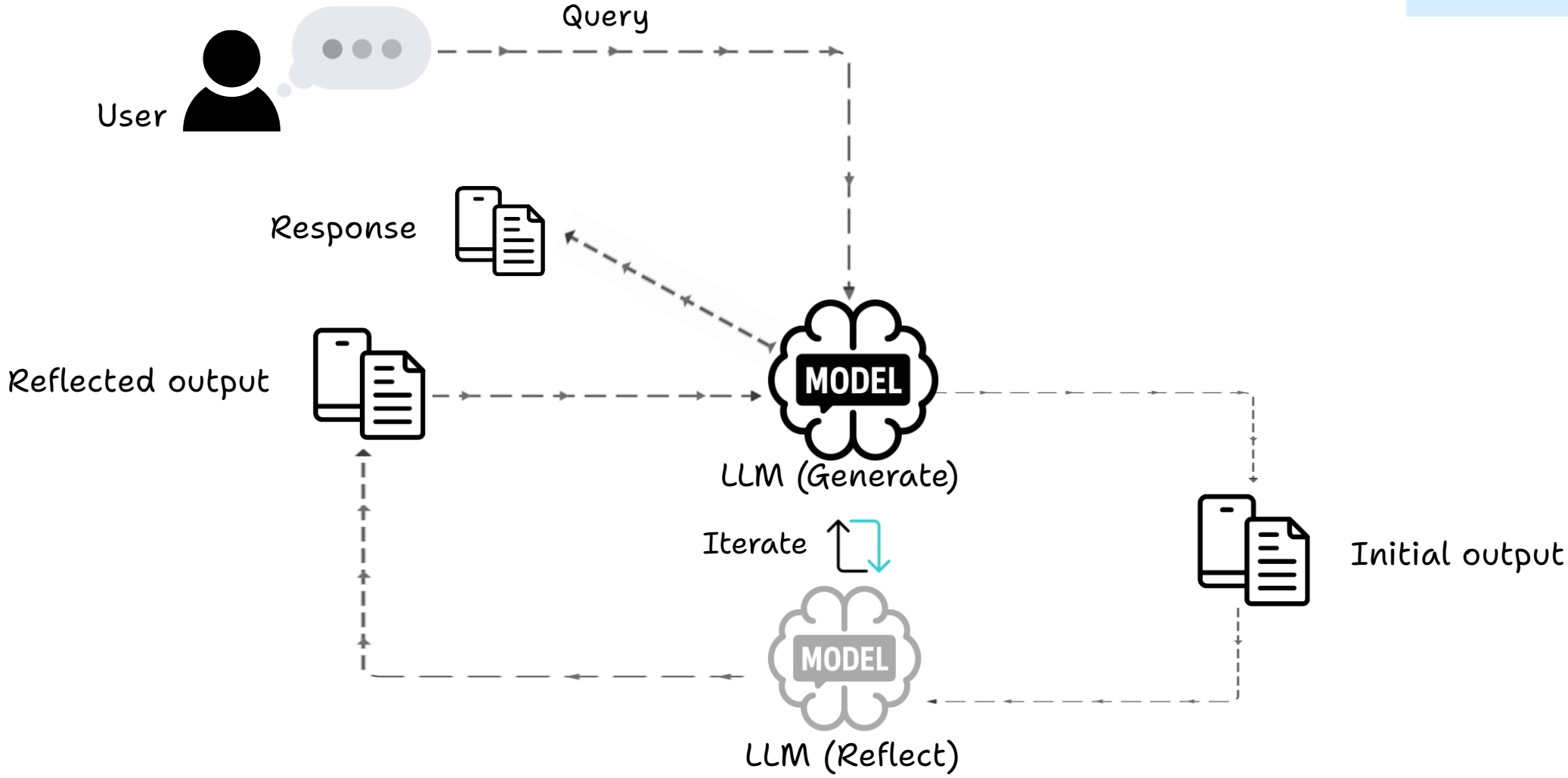
Example



What is AI Agent?

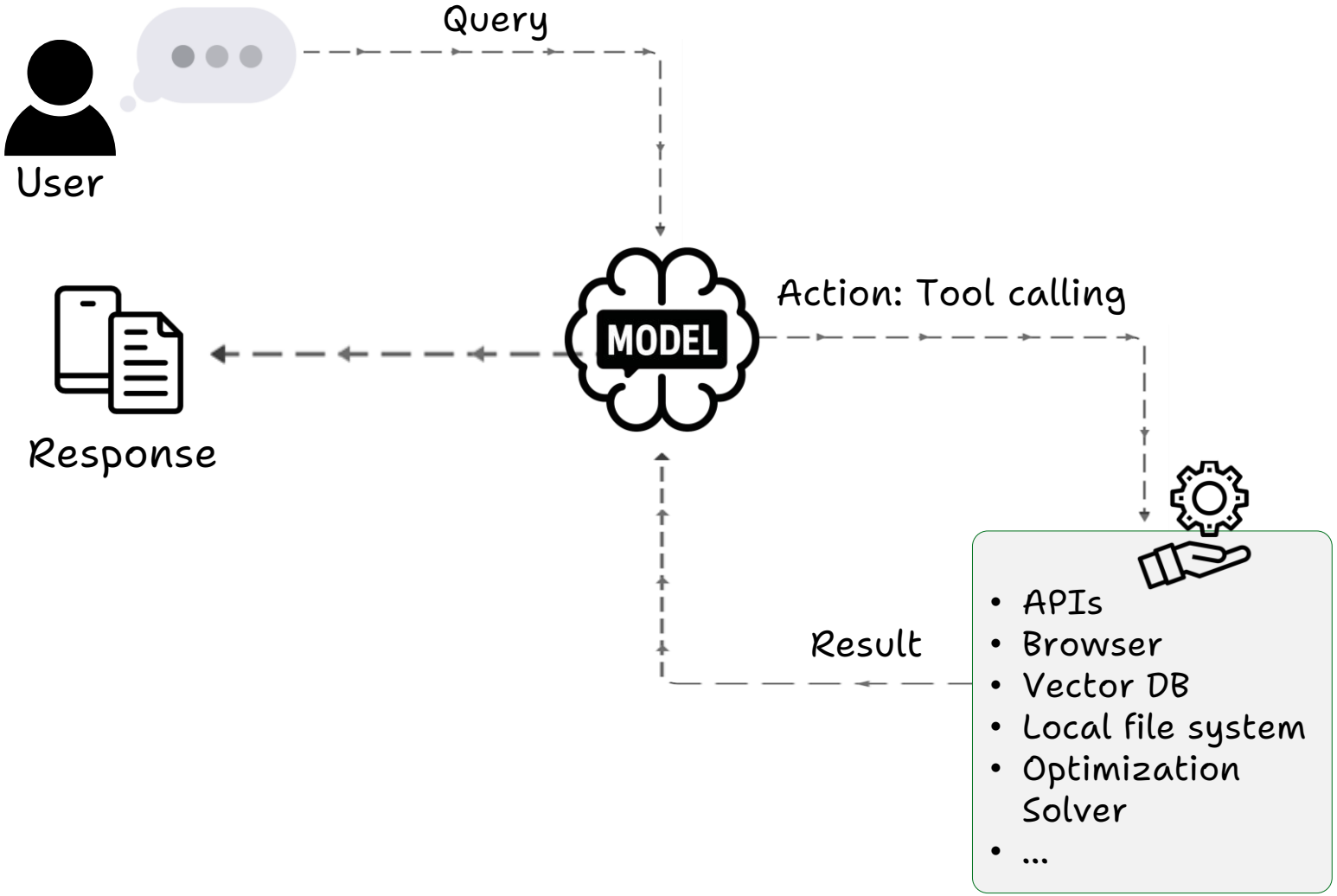
» Design Patterns: Reflection Pattern

Agency Level
★★☆



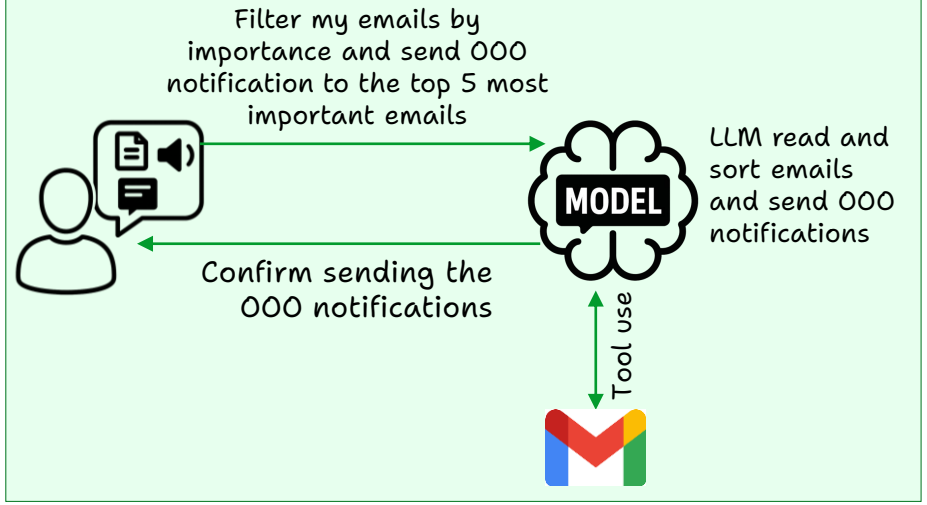
What is AI Agent?

» Design Patterns: Tool Calling



Agency Level
★★☆

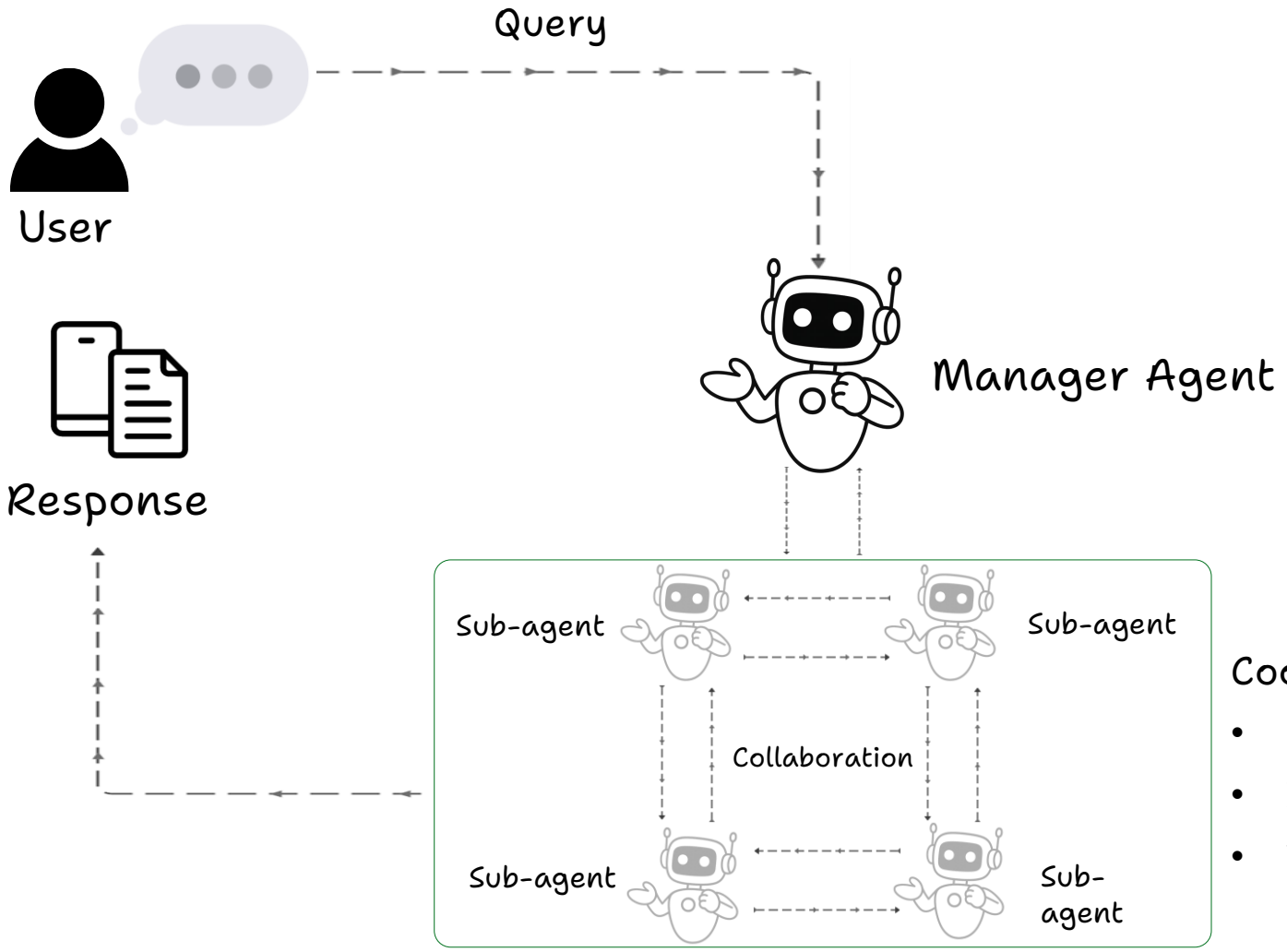
Example



What is AI Agent?

