LLMs in the Loop

Rethinking Testing for and with Language Models

2025-08-27, SIESTA, Lugano, Switzerland

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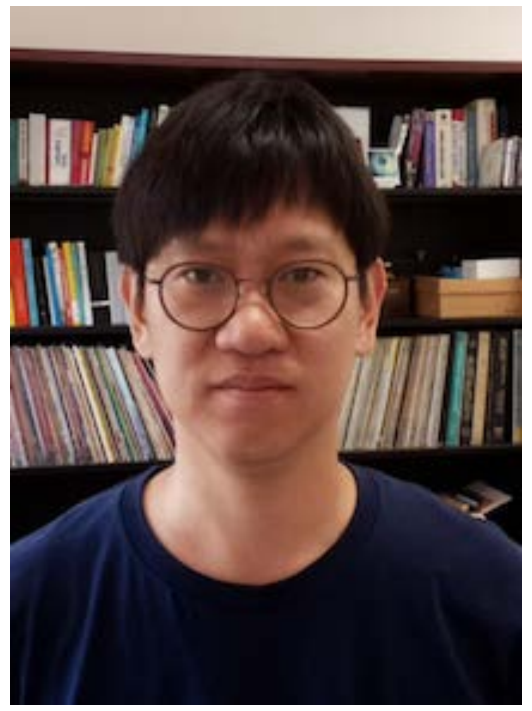
Credits elsewhere, faults mine

Shin Yoo &
amazing students



Shin Yoo

Jinhan Kim

Sungmin Kang

Juyeon Yoon

+ more…

Chalmers Applied AI Group

Yinan Yu

Arsham Ghoee

Shuai Wang

+ more…

Chalmers/GU Testing/SE groups

Many incl. R. Torkar, F. Dobslaw, S. Akbarova, J. Frattini…

My main (technical/topic) message

- AI4Testing has been a fact for years, and LLMs4Testing picking up steam
- Testing4AI is increasingly critical as AI merges with SW & society at large
    - Testing4AI is increasingly also Testing4SW (since rapid growth in hybrid AI-based/driven SW)
- Together they can create a powerful loop: AI4Testing4AI (with SW naturally along for the ride)
    - AI/LLM improves testing; better testing helps create more robust & capable AI+SW
    - Co-evolutionary spirals that gives us very powerful testing tools!?
- AI/LLMs introduces some new challenges for testing (but maybe not fundamentally new!?)
- Testing AI/LLM with AI/LLM can have double benefits
    - Even if no/slow co-evolution: Improved testing techniques + learning to create hybrid SW/AI systems
- Self-improving systems will be in the Future of SW Testing
    - Autonomous testing agents that improves themselves & the systems they test
    - Human-in-the-loop yes, but as “Messy (A)synchronous Co-Augmentation”

But there are also two meta-talks here…

- 1. Your AI/SE Stance:
    - Are you clear what it is?
    - Is it defendable?
    - Will you keep or vary it throughout your PhD project?
- 2. What lead to these studies/results and what might you learn from it?
    - “Recent” events (proximate causes) that lead to it
    - What earlier actions/events actually lead up to these recent events?
    - What does “my journey” imply for the one you’re on?

Causes + implications for you

- Academic seniors are very busy => Reuse results and slides => Might miss later reflections/ideas and audience adaptation
- Potential learnings:
  - Always think about your audience - what might be good/useful for them
  - Consider if you really want to become a senior academic ;)
  - Really learn to say no. Really.
  - But saying no is so hard. Best is if you can study a master.
  - Beware of potential problem of saying no. You might miss oppos and be less open to new connections.
  - To focus is generally good but can also lock things out.
  - If they ask for slides weeks/days in advance, explain that is not how you work ;)

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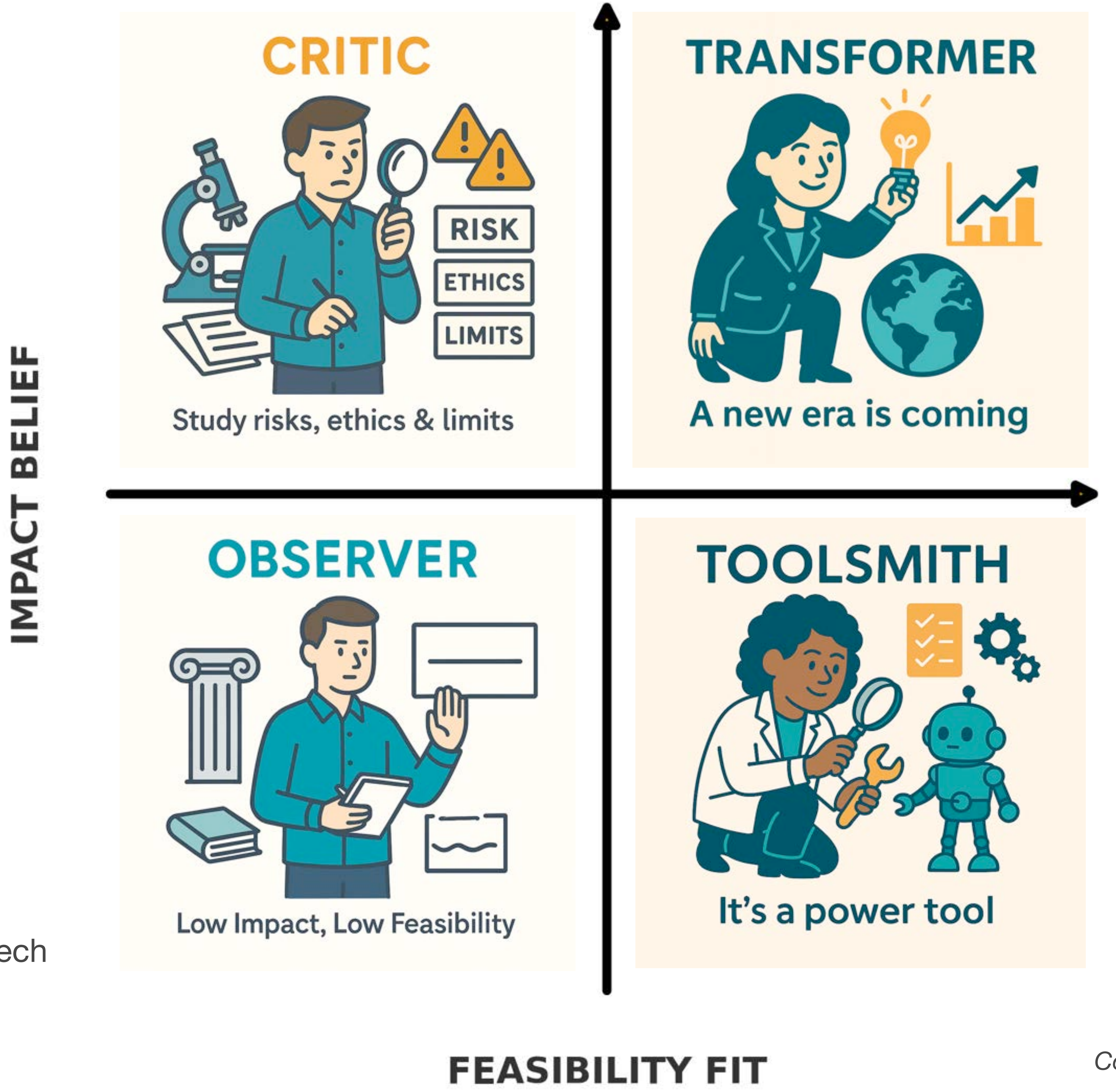
AISE Stance Map



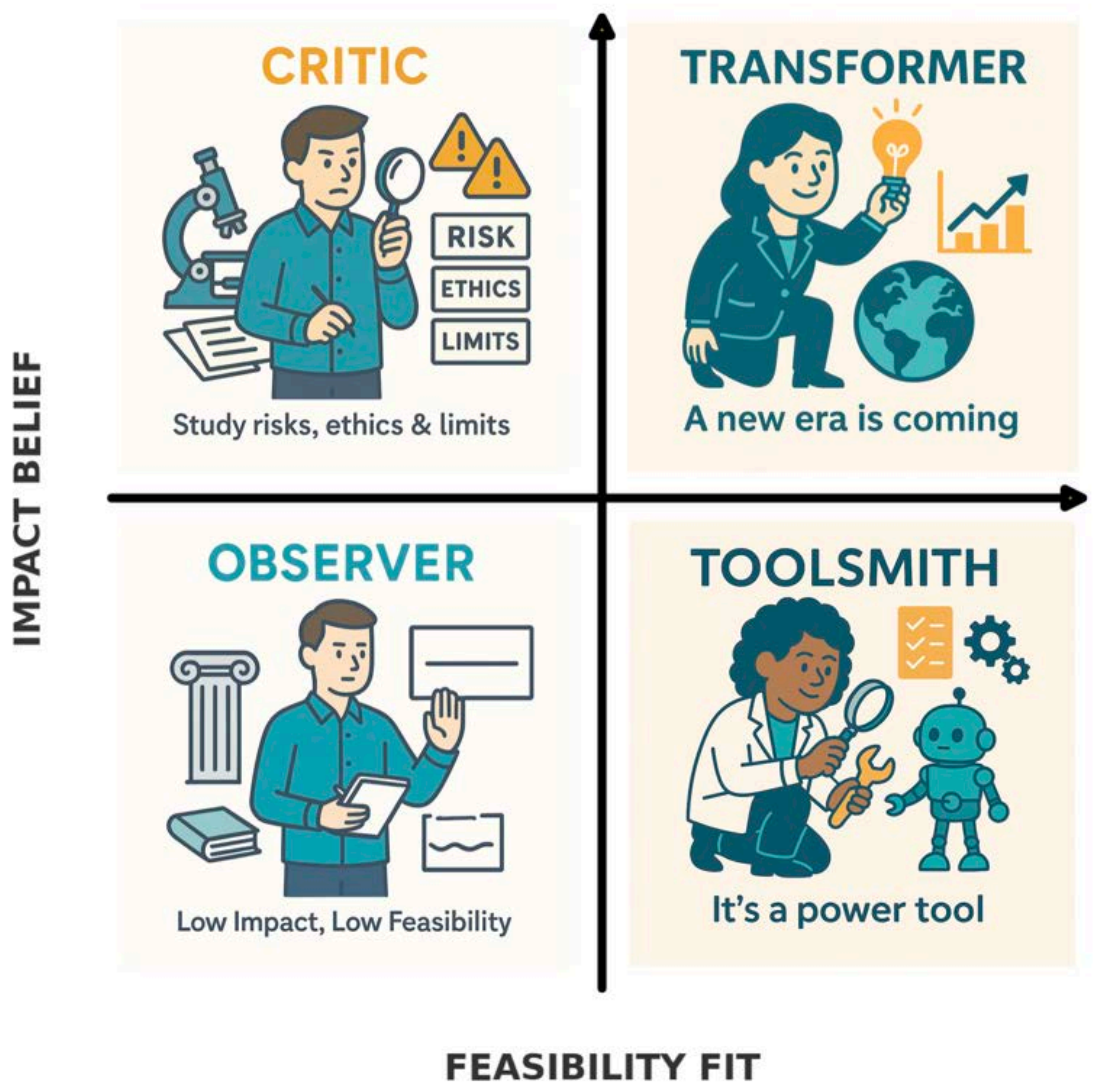
AI **SEAT** =
Stance Evaluation for AI in sw eng/Tech