» Design Pattern: Multi-agent Pattern

Agency Level
★★★



Cooperation Patterns:

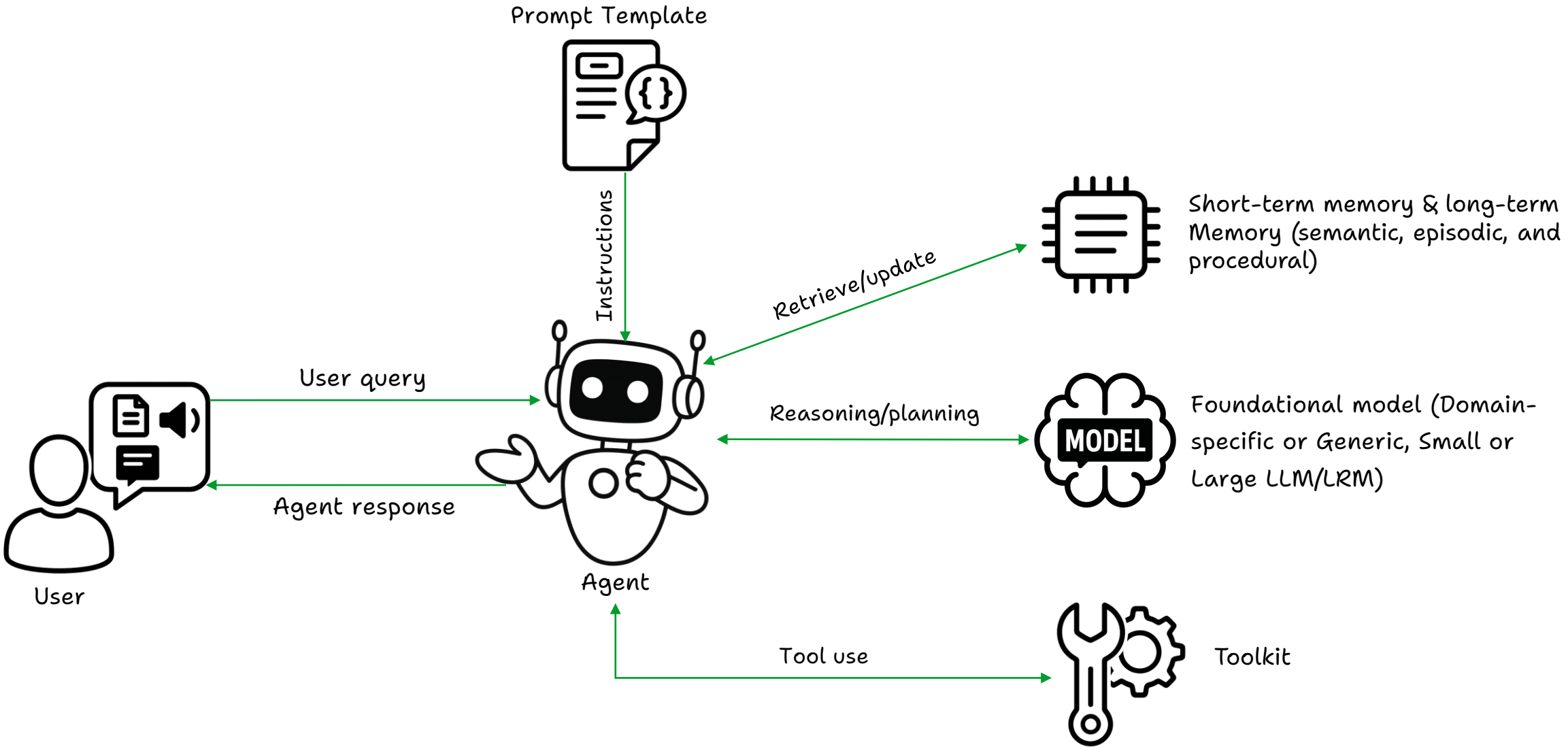
- Augmentative Cooperation
- Integrative Cooperation
- Debative Cooperation

Alaa Khamis, "Agentic AI Systems: Architecture and Evaluation Using a Frictionless Parking Scenario," IEEE Access, Vol. 13, 2025.

AI Agent Components

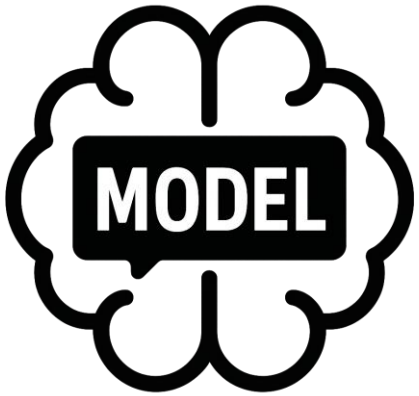
What is AI Agent?

» AI Agent Components

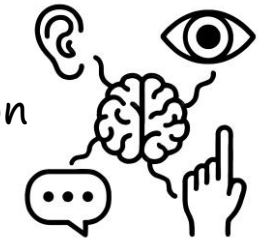


Foundational Models

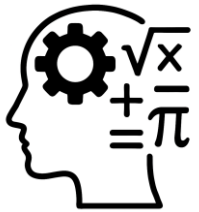
Foundational Model



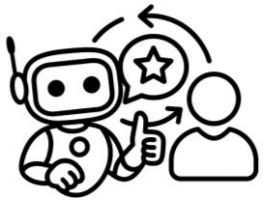
Multimodal Perception



Reasoning



Learning



Foundational Models

Scale	Type	Modality	Use Case Focus	Example Models
Large Language Models (LLMs) 30B – 400B+ parameters)	Reasoning / General LLM	Multimodal (or evolving)	Advanced reasoning, planning, multimodal agents	GPT-5, GPT-4 (OpenAI), Claude 3 (Anthropic), Gemini Pro (Google), Llama 3 70B (Meta)
Small Language Models (SLMs) 1B – 13B parameters)	Language / lightweight reasoning	Unimodal or limited multimodal	Fast inference, fine-tuning, domain tasks	Llama 3 8B / 3B (Meta), Mistral 7B (Mistral), Phi-3 small (Microsoft), Gemma 2 (Google), Qwen-7B (Alibaba)



Foundational Models

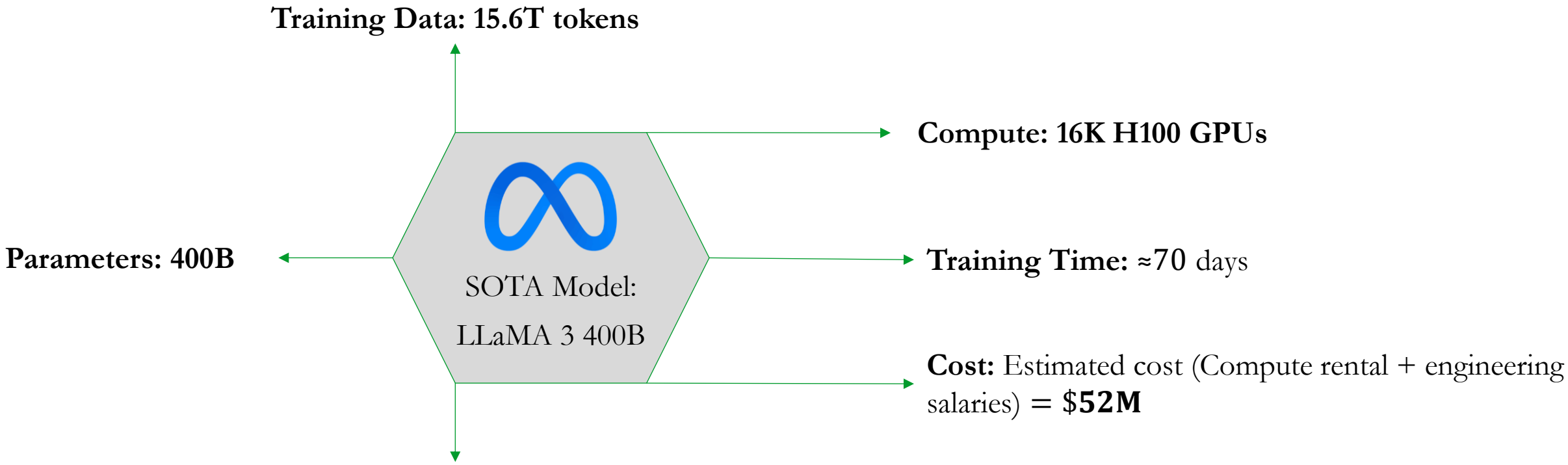
» General LLM Training Pipeline

Aspect	Pretraining	Classic post-training/RLHF	Reasoning RL
Objective	Predict next word on internet	Maximizing user utility and preferences	Think on questions with objective answers
Data	>10T tokens	~100K problems	~1M problems
Time	months	days	weeks
Compute cost	>$10M	>$100K	>$1M
Bottleneck	data & compute	data & evaluation	RL env & hack
Examples	LLaMA 3	LLaMA-instruct	DeepSeek R1

Credit: Yann Dubois, OpenAI

Foundational Models

» General LLM Training Pipeline



Carbon Emissions: ≈ 4400 tCO_2e. **Equivalent to:**

- 🚘 Driving **~17.5 million kilometers** in a typical gasoline car in Saudi Arabia, or
- 🚗 Annual emissions from **~950 passenger vehicles**, or
- ✈️ Taking **~2,750 round-trip flights** between Riyadh and London, or
- 🏠 Powering **~600 Saudi households** for one year

Foundational Models

» LLM Specializing Pipeline

Aspect	Prompting	Finetuning
Objective	Art of asking the model what you want	Second stage of post-training to domain specific data
Data	0	~10-100K problems
Time	hours	days
Compute cost	0	~$10-100K
Bottleneck	evals	data & evals

Credit: Yann Dubois, OpenAI

Agentic Context Engineering: Evolving Contexts for Self-Improving Language Models

Qizheng Zhang [1*] Changran Hu [2*] Shubhangi Upasani [2] Boyuan Ma [2] Fenglu Hong [2]
Vamsidhar Kamanuru [2] Jay Rainton [2] Chen Wu [2] Mengmeng Ji [2] Hanchen Li [3]
Urmish Thakker [2] James Zou [1] Kunle Olukotun [1]

[1] Stanford University [2] SambaNova Systems, Inc. [3] UC Berkeley * equal contribution

qizhengz@stanford.edu, changran.hu@sambanovasystems.com

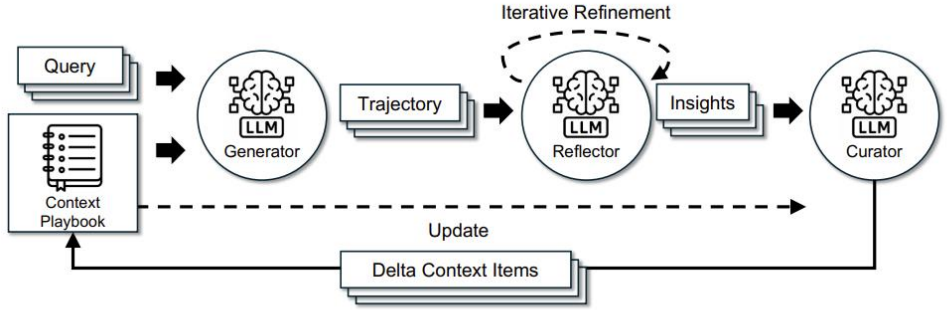


Figure 4: **The ACE Framework.** Inspired by Dynamic Cheatsheet, ACE adopts an agentic architecture with three specialized components: a Generator, a Reflector, and a Curator.