"Take your AI SEAT"

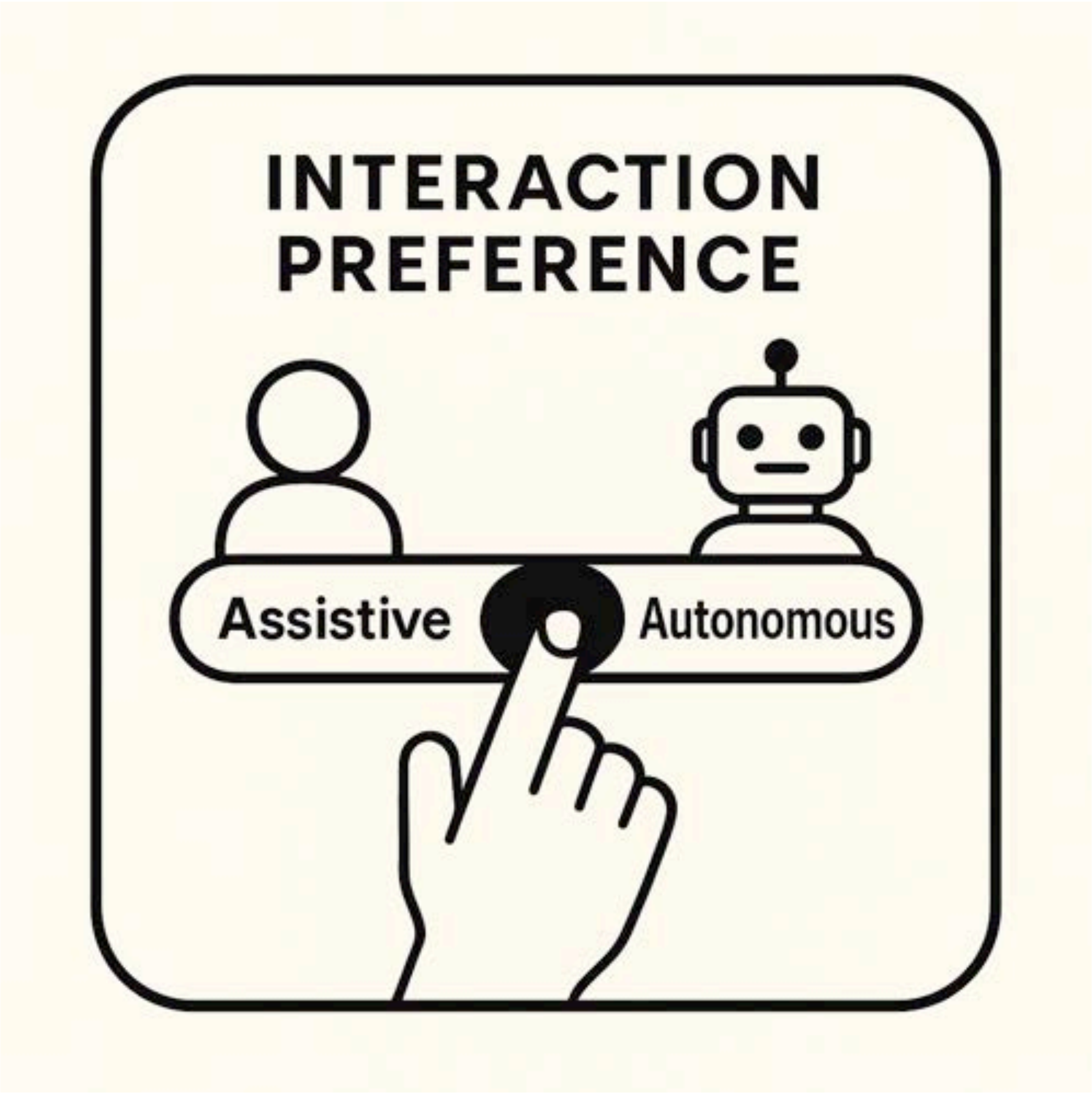
Why a stance map?

- AI/LLMs affect SE unevenly
  - Your stance shapes **what to study**, **which tools** to try, and **how to eval**
- Making your stance explicit can reduce
  - hand-wavy debates, and
  - scope creep in projects and reviews.
- Map can give more neutral language for collaborators/reviewers to
  - locate a project and choose next steps
- Deliberately simple model
  - won't capture every nuance—but it's fast, transparent, & hopefully useful

Overlays


CRITIC
RISK
ETHICS
LIMITS
Study risks, ethics & limits
TRANSFORMER
A new era is coming
OBSERVER
Low Impact, Low Feasibility
TOOLSMITH
It's a power tool
IMPACT BELIEF
FEASIBILITY FIT


[CONSTRAINED] CONTEXT
Blocks even a small trial


INTERACTION PREFERENCE
Assistive
Autonomous

Self-placement (10 minutes)

- Impact Belief - Agree/Disagree
  - “AI/LLMs will **meaningfully change** my subfield’s questions, methods, benchmarks, and/or workflows in the **coming 18 months**.”
- Feasibility Fit (current project) — Agree/Disagree
  - “In my current project, there is at least one specific task where an AI tool **could plausibly help**, and **I could tell soon** if it helped.”
- ([Constrained] Context):
  - “Right now, external constraints (data/privacy, compute/cost, policy/ethics, time/teaching load) would block even a small trial.”
- (Interaction Preference):
  - “For this project, I prefer **assistive, human-in-the-loop** use over **autonomous agents/solution**.”

Revisiting a vision: Autonomous Testing Agents

Towards Autonomous Testing Agents via Conversational Large Language Models

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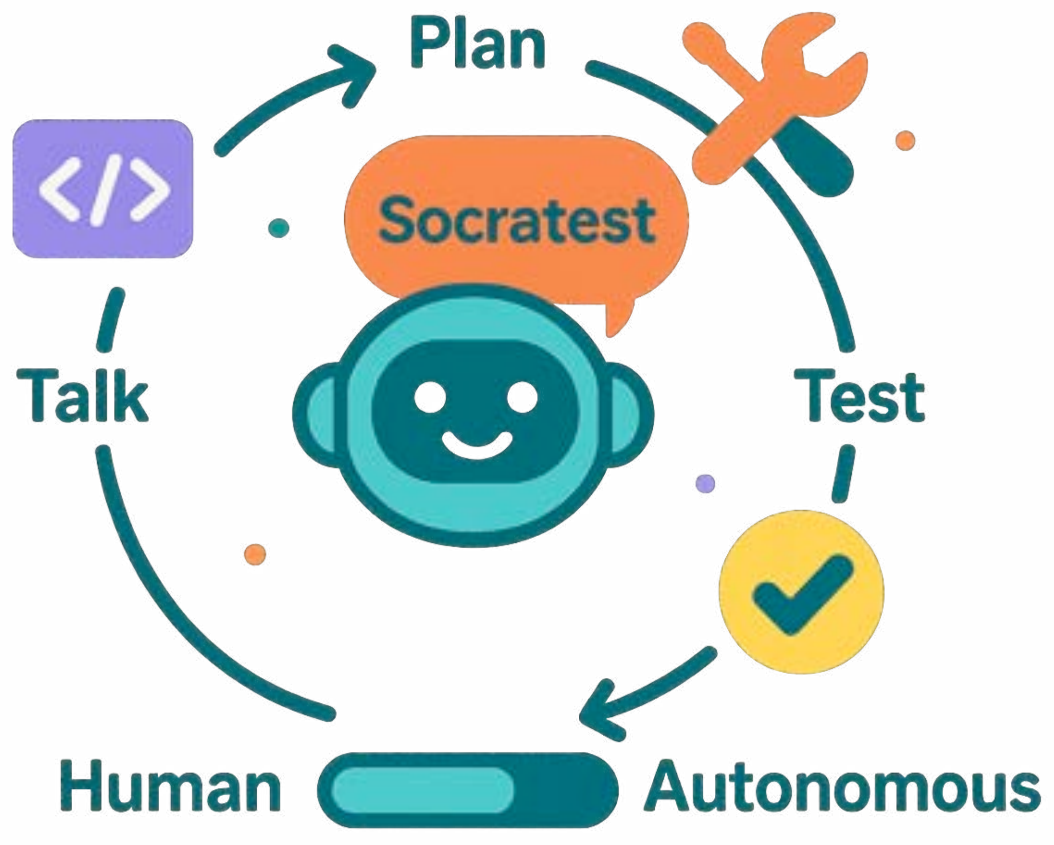
https://arxiv.org/abs/2306.05152

Elevator pitch summary



- proposes **SOCRATEST**, a vision for
  - conversational, increasingly autonomous testing agents powered by large language models (LLMs),
  - supported by a middleware that grants tool access, memory, and planning
- introduces a **taxonomy of LLM use in software testing**
  - arguing that higher autonomy unlocks greater developer benefits.
- **Illustrative** GPT-4 session shows: dialogue can surface subtle specification issues
- **Maps some limitations**
  - lack of native tools use, weak planning, costs

Revisiting a vision: Autonomous Testing Agents

TABLE I
TAXONOMY OF LLM USES IN SOFTWARE TESTING

Mode of Usage	Driver	Interactive	Available Information	Autonomy
Conversational Testing Agents	Human, Middleware, LLM	Yes	Extensive:, information from both user and the tools in middleware	High
Conversational Testing with Tools	Human, Middleware	Yes	High, additional outputs from algorithms & methods	Low
Conversational Testing	Human	Yes	Rich: a mixture of templates, contexts, examples, and explanations	No
Contextual Prompting	Front-end, Testing SW	No	Medium: templates with contexts & examples	No
Completion & Infilling	Front-end, Testing SW	No	Low: typically autocompletion of given code	No

IMHO, we were naive in applying old SE concept (middleware) here: Multi-agent LLM-driven Test Systems!