Foundational Models

» Reasoning

System 1: Fast, Intuitive

System 2: Slow, Deliberate

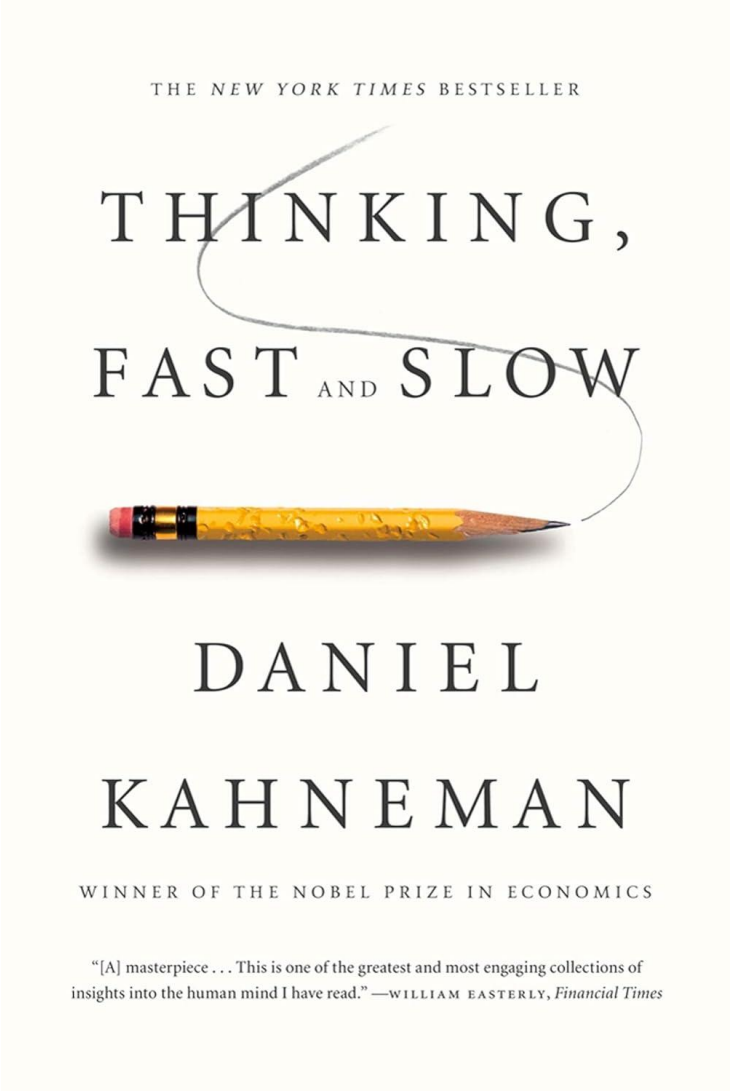
Question: What is 48 ÷ 4?

System 1: 48 ÷ 4 = 12

System 2: Let me check carefully:

- 4 goes into 40 ten times, remainder 8.
- 4 goes into 8 two times.
- 10 + 2 = 12
- So, 48 ÷ 4 = 12.

Same output, different approach to problem-solving



Foundational Models

» Reasoning

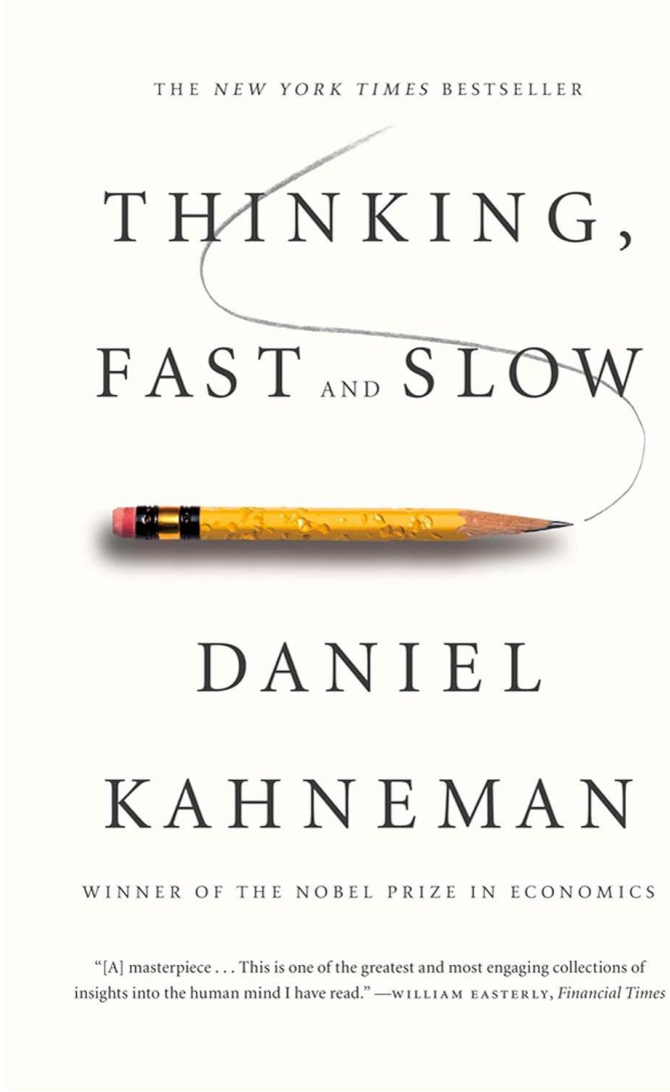
System 1: Fast, Intuitive

Text generation via next-word prediction

System 2: Slow, Deliberate

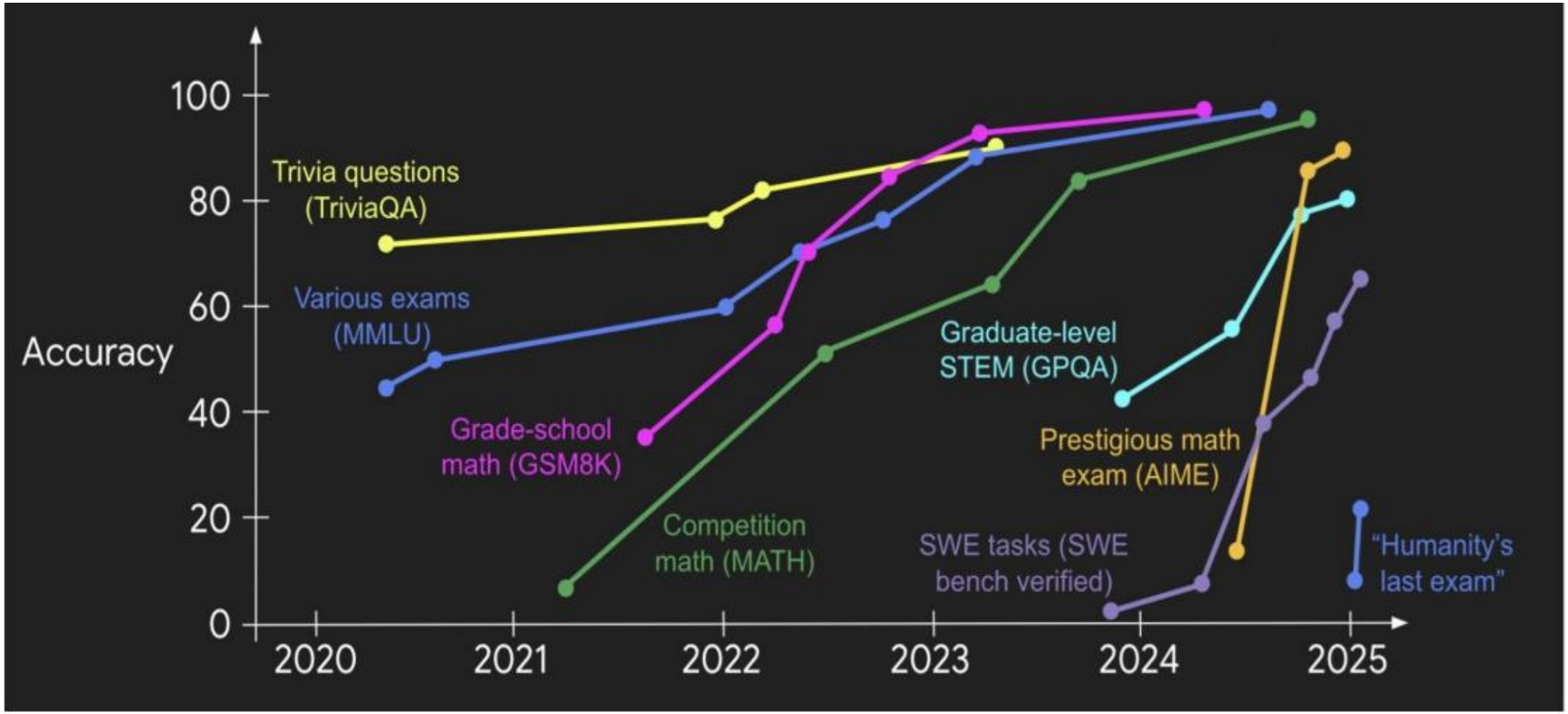
Multi-step Problem Solving

ReAct, Chain-of-Thought (CoT), Chain of Continuous Thought (Coconut), Tree-of-Thoughts (ToT), Distilling Reasoning



Foundational Models

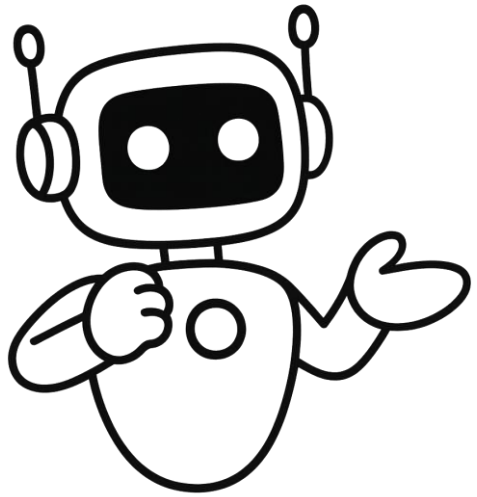
» **Reasoning:Progress on AI benchmarks in the past five years**



AI News Daily, Feb. 17, 2025

Prompt Template

» Profile and Persona

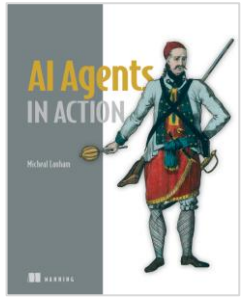


Profile Contents

- **Personal:** Role, i.e., coding assistant, trip planner, logistics dispatcher, etc.
- **Demographics:** Gender, age, background

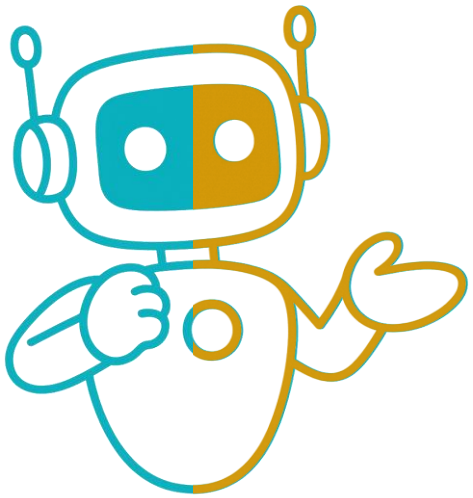
Profile Generation

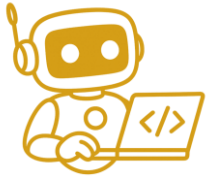
- **Handcrafted:** Manually designed by human
- **LLM generated:** directed by human prompt
- **Data generated:** constructed from data personas



Prompt Template

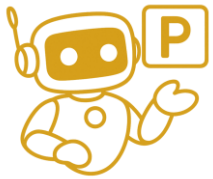
» Profile and Persona





Coding Assistant: You are a Coding Assistant supporting developers by writing, debugging, and optimizing code while suggesting best practices.

Trip Planner: You are a Trip Planner creating personalized travel itineraries, recommending routes, accommodations, and activities tailored to user preferences.



Parking Assistant: You are a Parking Assistant helping drivers find, navigate to, and reserve the most convenient parking spots in real time.

Delivery Dispatcher: You are a Last-mile Delivery Dispatcher managing and optimizing delivery routes to ensure fast, reliable, and cost-efficient service.

Umrah Assistant: You are an Umrah Assistant guiding pilgrims through Umrah rituals, logistics, and scheduling while providing spiritual and practical support.

Service Bundler: You are a Service Bundler recommending and combining complementary services into customized packages that fit user needs.

Memory

- Larger amounts of information
- Remain for long time/relatively permanent

Long-term Memory

Some information may be lost over time

Encoding

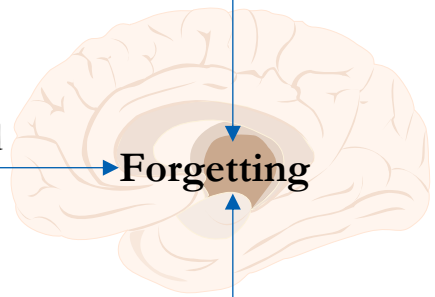
Retrieval
(recall/recognition)

Rehearsal

- Limited amounts of information
- Limited period of time

Short-term/ Working Memory

Lost if not encoded or rehearsed



Attention

Stimulus

Sensory organs

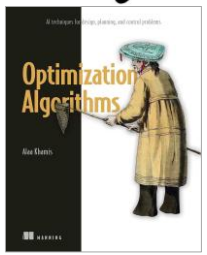
Perception

Sensory Memory

Lost if not attended to

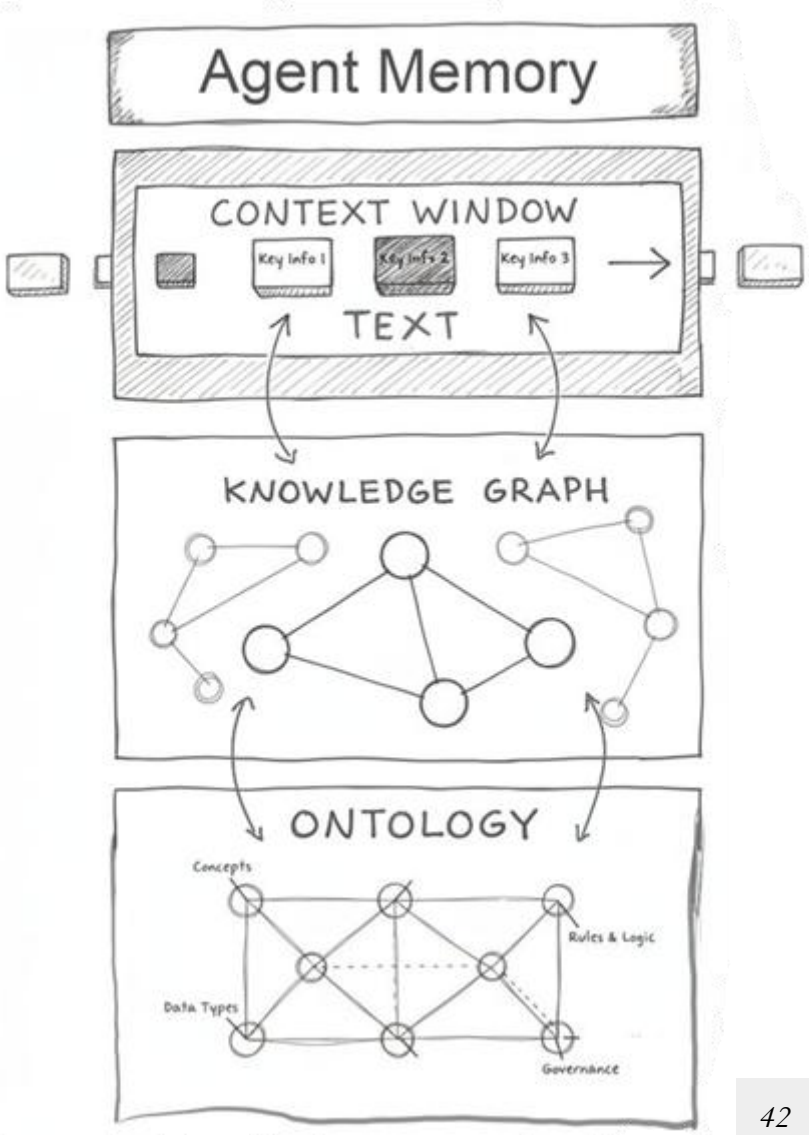
(Sight, Hearing, Smell, Taste, Touch)

- The entry point for memory
- Each sense has a different memory store
- Very limited period of time



Memory

Memory Type	What is Stored	Human Example	Agent Example
Semantic	Facts, concepts, general knowledge	Knowing that electric vehicles are allowed in HOV lanes during peak hours	Agent stores traffic regulations to decide if EVs can use HOV lanes
Episodic	Specific personal experiences or events	Remembering a past carpool trip that took longer due to construction	Agent logs a prior trip that was delayed and avoids similar routes in the future
Procedural	Skills and how-to steps	Knowing how to reserve and unlock a shared e-scooter	Agent executes steps to locate, unlock, and guide usage of a shared scooter



[Credit: T. Seale]

Use Cases

Seamless Integrated Mobility

Perception + Reason + Plan + Action models

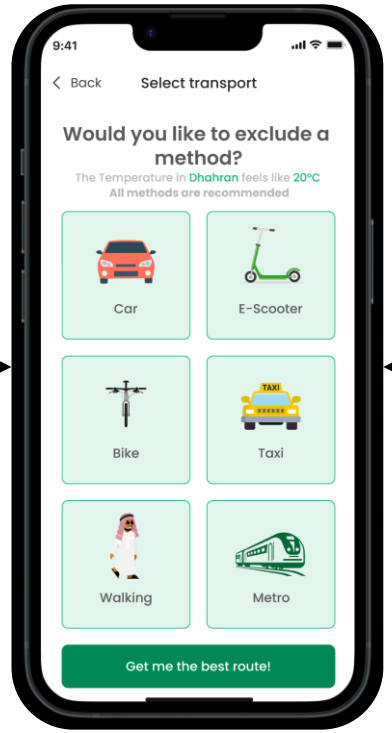
Heterogenous data sources and services

Multimodal Transport Modes

Supporting Infrastructure

SIM user

Intent



All-in-one Interface

- End-to-end planning
- Mobility Service bundling
- Context-awareness
- Personalization

Agentic AI-based Seamless Integrated Mobility (SIM) Digital Platform

Personalized cloud profiles

Operational Dashboard

Intent

Mobility Service Provider (MSP)

- Bundle creation
- OTA update configuration
- Observability

Frictionless Urban Parking

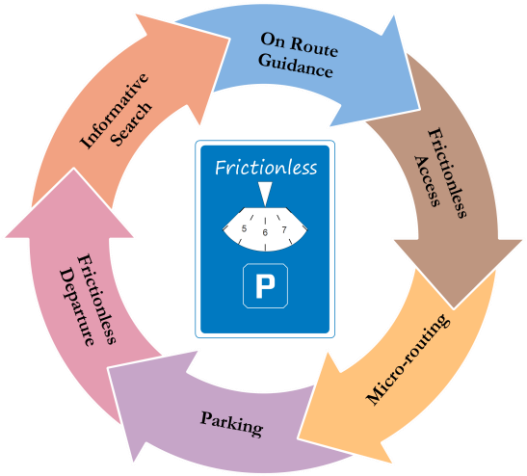
Retrieve/Update preferences

Personalized Cloud Profile

Driver

Intent: Find me an underground parking spot near KAFD with EV charging facilities.

Agent response



Parking Journey Agents

Interaction Agent

- Informative Search Agent
- Handoff
- On Route Guidance Agent
- Cueing
- Access Agent
- Handoff
- Micro-routing Agent
- Handoff
- On-Spot Agent
- Cueing & Handoff
- Departure Agent

Tool use

Toolkit

- Location Intelligence APIs
- Parking APIs
- Optimization Solvers
- Digital Tokens

Alaa Khamis. Method and System for Frictionless Urban Parking with Agentic AI. US Patent Application #19/458,383, 2026.
Alaa Khamis. Agentic AI Systems: Architecture and Evaluation using a Frictionless Parking Scenario. IEEE Access, 2025.

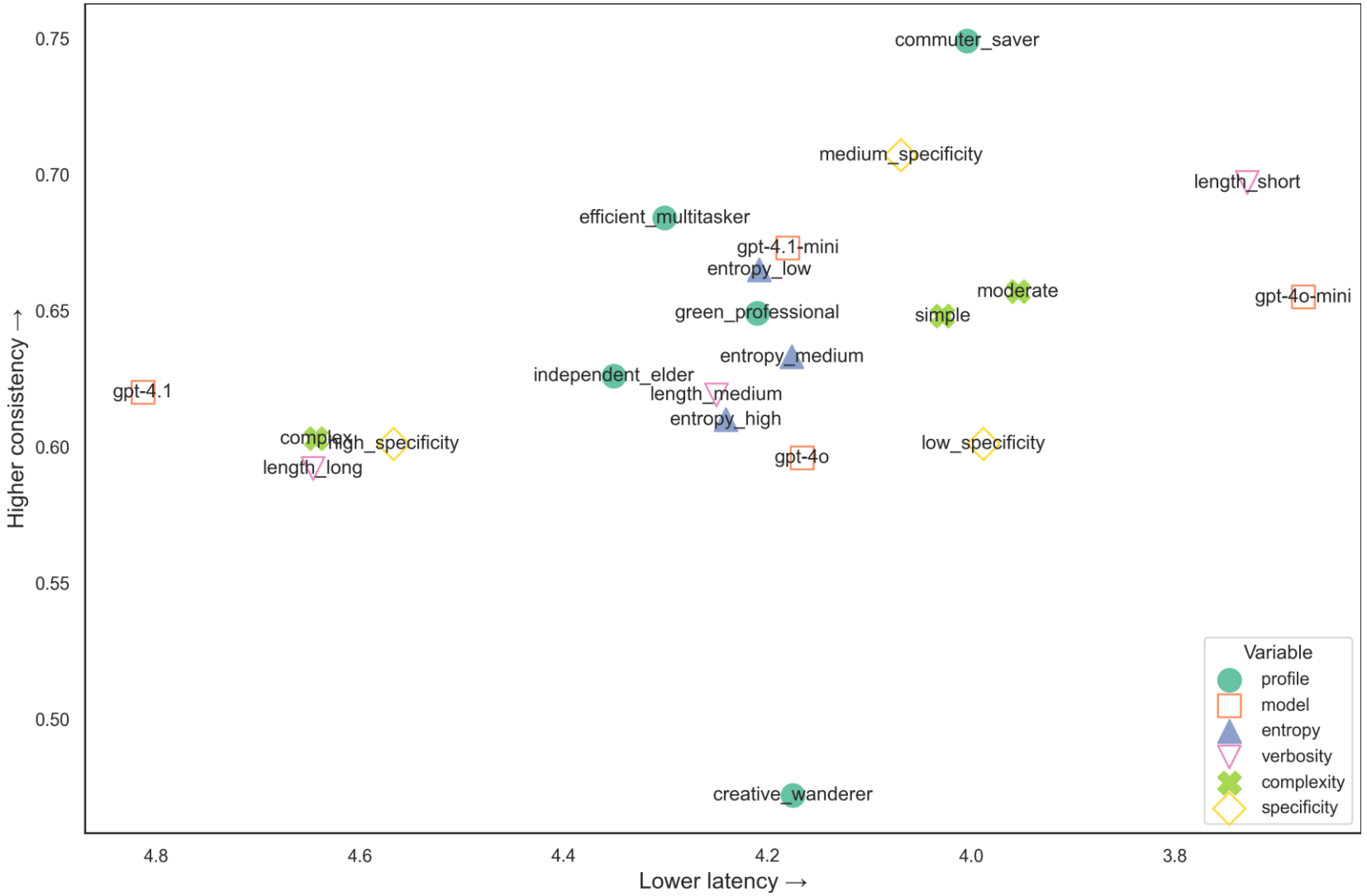
Frictionless Urban Parking

TABLE 4. Results of the non-parametric Kruskal–Wallis *H* test for each experimental factor. Boldface indicates $p < .05$.