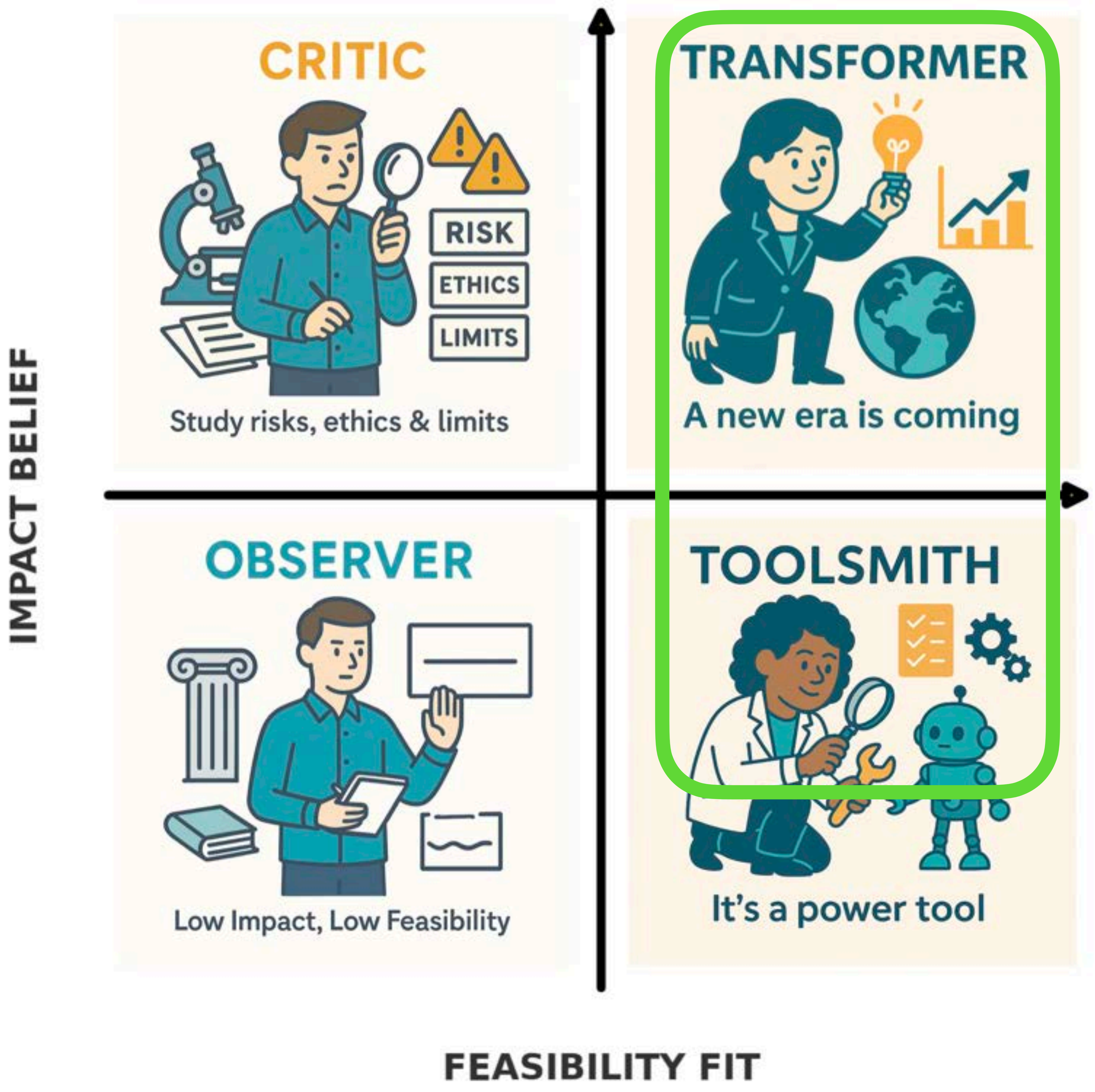
Human-in-the-loop yes, but not as controller or arbiter but as co-creator:

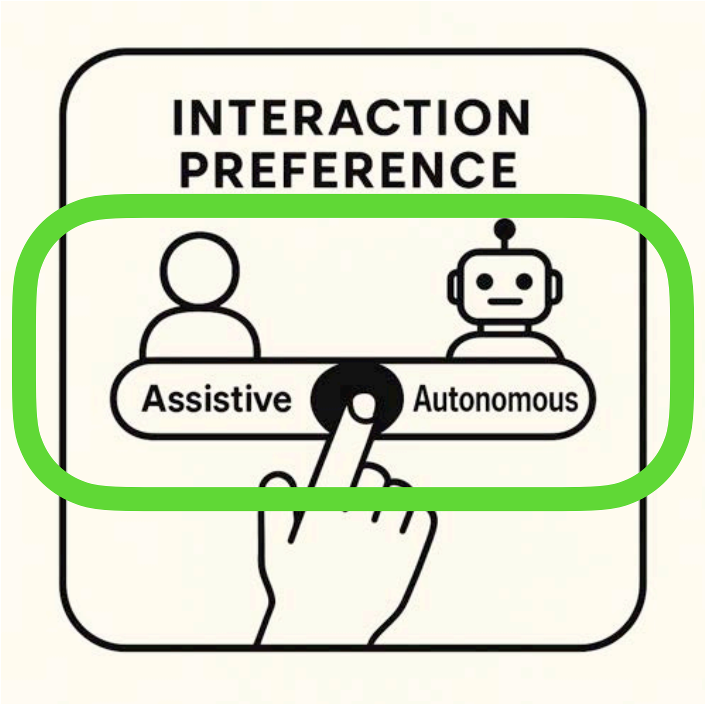
“Messy Asynchronous Co-Augmentation” - continuous testing when we are not around +
our input/direction at times (but that is bi-directional not from “us to them”)

Causes + implications for you

- Visited Shin Yoo in South Korea in December 2023, right after ChatGPT
- Almost every year I go visit Shin Yoo & his lab in South Korea for 10-12 days
- We really “connected” at ICST 2009 & have now published >15 (top) papers
- His students shares what they are working on and we “riff off that”
- Potential learnings:
  - Don’t let (physical) distance stop you if intellectual/emotional connection is there
  - Trust your gut feeling for what is important/possible/interesting
  - Be open to the new and consider it (but maintain your strong convictions/goals)
  - Don’t reach for your old solutions automatically, when in the new

Towards Autonomous Testing Agents via Conversational Large Language Models





DroidAgent: LLMs automate Android GUI Testing

Autonomous Large Language Model Agents Enabling Intent-Driven Mobile GUI Testing

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ICST 2024, https://arxiv.org/abs/2311.08649

DroidAgent: Android GUI Testing

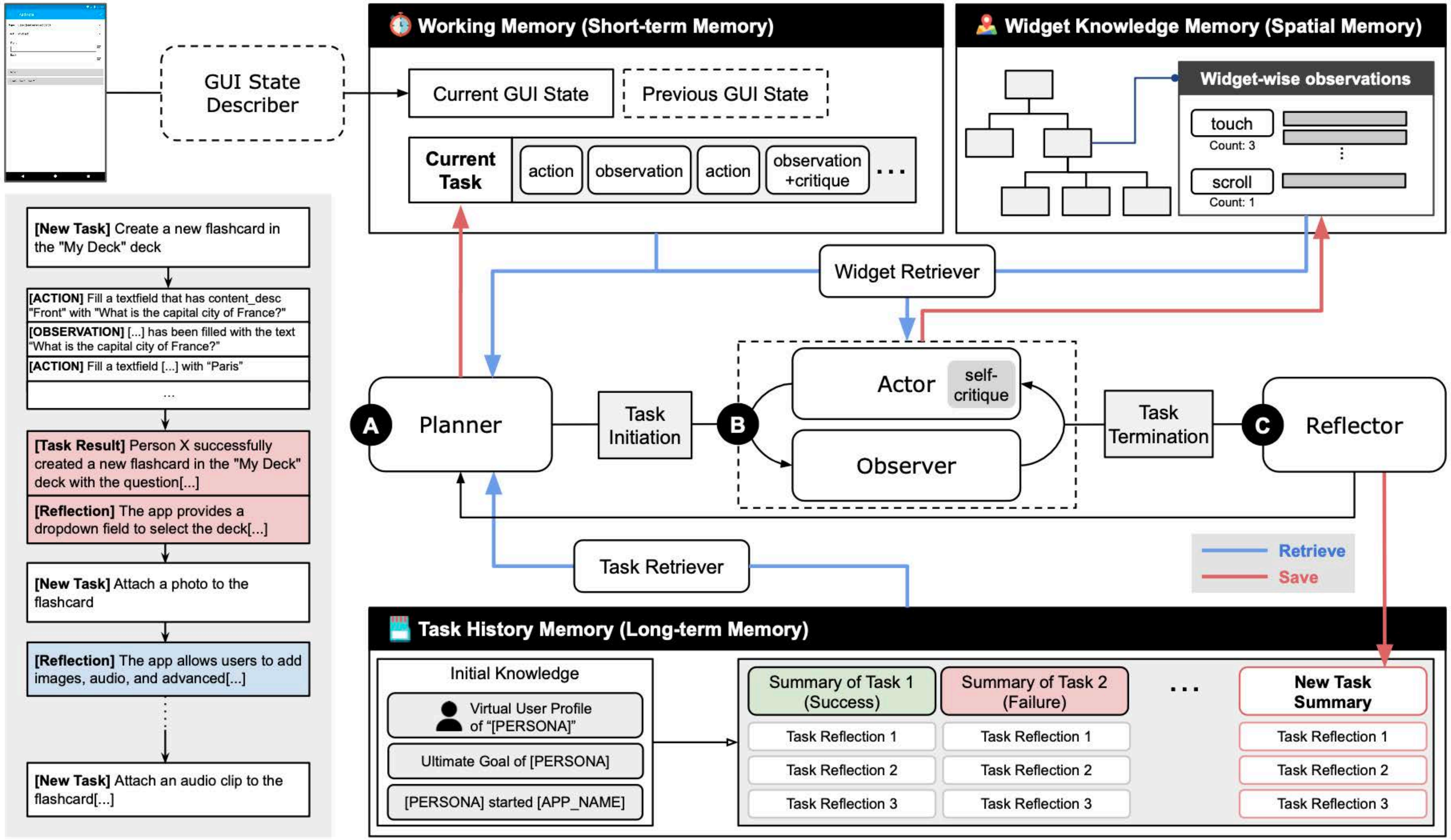


Fig. 1. Overview of DroidAgent with a task example.