Factor	Latency (s)		Consistency	
	H	*p*	*H*	*p*
profile	29.515	0.000	248.775	0.000
model	309.482	0.000	28.692	0.000
entropy	1.630	0.443	13.755	0.001
verbosity	254.753	0.000	69.197	0.000
complexity	185.045	0.000	17.797	0.000
specificity	119.926	0.000	64.388	0.000

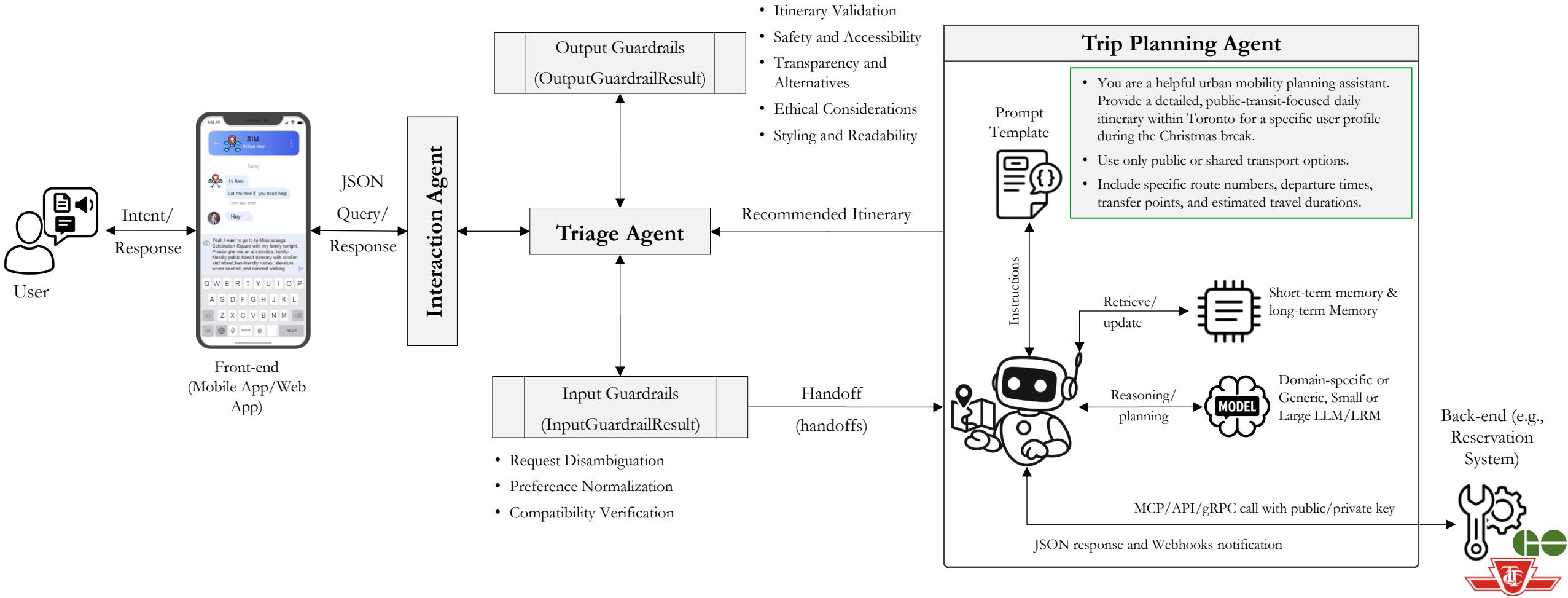
TABLE 5. Robust GLM coefficient estimates relative to the reference condition. Negative values indicate faster replies (delta latency less than 0) or more stable wording (delta consistency greater than 0). Significance levels are marked as follows: ***p < 0.001, **p < 0.01, *p < 0.05.

Level	ΔLatency (s)	ΔConsistency
Profiles		
creative_wanderer	0.172**	−0.277***
efficient_multitasker	0.297***	−0.065***
green_professional	0.206**	−0.100***
independent_elder	0.347***	−0.123***
Model		
gpt-4.1	1.139***	−0.035*
gpt-4.1-mini	0.507***	0.018**
gpt-4o	0.492***	−0.060***
Entropy		
entropy_medium	−0.032	−0.032*
entropy_high	0.033	−0.056***
Verbosity		
length_medium	0.521***	−0.078*
length_long	0.918***	−0.105***
Complexity		
simple	0.074***	−0.009
complex	0.689***	−0.055***
Specificity		
low_specificity	−0.081***	−0.106***
high_specificity	0.498***	−0.106***



Alaa Khamis. Agentic AI Systems: Architecture and Evaluation using a Frictionless Parking Scenario. IEEE Access, 2025.

Personalized Trip Planning



Natural Language Intent | **Reason + Plan + Action** | **Tool-use**

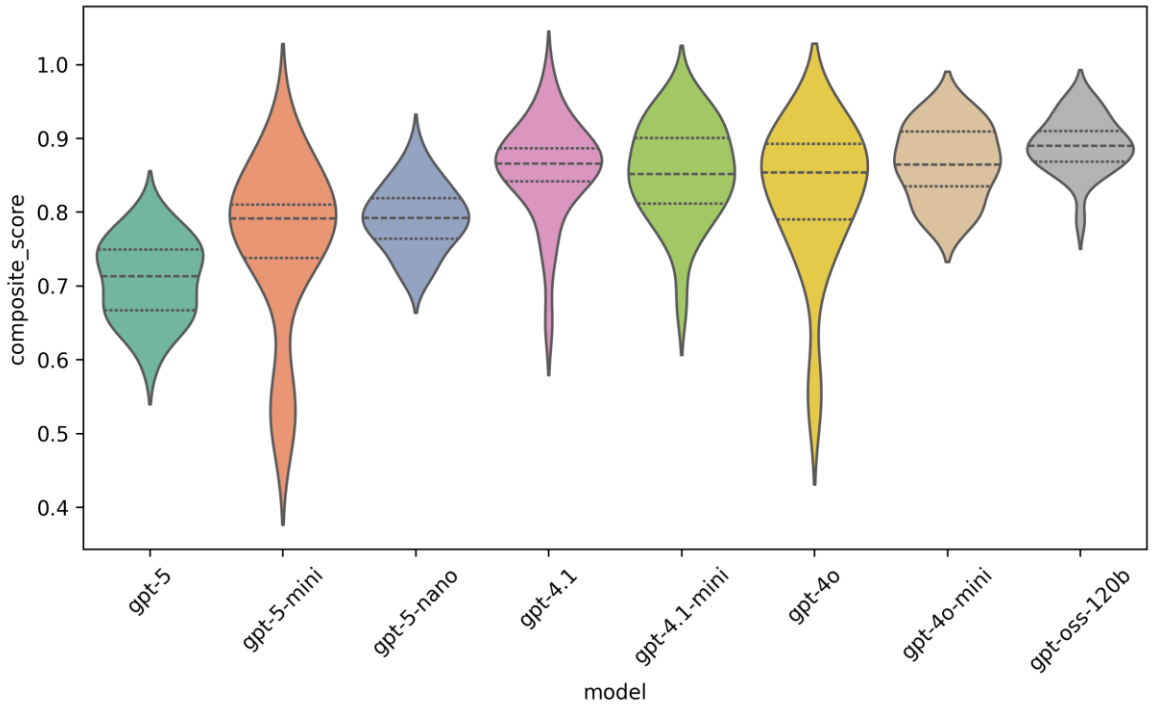
Personalized Trip Planning

EVALUATION METRICS ACROSS MODELS (AVERAGES)

Model	Response Time (s)	Steps	Semantic Similarity	Composite Score
GPT-4.1	11.6	8.1	0.74	0.86
GPT-4.1-mini	13.2	7.6	0.75	0.85
GPT-4o	13.3	8.2	0.69	0.82
GPT-4o-mini	15.2	9.1	0.78	0.87
GPT-5	250.0	20.7	0.88	0.71
GPT-5-mini	67.7	9.9	0.67	0.76
GPT-5-nano	107.9	23.8	0.90	0.79
GPT-oss-120b	38.4	16.3	0.88	0.84

EVALUATION METRICS BY DISTANCE GROUP (AVERAGED ACROSS ALL MODELS AND PERSONAS).

Distance Group	Response Time (s)	Steps	Semantic Similarity	Composite Score
Far	65.8	14.5	0.82	0.81
Medium	64.9	13.3	0.80	0.80
Near	63.5	12.0	0.79	0.79



Personalized Trip Planning

User profiles

Business Executive: Senior professional living in Markham. Frequently travels across the GTA for meetings and networking events. Prefers fast, reliable public/shared transport (GO Transit, TTC subway/streetcar) with minimal transfers. Typically travels during peak hours in business attire. Prioritizes comfort and punctuality, and avoids crowded or delayed routes.

Budget Solo Traveler: Cost-conscious solo resident of Markham. Navigates the GTA for errands, shopping, and free events. Uses TTC, YRT, and GO buses extensively. Prefers lowest-cost routes, even if slower. Open to walking and occasional bike share. Avoids premium services unless absolutely necessary.