DroidAgent: Evaluation

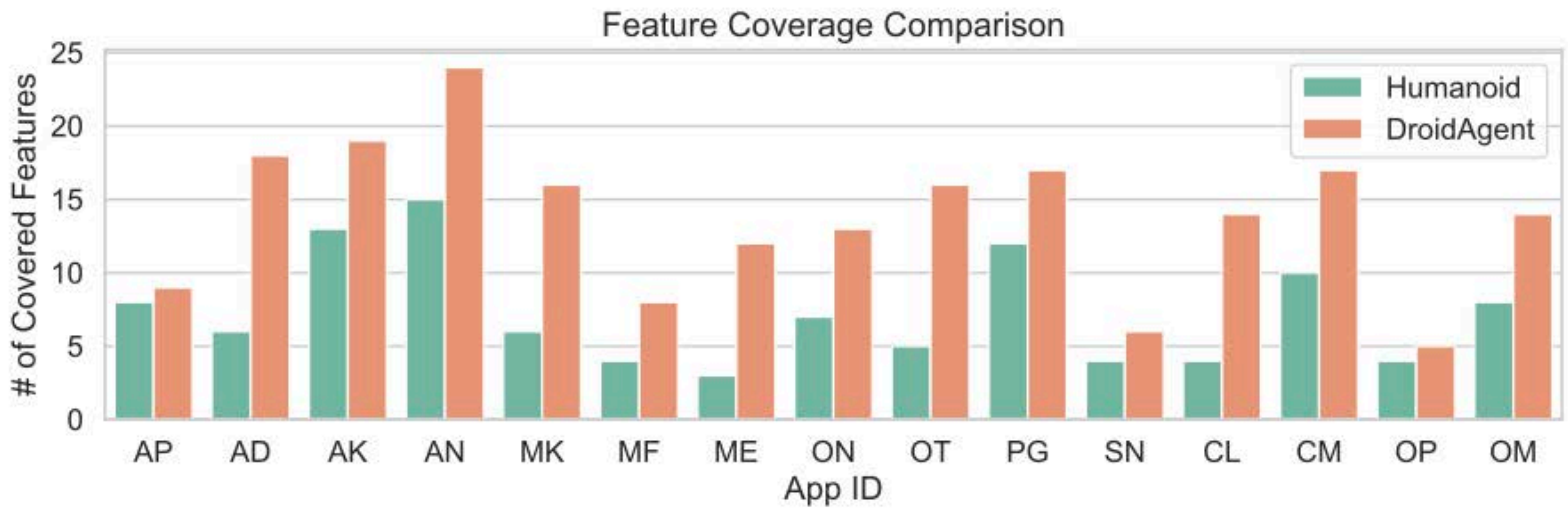
TABLE I
ANDROID APPLICATIONS USED IN DROIDAGENT'S EVALUATION.

App Name	App ID	From	Category	# of Activity	App Name	App ID	From	Category	# of Activity
ActivityDiary	AD	Themis	Personal Diary	10	openlauncher	OP	Themis	App Launcher	7
AnkiDroid	AK	Themis	Card Learning	22	osmeditor4android	OM	Themis	Map	18
AntennaPod	AN	Themis	Podcast Manager	10	MaterialFB	MF	F-Droid	Social	4
Markor	MK	Themis	Text Editor	9	collect	CL	F-Droid	Form Data Collector	37
Omni-Notes	ON	Themis	Notebook	12	APhotoManager	AP	F-Droid	Photo Manager	9
Phonograph	PG	Themis	Music Player	12	MyExpenses	ME	F-Droid	Expense Tracking	40
Scarlet-Notes	SN	Themis	Notebook	8	OpenTracks	OT	F-Droid	Sports & Health	24
commons	CM	Themis	Wikimedia	17					

TABLE II
NUMBER OF COVERED ACTIVITIES PER APP BY EACH TECHNIQUE

Subjects	DROIDAGENT	DroidBot	GPTDroid	Humanoid	Monkey	Total
APhotoManager	**5**	**5**	4	**5**	**5**	9
ActivityDiary	**10**	3	6	5	5	10
AnkiDroid	**15**	14	6	13	13	22
AntennaPod	4	3	1	**5**	3	10
Markor	4	4	4	**5**	**5**	9
MaterialFB	**3**	1	3	**3**	2	4
MyExpenses	**15**	7	12	7	11	40
Omni-Notes	5	3	5	**6**	3	12
OpenTracks	**16**	7	11	10	**16**	24
Phonograph	**11**	7	6	9	9	12
Scarlet-Notes	3	3	**4**	3	3	8
collect	**13**	12	2	9	9	37
commons	**14**	11	7	12	5	17
openlauncher	**6**	2	3	3	4	7
osmeditor4android	9	5	6	**12**	8	18
Total	**133**	87	80	107	101	239

IMHO, apps are realistic but also "simple", so harder to claim this will generalise to novel/new apps