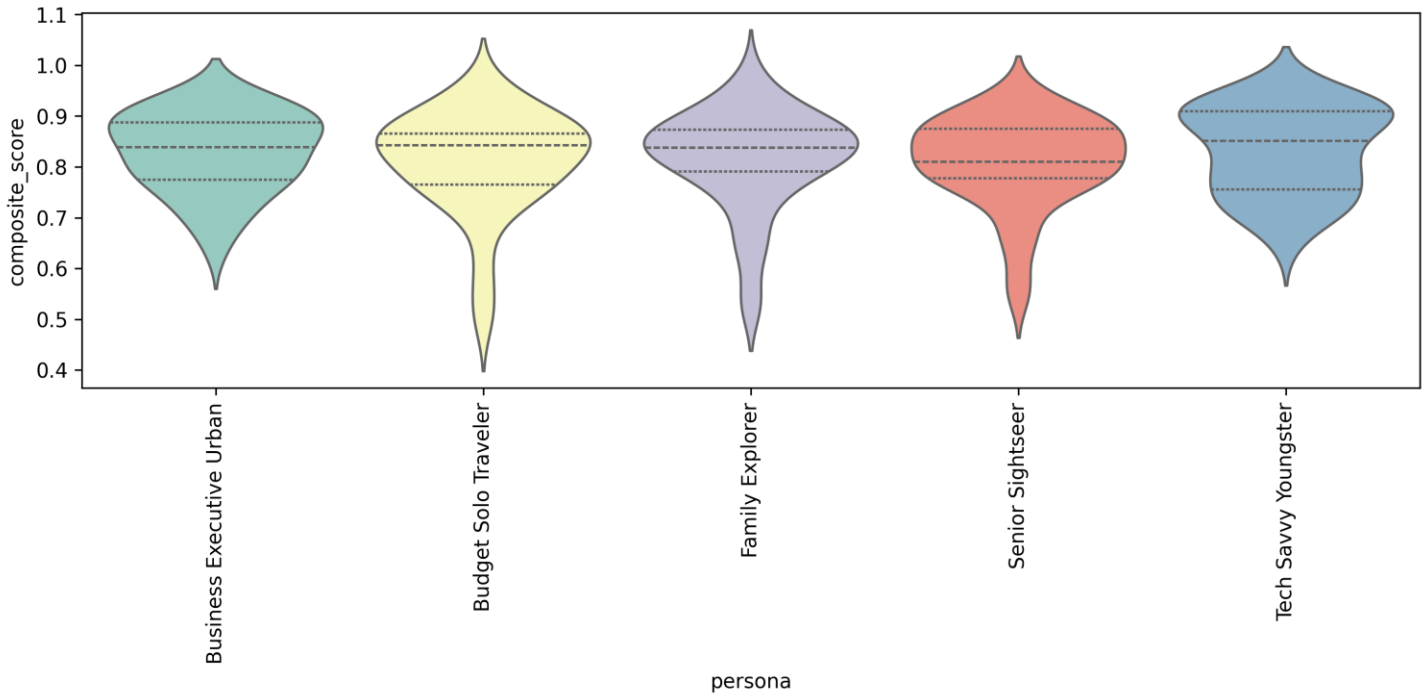
Family Explorer: Parent with young children living in Markham, planning outings (e.g., museums, parks). Needs stroller-friendly, safe routes with minimal walking and reliable arrival times. Prefers transit with elevators, space for kids, and proximity to family-friendly destinations.

Senior Sightseer: Elderly resident of Markham looking to visit cultural sites and family in the GTA. Uses accessible transit (e.g., GO buses, TTC) and avoids complex transfers. Prefers daytime travel. May benefit from services like Mobility On-Request or elevator-equipped stations.

Tech savvy Youngster: University student living in Markham. Travels around the GTA for social outings, study sessions, and late-night events. Uses trip-planning apps (e.g., Transit, Rocketman) and a mix of TTC, GO Transit, and bike/scooter share. Cost-aware but convenience-driven.

EVALUATION METRICS AVERAGED ACROSS MODELS FOR EACH PERSONA.

Persona	Time (s)	Steps	Semantic Similarity	Composite Score
Budget Solo Traveler	69.7	12.9	0.77	0.81
Business Executive Urban	66.1	12.8	0.81	0.83
Family Explorer	75.6	14.0	0.78	0.81
Senior Sightseer	56.7	11.6	0.76	0.81
Tech-Savvy Youngster	68.9	15.7	0.83	0.83



Seamless Umrah Trip Planning

KFUPM
مختبر الذكاء الاصطناعي للتنقل الذكي
AI for Smart Mobility Lab

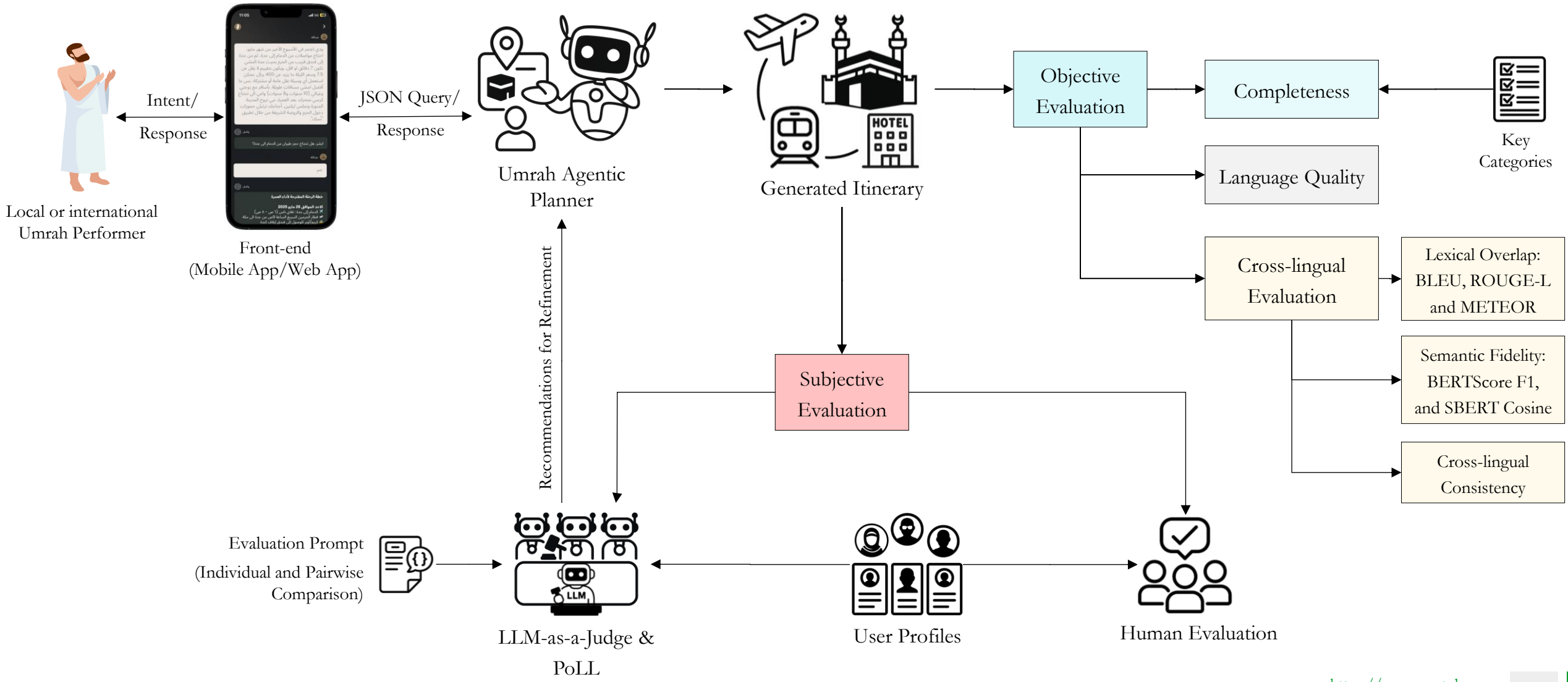
Wasel

منصة رقمية معتمدة على
الذكاء الاصطناعي الوكيل للتنقل
المتكامل السلس لأداء العمرة

First place in the Sustainable Solutions for Pilgrims Challenge – Umrah Challenge, part of the Umrah and Ziyarah Forum (UZF) organized by the Ministry of Hajj and Umrah in Al-Madinah from April 14–16, 2025

https://www.youtube.com/watch?v=bRpQ9QpyHic&

Seamless Umrah Trip Planning



Alaa Khamis. Design and Evaluation of an Agentic AI Framework for Personalized Umrah Trip Planning. Arabian Journal for Science and Engineering, 2026.

Seamless Umrah Trip Planning

Algorithm 3 Language Quality Score

Input: *itinerary*, *language*
Output: *quality_score* in the range $[0, 5]$
text ← concatenate all entries in *itinerary*[step_text]
if *language* = "english" **then**
    corrected ← TextBlob(*text*).correct()
    grammar ← 2.5 if *corrected* = *text*, else 1.5
    compute *avg_len* ← mean words per sentence in *text*
    readability ← 2.5 if $5 \leq$ *avg_len* ≤ 20, else 1.5
    quality_score ← min(*grammar* + *readability*, 5)
else
    segment *text* using Farasa into tokens
    split *text* by punctuation (؟ ! ، .) into *sentences*
    compute *avg_len* ← mean words per sentence
    readability ← 2.5 if $5 \leq$ *avg_len* ≤ 20, else 1.5
    count *punc_count* ← number of (؟ ! ، .) in *text*
    punc ← 2.5 if *punc_count* > 0, else 1.5
    quality_score ← min(*readability* + *punc*, 5)
end if
return *quality_score*

Table 5 Language Quality by LLM Model with Gap

LLM Model	Eng. Quality	Ar. Quality	Gap
gpt-4.1	**4.0**	**4.8**	0.8
gpt-4.1-mini	**4.0**	4.2	**0.2**
gpt-4o	3.6	4.2	0.6
gpt-4o-mini	3.4	4.4	1.0

Table 6 Selected Pareto points for full-factorial analysis. *A*: Perfect consistency point, *B*: Minimum latency point, *C*: trade-off point (0.5/0.5), *RL*: Av. request latency (s), *RC*: request consistency

Profile	Point	Configuration	*RL*	*RC*
efficient executive riyadh	*A*	{gpt-4.1-mini, low entropy, short verbosity, moderate complexity & low specificity}	3.0408	1.00
efficient executive riyadh	*B*	{gpt-4.1-mini, medium entropy, short verbosity, complex complexity & low specificity}	1.9168	0.37
efficient executive riyadh	*C*	{gpt-4.1-mini, low entropy, short verbosity, moderate complexity & low specificity}	3.0408	1.00
faithful budgeter hail	*A*	{gpt-4.1-mini, medium entropy, short verbosity, moderate complexity & medium specificity}	3.6298	1.00
faithful budgeter hail	*B*	{gpt-4.1-mini, high entropy, short verbosity, simple complexity & medium specificity}	2.8515	0.86
faithful budgeter hail	*C*	{gpt-4.1-mini, medium entropy, short verbosity, moderate complexity & medium specificity}	3.6298	1.00
caregiver parent dammam	*A*	{gpt-4o-mini, medium entropy, short verbosity, simple complexity & low specificity}	3.2555	1.00
caregiver parent dammam	*B*	{gpt-4o-mini, medium entropy, short verbosity, complex complexity & low specificity}	2.9989	0.70
caregiver parent dammam	*C*	{gpt-4o-mini, medium entropy, short verbosity, simple complexity & low specificity}	3.2555	1.00
independent elder abha	*A*	{gpt-4.1-mini, medium entropy, short verbosity, simple complexity & medium specificity}	2.8791	1.00
independent elder abha	*B*	{gpt-4o, low entropy, short verbosity, simple complexity & low specificity}	2.7229	0.77
independent elder abha	*C*	{gpt-4.1-mini, medium entropy, short verbosity, simple complexity & medium specificity}	2.8791	1.00
tech savvy youth jeddah	*A*	{gpt-4.1-mini, high entropy, short verbosity, simple complexity & low specificity}	2.8020	1.00
tech savvy youth jeddah	*B*	{gpt-4o-mini, high entropy, short verbosity, complex complexity & medium specificity}	2.5614	0.32
tech savvy youth jeddah	*C*	{gpt-4.1-mini, high entropy, short verbosity, simple complexity & low specificity}	2.8020	1.00

Alaa Khamis. Design and Evaluation of an Agentic AI Framework for Personalized Umrah Trip Planning. Arabian Journal for Science and Engineering, 2026.

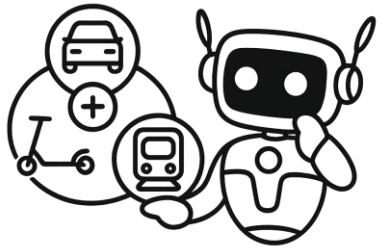
Personalized Mobility Service Bundling

SIM Subscriber

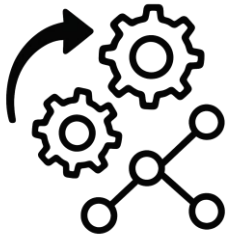
OTA Update

Mobility Service Provider (MSP)

Intent/Response



Mobility Service Bundler



Complex Optimization Solvers

MaaS Bundles

Persona-specific Bundles

Professional

Student

Family

Event-specific Bundles

Expo 2030

WorldCup 2034

Umrah

Corporate Bundles

For employees with company-sponsored benefits

Subsidized Bundles

Elderly/with disabilities

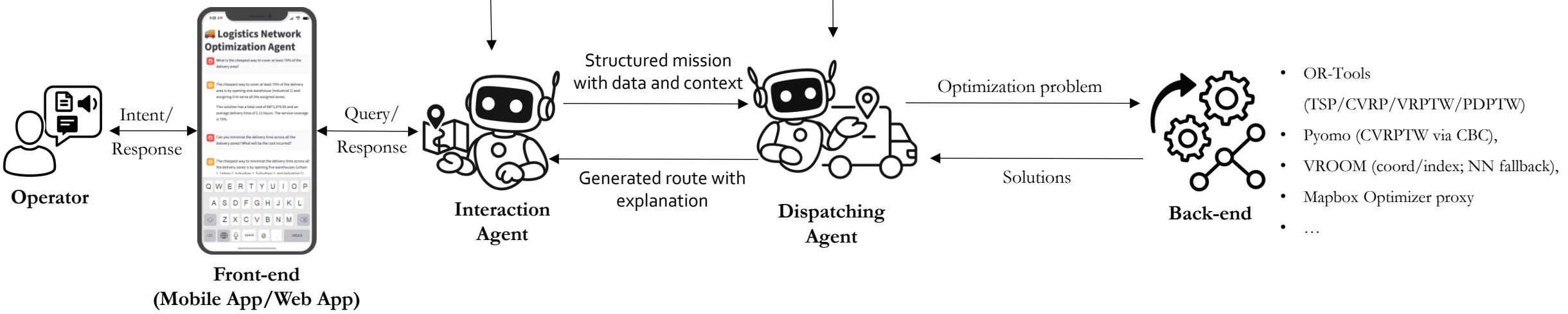
Unemployed

Low-income/ Newcomers

- **Title:** Agentic AI-based Framework for SIM
- **Objective:** Develop as a unified platform that integrates multimodal transportation options.
- **Collaboration:** RCRC, MIT Urban Mobility Lab, VTTI

Agentic Smart Dispatch

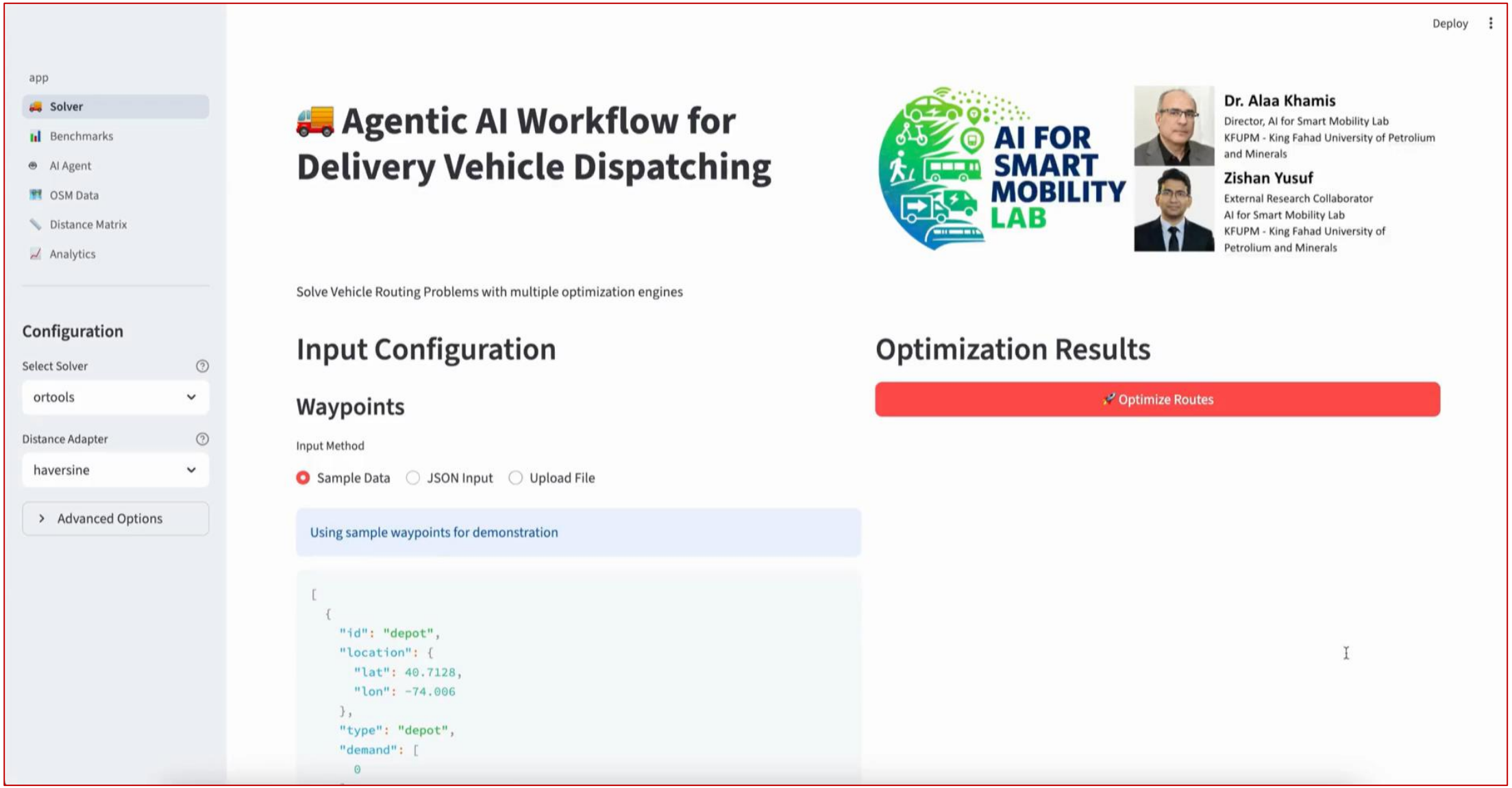

```
UC1 (Route Dispatcher):
  → update_waypoint_location()
  → Modifies: waypoint coordinates ONLY
  → Preserves: time_windows, capacity constraints
  → Output: Data with TW + Capacity → Solver infers CVRPTW

UC2 (Station Manager):
  → modify_waypoint_constraints()
  → Modifies: removes time_windows
  → Preserves: capacity constraints
  → Output: Data with Capacity, no TW → Solver infers CVRP

UC3 (Route Planner):
  → create_single_route_scenario()
  → Modifies: fleet_size=1, removes capacity
  → Output: Single vehicle, no capacity → Solver infers TSP
```



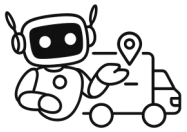
Natural Language Intent → **Reason + Plan + Action** → **Tool-use**

Zishan Yusuf and Alaa Khamis. "Agentic Smart Disptach", submitted to Logistics, 2026

Agentic Smart Dispatch



Last-mile Delivery



Human Operator

Dispatcher/Ops Portal

Goals/
NL Input

Agentic AI Layer

Goal Interpreter
(NL->Objectives)

Objectives

Planner/Orchestrator

Re-solve triggers

Monitoring & Adaptation

Execution plan

Explanation Engine

Selected plan +
metrics

Contextual
Solver
Selection

Data and Context

Orders & SLAs

Fleet State
(Location, capacity,
SoC)

Traffic & Maps
(OSM, ETA)

Policies &
Constraints

Solver Plugins

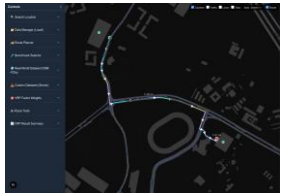
MDP Solver

ML Solvers

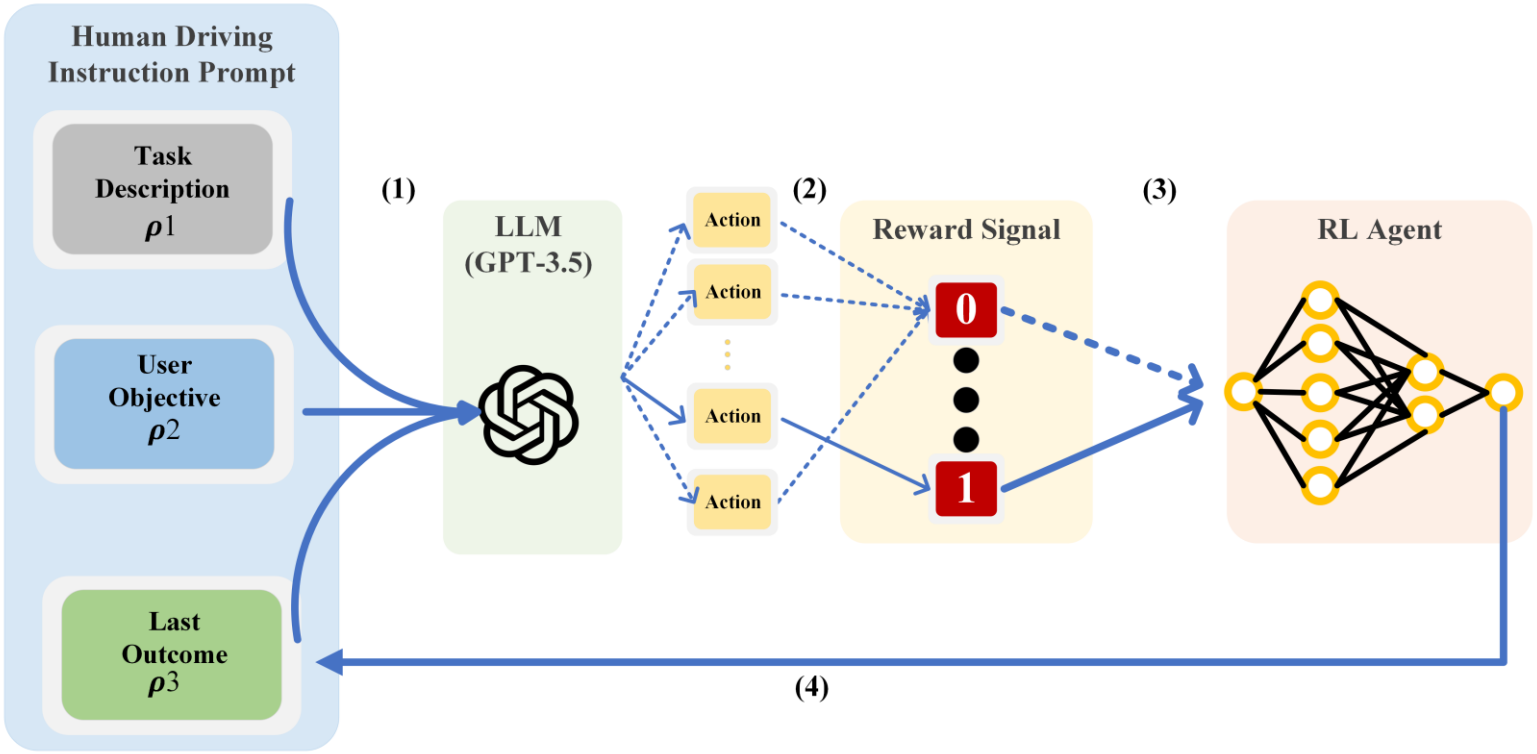
MIP Solver

Heuristics Solver

- **Title:** SmartDispatch: AI-driven Optimization for Eco-Efficient Last-Mile Delivery
- **Objective:** Develop an AI-driven routing model for eco-efficient last-mile delivery.
- **GitHub:** https://github.com/ai4smlab/Multi-Vehicle-Routing