DroidAgent understands apps more deeply

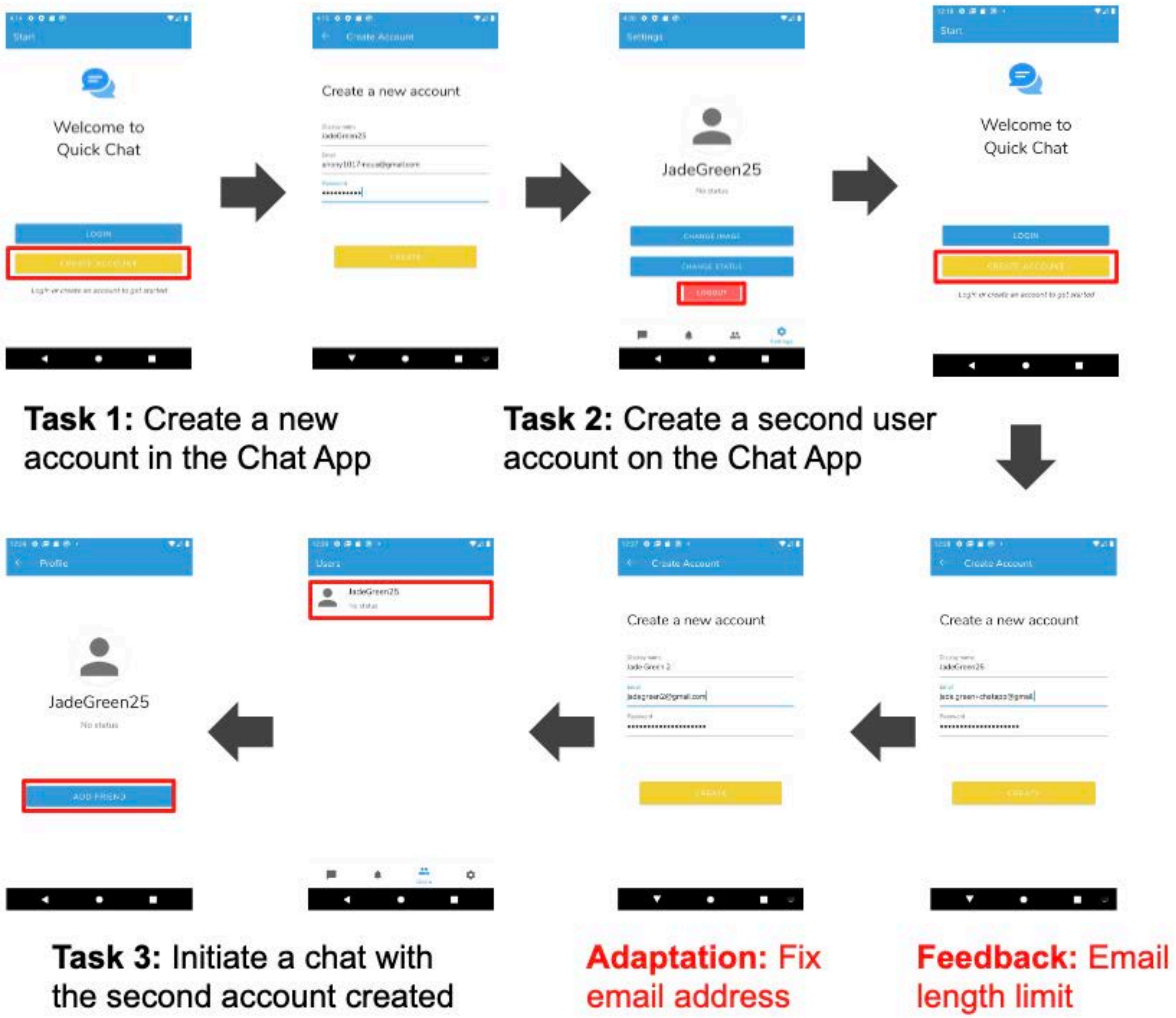
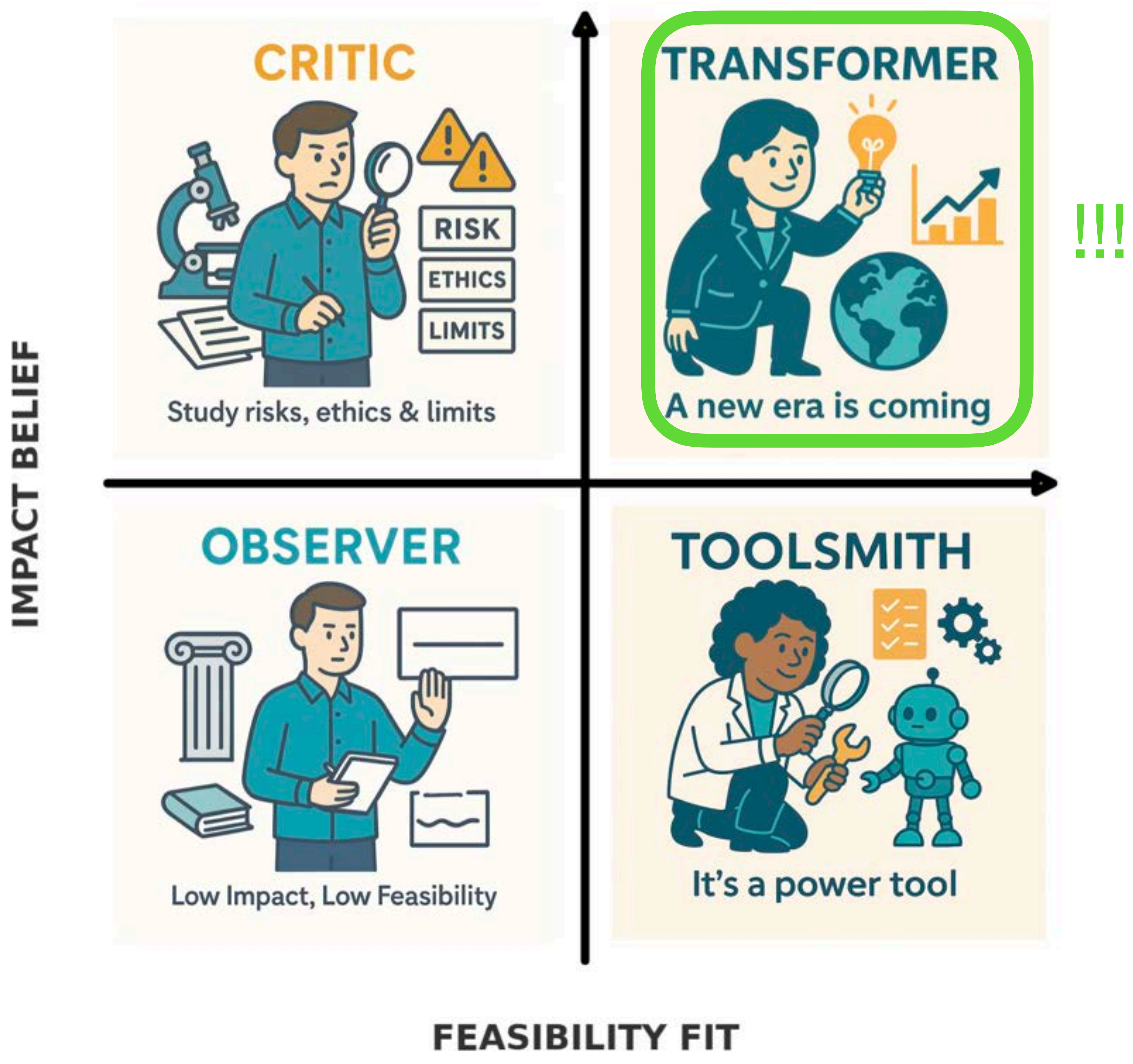
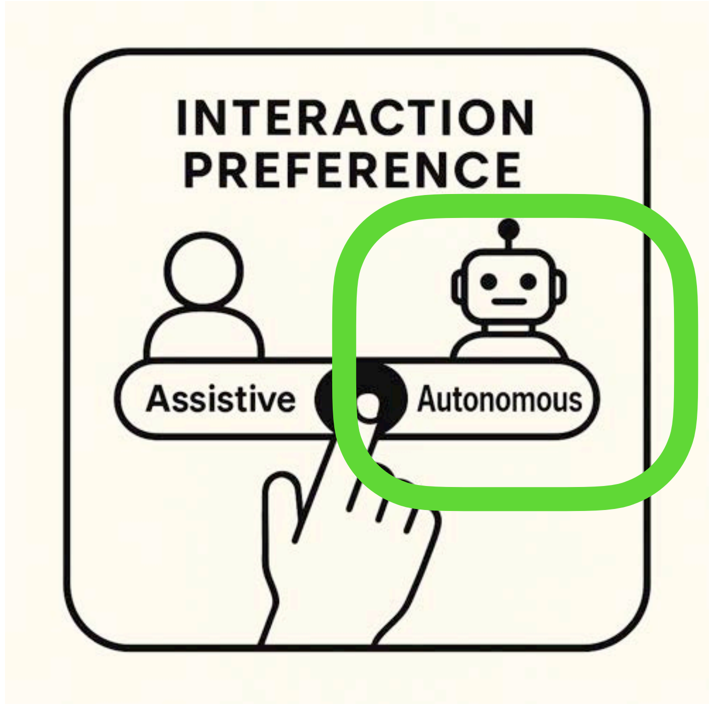


Fig. 10. Example of testing scenarios by DroidAgent for creating multiple accounts in a simple chat app.

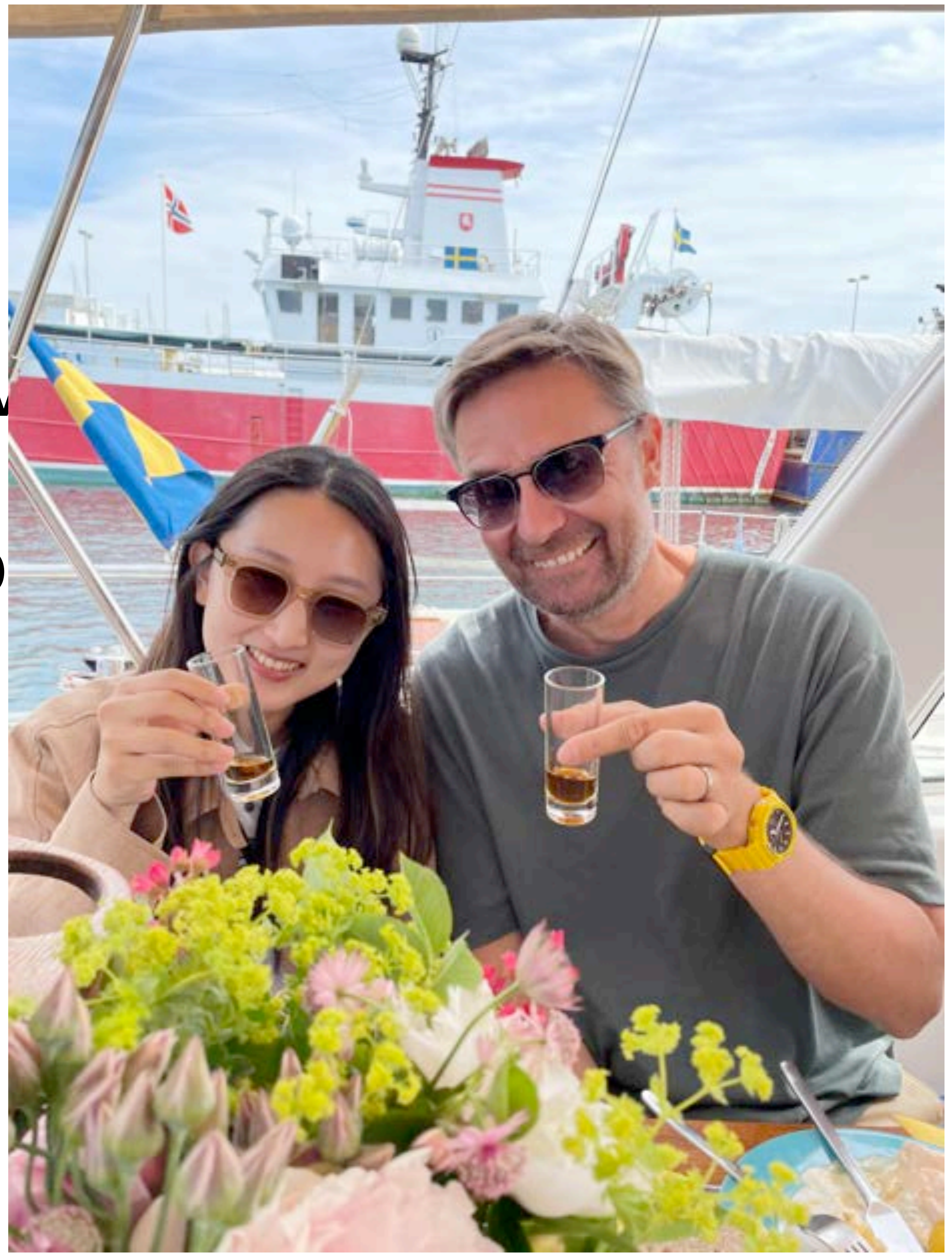
Autonomous Large Language Model Agents Enabling Intent-Driven Mobile GUI Testing





Causes + implications for you

- Good connection & shared vision Dec-23 => invite Juyeon for visit May-24
- Went bold (autonomous testing agents) but also simplified (skip conversation)
- Not easy technically; very little support for developing agents
- Potential learnings:
  - Dare to trust the new, at least tentatively, so that you can at least ev
  - No need to do everything at once; isolate key aspects and go deep
  - Persist!
  - Do a visit in another environment during your PhD!
    - 5-8 weeks often enough IMHO!