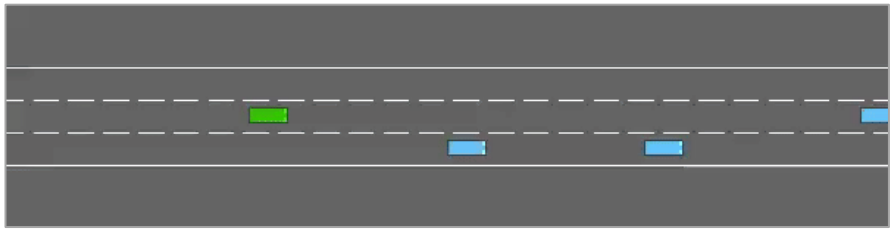
Automated Driving



$$R_{\text{total}}(s,a) = \alpha R_{\text{safety}}(s,a) + \beta R_{\text{efficiency}}(s,a) + \gamma R_{\text{LLM}}(s,a)$$

An example of conservative model

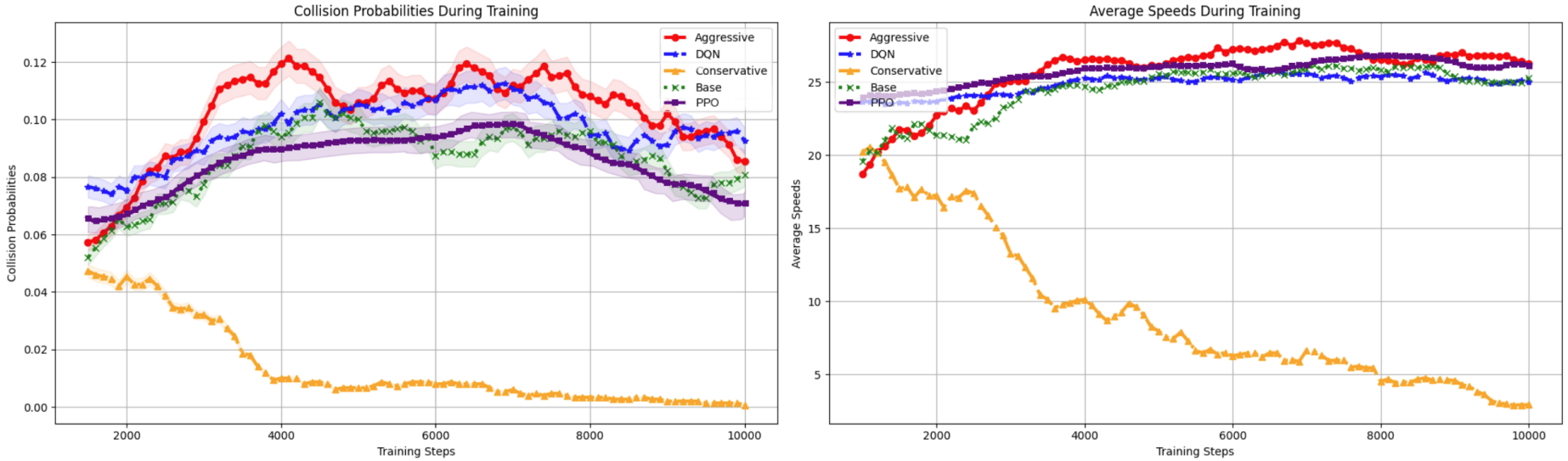
An example of aggressive model



Index	Mean Reward	Lane Change	Speed Up
DQN baseline	0.82824	0.30681	0.42045
Aggressive	**0.83888**	0.02326	**0.83721**
Conservative	0.71391	**0.01333**	0.00666
Base	0.80140	0.10345	0.10345

Ziqi Zhou, Jingyue Zhang, Jingyuan Zhang, Boyue Wang, Tianyu Shi, Alaa Khamis. Human-centric Reward Optimization for Reinforcement Learning-based Automated Driving using Large Language Models. ITRB Annual Meeting, Washington, D.C. 2026, arXiv:2405.04135, 2024.

Automated Driving



(a) Collision probabilities for different driving styles.

(b) Average speed for different driving styles.

Fig. 6: Training results for driving style agents.

TABLE I: Experiment result: behavior analysis including PPO baseline.

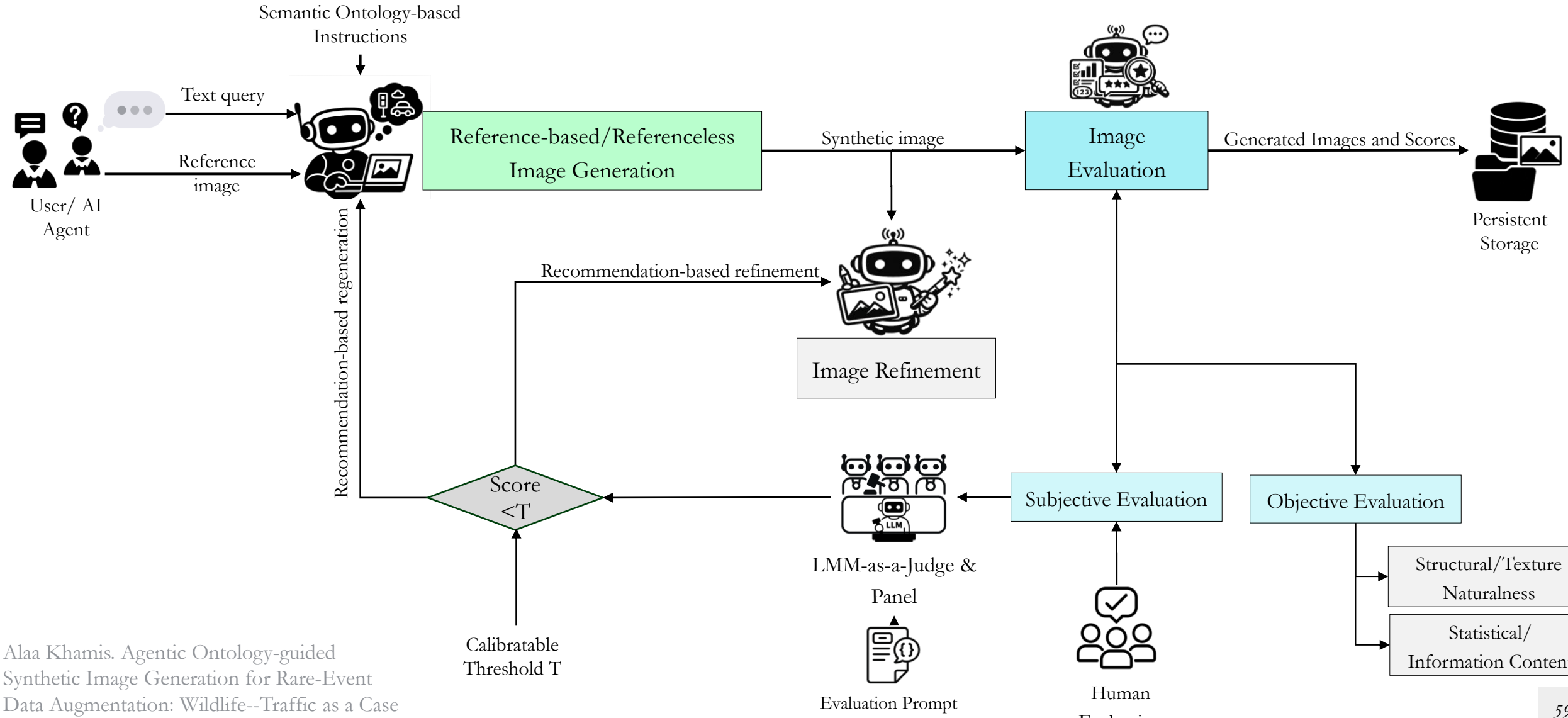
Index	Mean Score	Lane Change Score	Speed Up Score
DQN baseline	0.82824	0.30681	0.42045
PPO baseline	0.81000	0.20000	0.50000
Aggressive	0.83888	0.02326	0.83721
Conservative	0.71391	0.01333	0.00666
Base	0.80140	0.10345	0.10345
BC-SAC [33]	0.83410	0.01750	0.75530
LLM-RL	**0.84532**	**0.01045**	**0.81233**

TABLE II: Reward ablation study: reward breakdown.

Configuration	Collision Score	Lane Change Score	High Speed Score
Safety Only	**-0.05**	0.23	0.18
Efficiency Only	-0.20	**0.48**	**0.72**
LLM Only	-0.10	0.31	0.33
Safety + Efficiency	-0.12	0.35	0.55
Safety + LLM	-0.08	0.28	0.42
Efficiency + LLM	-0.15	0.41	0.63
All (Full Reward)	-0.12	**0.53**	0.75

Ziqi Zhou, Jingyue Zhang, Jingyuan Zhang, Boyue Wang, Tianyu Shi, Alaa Khamis. Human-centric Reward Optimization for Reinforcement Learning-based Automated Driving using Large Language Models. ITRB Annual Meeting, Washington, D.C. 2026, arXiv:2405.04135, 2024.

Rare-Event Data Augmentation

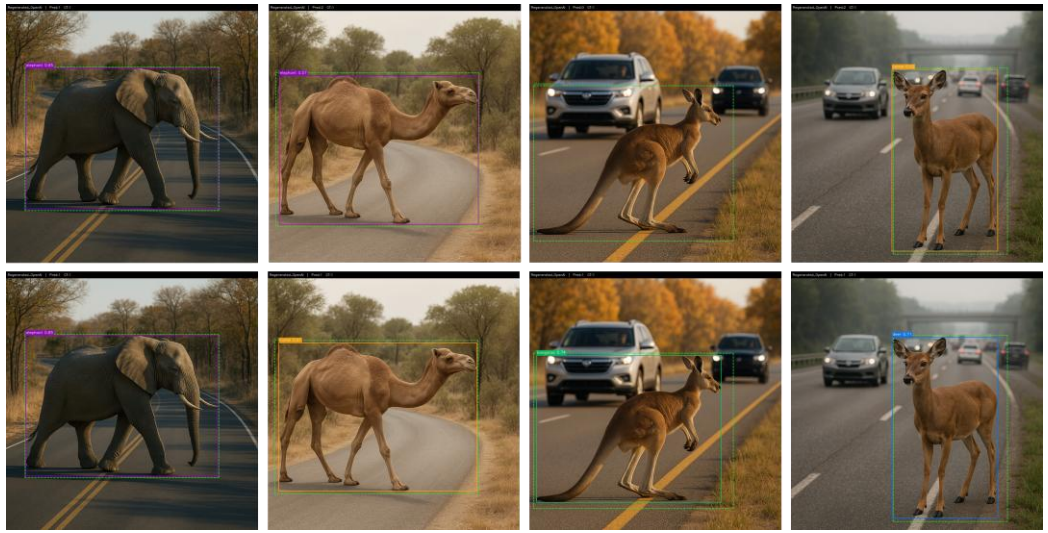


Alaa Khamis. Agentic Ontology-guided Synthetic Image Generation for Rare-Event Data Augmentation: Wildlife--Traffic as a Case Study. Submitted to Array, 2026. GitHub

Rare-Event Data Augmentation

Figure: Examples of generated images using a referenceless ontology-guided approach. (1) GPT-5 synthesis, (b): gpt-image-1 refinement, (c) Recommendation-driven regeneration, (d) Gemini 3 Pro synthesis.

Method	BRISQUE ↓	ILNIQE ↓	PIQE ↓	NRQM ↑
Naturalistic Reference	12.62	42.20	28.76	8.09
Referenceless OpenAI (Generated)	19.90	47.50	39.76	7.57
Referenceless OpenAI (Recommendation-driven Refined)	20.77	48.03	35.90	7.13
Referenceless OpenAI (Recommendation-driven Regen)	19.47	48.76	34.10	7.39
Referenceless Gemini 3 Pro	**9.67**	**41.31**	**32.12**	**8.36**



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Thank you!

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April 16, 2026