Early successes: LLMs really can help with testing

ICSE 2025, https://arxiv.org/abs/2502.04008

Automating a Complete Software Test Process Using LLMs: An Automotive Case Study

Shuai Wang[1], Yinan Yu[1], Robert Feldt[1], Dhasarathy Parthasarathy[2]
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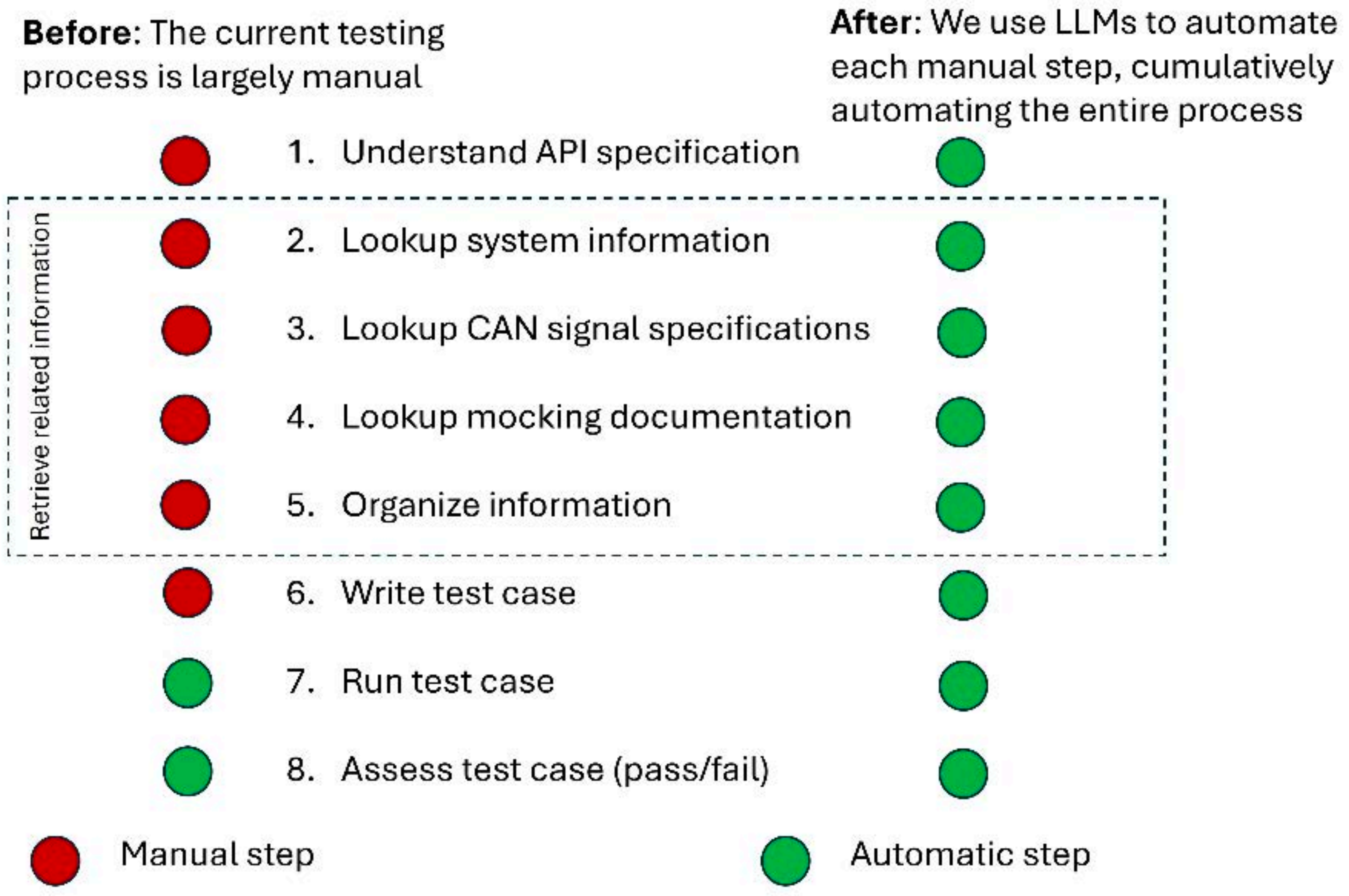


Fig. 1. We present the case of automatically testing SPAPI, an in-vehicle web server. Previously, the multistep process of testing SPAPI was largely manual. Using LLMs to automate each manual step, we achieve complete automation.

- LLM pipeline to fully automate API testing
- Modeled on the previous, manual process:
  - Understand API-relevant specs and docs
  - Semantic & fuzzy matching across sources
  - Generates internal mappings, then generate test cases
- Benefits
  - End2End autom. of judgment-heavy (not creative) task
  - Massive time savings (1-3 days => 11 seconds)
  - Reliable results + test logs, so human can step in

SPAPI-Tester Workflow

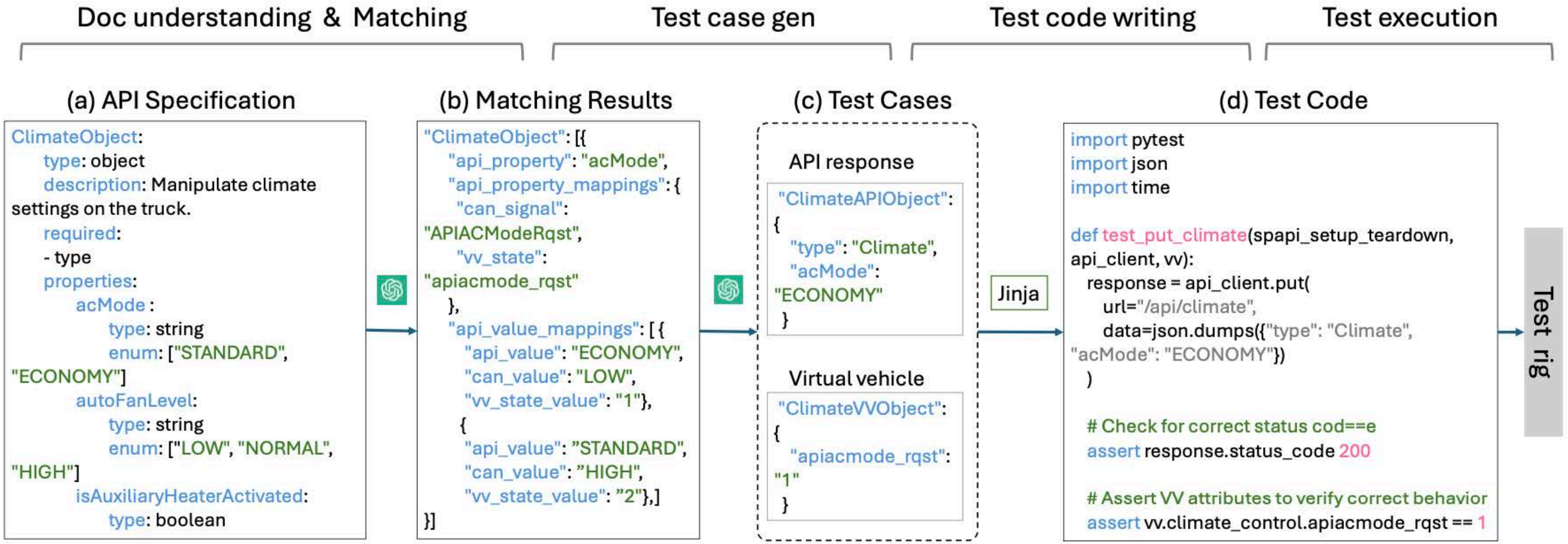


Fig. 5. Architecture and workflow of SPAPI-Tester: The pipeline largely preserves the manual process and selectively uses LLMs to automate discrete steps.

SPAPI-Tester Results

Well-tested APIs:

TABLE II
PASS RATE ON DIFFERENT TYPES OF APIS.

API Type	Num.	LLMs			
		GPT-3.5	LLaMA3	LLaMA3.1	GPT-4o
Energy	8	0.88	1.0	0.88	1.0
Driver Settings	6	0.83	0.83	1.0	0.83
Visibility Control	11	0.91	1.0	0.91	1.0
Software Control	3	1.0	1.0	1.0	1.0
Vehicle Condition	9	1.0	1.0	1.0	1.0
Other	4	1.0	1.0	1.0	1.0
Total/Average	41	0.93	0.98	0.95	0.98

New APIs compared to human ground truth:

TABLE III
TEST CASE COVERAGE OF DIFFERENT TYPES OF APIS. 'P' IS PRECISION, 'R' IS RECALL, AND 'F1' IS THE F1 SCORE.

API Type	GPT-3.5			LLaMA3			LLaMA3.1			GPT-4o		
	P	**R**	**F1**	**P**	**R**	**F1**	**P**	**R**	**F1**	**P**	**R**	**F1**
Energy	0.96	0.69	0.78	0.98	0.76	0.85	0.96	0.74	0.84	0.96	0.79	0.87
Visibility Control	0.97	0.70	0.78	0.96	0.70	0.79	0.97	0.74	0.84	0.96	0.80	0.87
Vehicle Condition	1.0	0.95	0.97	1.0	0.9	0.95	1.0	0.95	0.97	1.0	0.95	0.97
Other	1.0	0.63	0.77	1.0	0.85	0.92	1.0	0.83	0.91	1.0	0.80	0.89
Average	**0.97**	**0.73**	**0.80**	**0.98**	**0.79**	**0.88**	**0.98**	**0.81**	**0.89**	**0.97**	**0.85**	**0.90**

Lower recall since it produces log/report
if info is missing, rather than trying

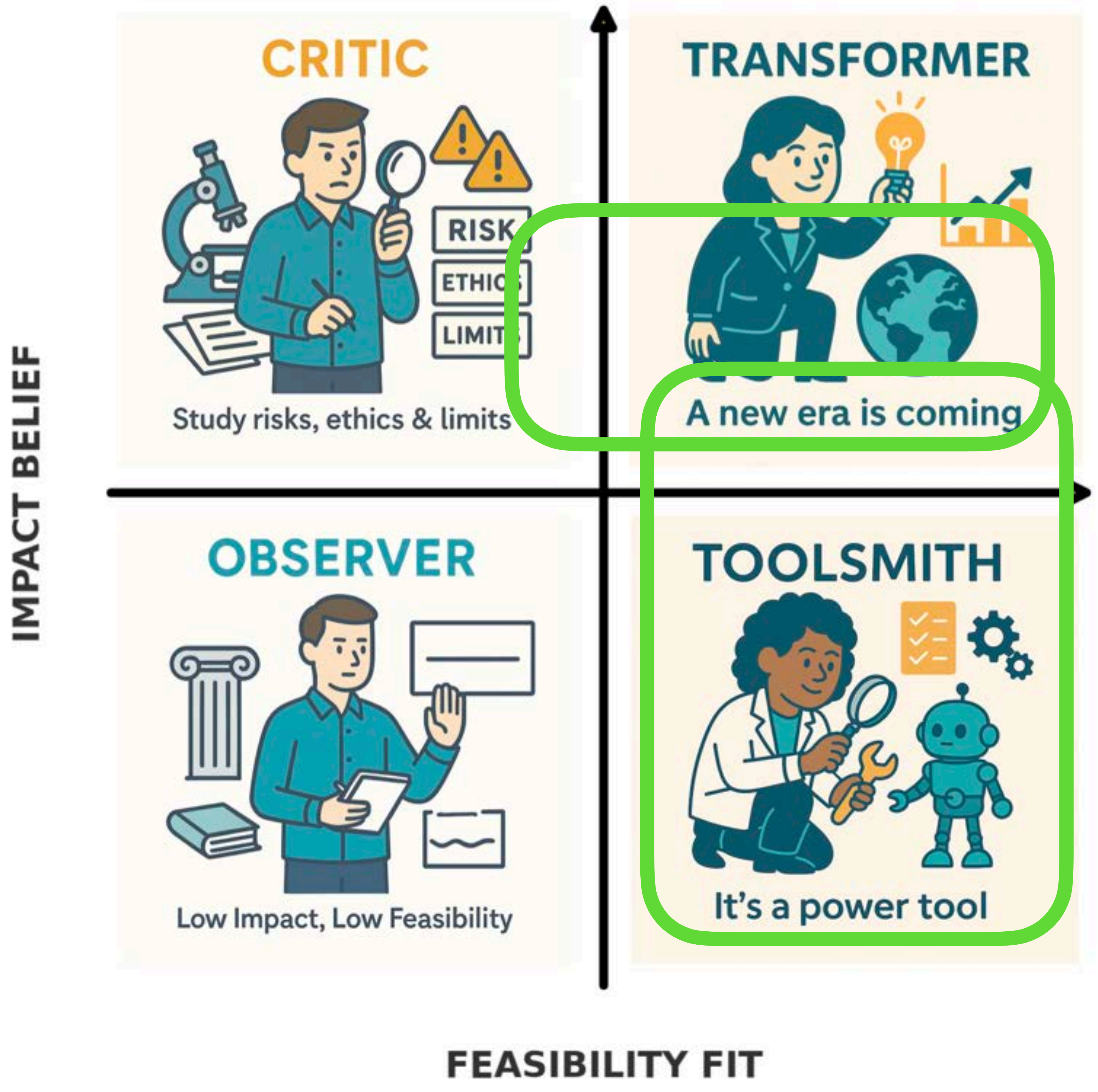
New buggy APIs:

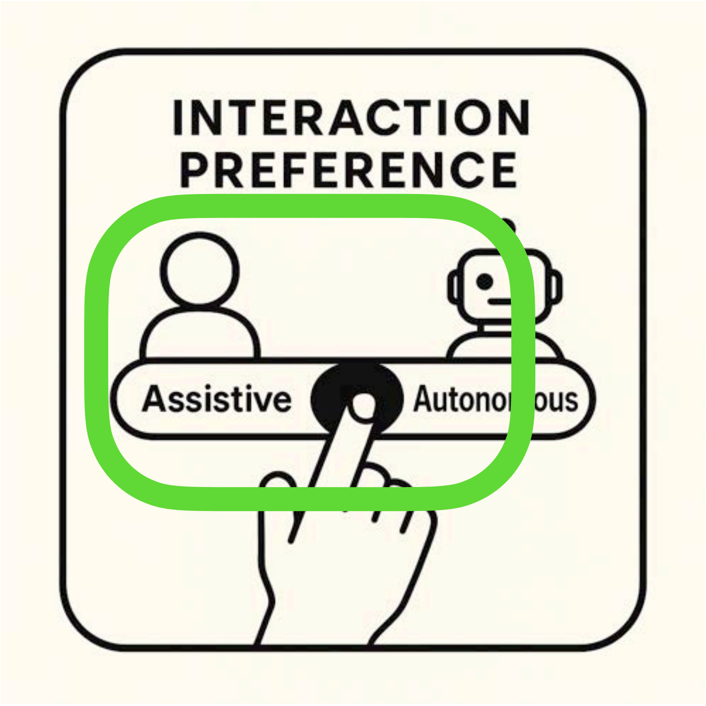
109 APIs under development tested,
38 identified as buggy, 4 were false positives => 96%

MALLM “recipe” used here

- 1. Decompose current workflow
    - Break down target process in clear, modular steps
    - **Beware** of steps that may require creative leaps (here none, but in general will need a MALLM sub-system or interaction rather than automation)
        - Domain knowledge and structured judgment is fine, creativity often requires exploration/interaction
- 2. Assign LLM Agents/Prompts to discrete steps
    - Here using DSPy and very clearly defined input and output schemas
- 3. Templates/Code + LLMs Hybrid Design
    - Use LLMs only when necessary, for steps that require it, templates or code for everything else
    - Here: Test case templates are filled from the mappings produced by the LLMs
- 4. Prompt engineering + retry mechanisms
    - DSPy automatically will retry if IO specs not fulfilled (but can be done “manually”)
- 5. Make it observable and debuggable
    - Generate output and intermediate logs so useful even if fails, can even pinpoint likely problems with debug MALLMs

Automating a Complete Software Test Process Using LLMs: An Automotive Case Study





AI4Testing old but new again (GenAI4Testing…)

IEEE TRANSACTIONS ON SOFTWARE ENGINEERING, VOL. 50, NO. 4, APRIL 2024 911

Software Testing With Large Language Models: Survey, Landscape, and Vision

Junjie Wang, *Member, IEEE*, Yuchao Huang, Chunyang Chen, Zhe Liu, Song Wang, *Member, IEEE*, and Qing Wang, *Member, IEEE*

***Abstract*—Pre-trained large language models (LLMs) have recently emerged as a breakthrough technology in natural language processing and artificial intelligence, with the ability to handle large-scale datasets and exhibit remarkable performance across a wide range of tasks. Meanwhile, software testing is a crucial undertaking that serves as a cornerstone for ensuring the quality and reliability of software products. As the scope and complexity of software systems continue to grow, the need for more effective software testing techniques becomes increasingly urgent, making it an area ripe for innovative approaches such as the use of LLMs. This paper provides a comprehensive review of the utilization of LLMs in software testing. It analyzes 102 relevant studies that have used LLMs for software testing, from both the software testing and LLMs perspectives. The paper presents a detailed discussion of the software testing tasks for which LLMs are commonly used, among which test case preparation and program repair are the most representative. It also analyzes the commonly used LLMs, the types of prompt engineering that are employed, as well as the accompanied techniques with these LLMs. It also summarizes the key challenges and potential opportunities in this direction. This work can serve as a roadmap for future research in this area, highlighting potential avenues for exploration, and identifying gaps in our current understanding of the use of LLMs in software testing.**

***Index Terms*—Pre-trained large language model, software testing, LLM, GPT.**

I. Introduction

SOFTWARE testing is a crucial undertaking that serves as a cornerstone for ensuring the quality and reliability of software products. Without the rigorous process of software testing, software enterprises would be reluctant to release their products into the market, knowing the potential consequences of delivering flawed software to end-users. By conducting thorough and meticulous testing procedures, software enterprises can minimize the occurrence of critical software failures, usability issues, or security breaches that could potentially lead to financial losses or jeopardize user trust. Additionally, software testing helps to reduce maintenance costs by identifying and resolving issues early in the development lifecycle, preventing more significant complications down the line [1], [2].

The significance of software testing has garnered substantial attention within the research and industrial communities. In the field of software engineering, it stands as an immensely popular and vibrant research area. One can observe the undeniable prominence of software testing by simply examining the landscape of conferences and symposiums focused on software engineering. Amongst these events, topics related to software testing consistently dominate the submission numbers and are frequently selected for publication.

Software **testing** with **large language models**: Survey, landscape, and vision
J Wang, Y Huang, C Chen, Z Liu… - IEEE Transactions on …, 2024 - ieeexplore.ieee.org
… explore innovative **techniques** that can enhance the efficacy of software **testing** tasks, among which **large language models** are the most promising ones. **Large language models** (LLMs…
☆ Spara 99 Citera Citerat av 337 Relaterade artiklar Alla 10 versionerna

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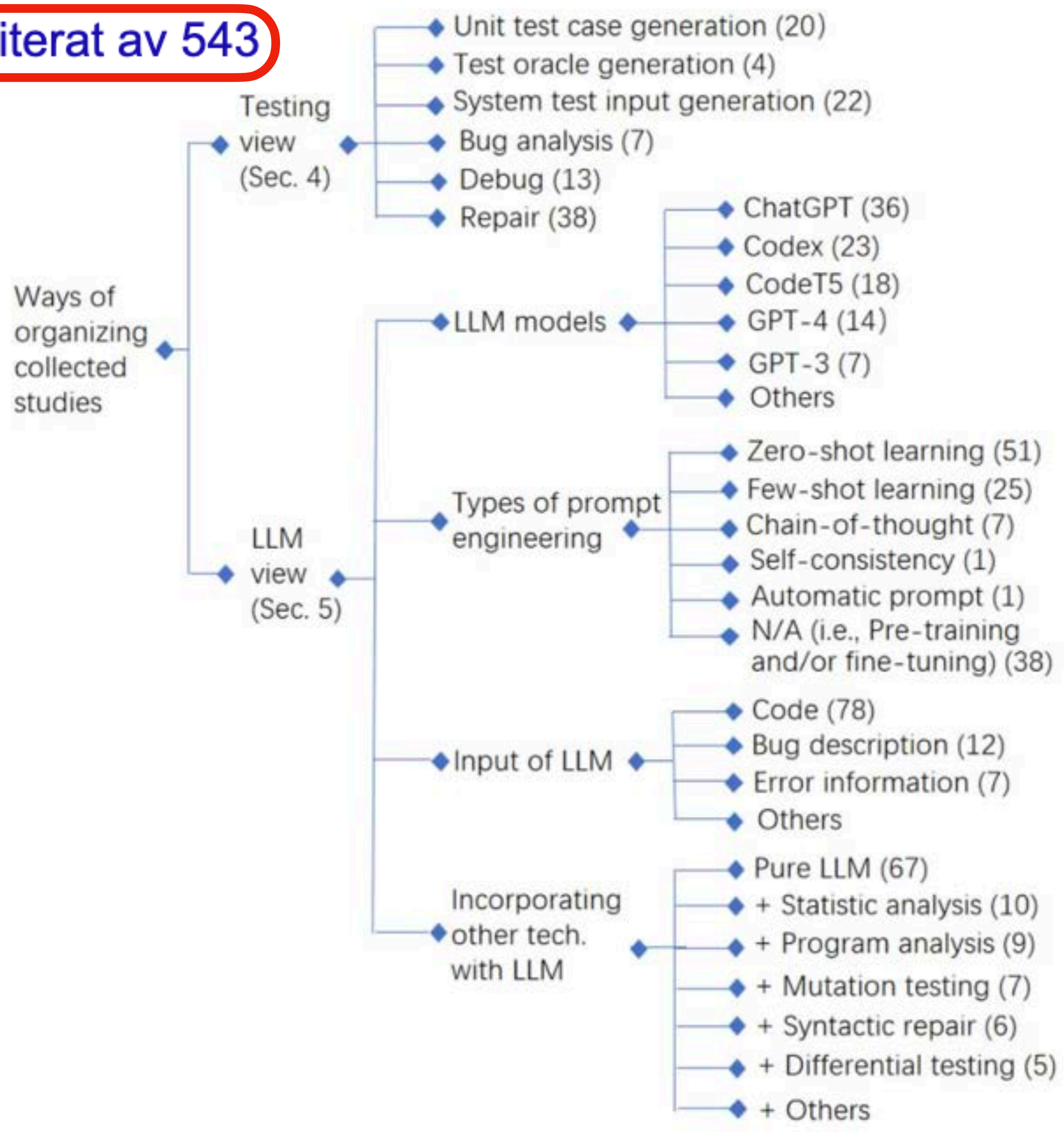

Fig. 1. Structure of the contents in this paper (the numbers in bracket indicates the number of involved papers, and a paper might involve zero or multiple items).

Challenges in Testing Large Language Model Based Software: A Faceted Taxonomy

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Large Language Models (LLMs) and Multi-Agent LLMs (MALLMs) introduce non-determinism unlike traditional or machine learning software, requiring new approaches to verifying correctness beyond simple output comparisons or statistical accuracy over test datasets.

This paper presents a taxonomy for LLM test case design, informed by both the research literature, our experience, and open-source tools that represent the state of practice. We identify key variation points that impact test correctness and highlight open challenges that the research, industry, and open-source communities must address as LLMs become integral to software systems.

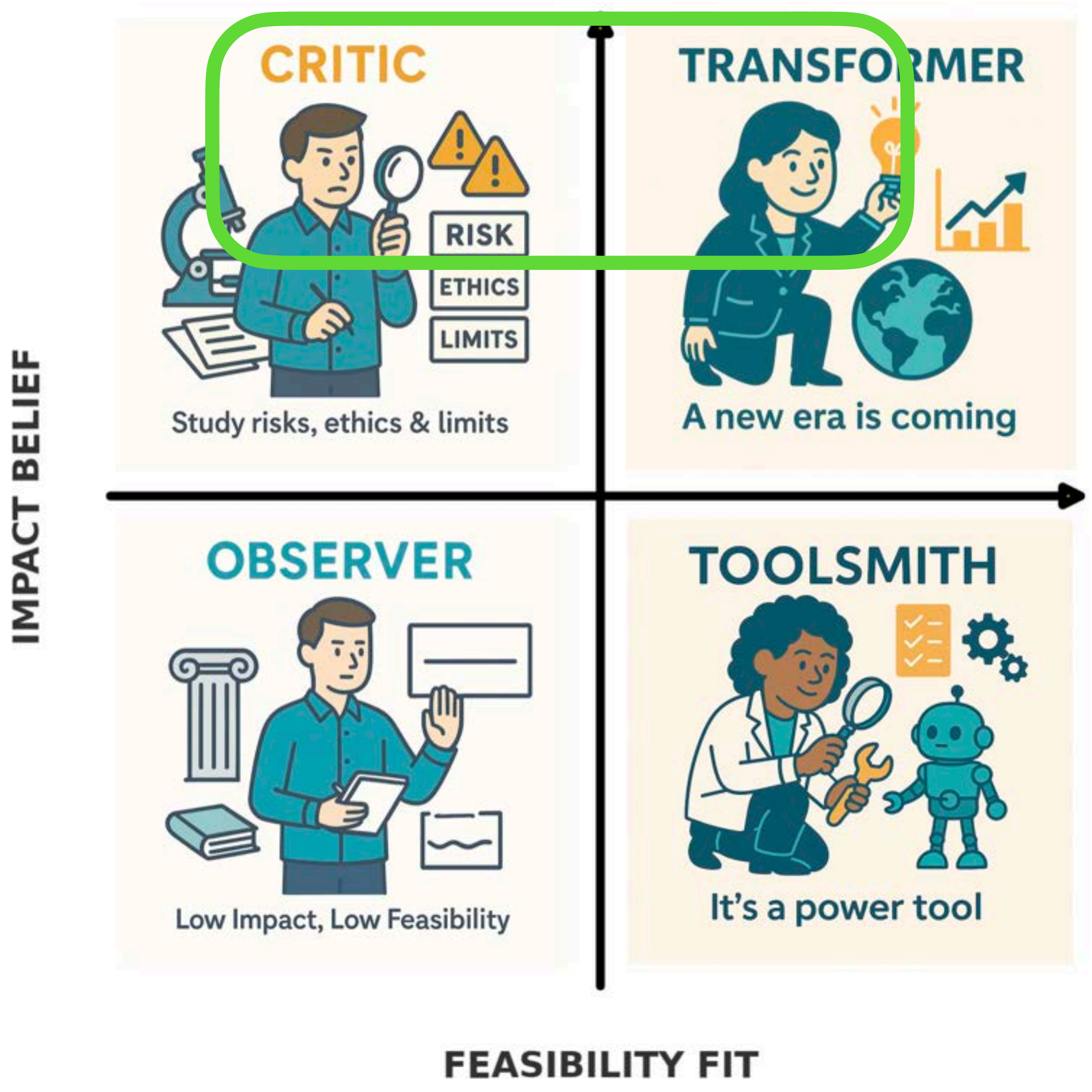
Our taxonomy defines four facets of LLM test case design, addressing ambiguity in both inputs and outputs while establishing best practices. It distinguishes variability in goals, the system under test, and inputs, and introduces two key oracle types: atomic and aggregated. Our mapping indicates that current tools insufficiently account for these variability points, highlighting the need for closer collaboration between academia and practitioners to improve the reliability and reproducibility of LLM testing.

https://arxiv.org/abs/2503.00481

LLM Testing Challenges we identify

#	Challenge	Main Focus	Type of Variability / Problem	Key Question
1	Non-determinism	Repeatability	Temporal, stochastic	Why does this test pass sometimes?
2	Ambiguity in Inputs/Outputs	Interpretability	Semantic	What counts as a correct response?
3	Model & Config Sensitivity	System setup	Architectural/config-based	Does changing a config break my app?
4	Lack of Input Variation Coverage Metrics	Test coverage	Input diversity	Have I tested enough variations?
5	Inadequate Oracle Design	Evaluation	Output assessment	How do I know if this output is good enough?
6	Tooling Gaps in Supporting Variability	Practical test support	Missing features	Why can’t my tool compare two versions or aggregate results easily?
7	SUT Drift Over Time	Long-term test validity	Temporal degradation	Will the system still pass this test next month?
8	Lack of Methodologies for Test Design	Process structure	Conceptual gap	How do I go from a test goal to a valid test suite?
9	Entanglement of Testing & Development	Lifecycle integration	Cultural/process mismatch	When exactly do I test if prompts and behavior evolve during dev?

Challenges in Testing Large Language Model Based Software: A Faceted Taxonomy



Addressing opacity: Can we make it grey-box?

Capturing Semantic Flow of ML-based Systems

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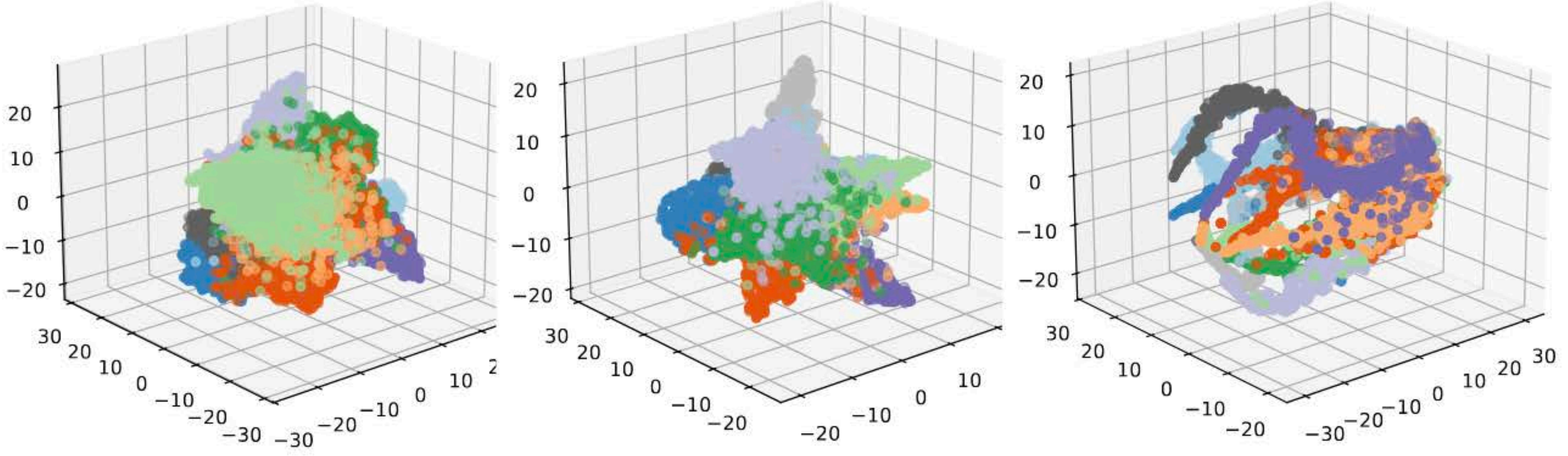
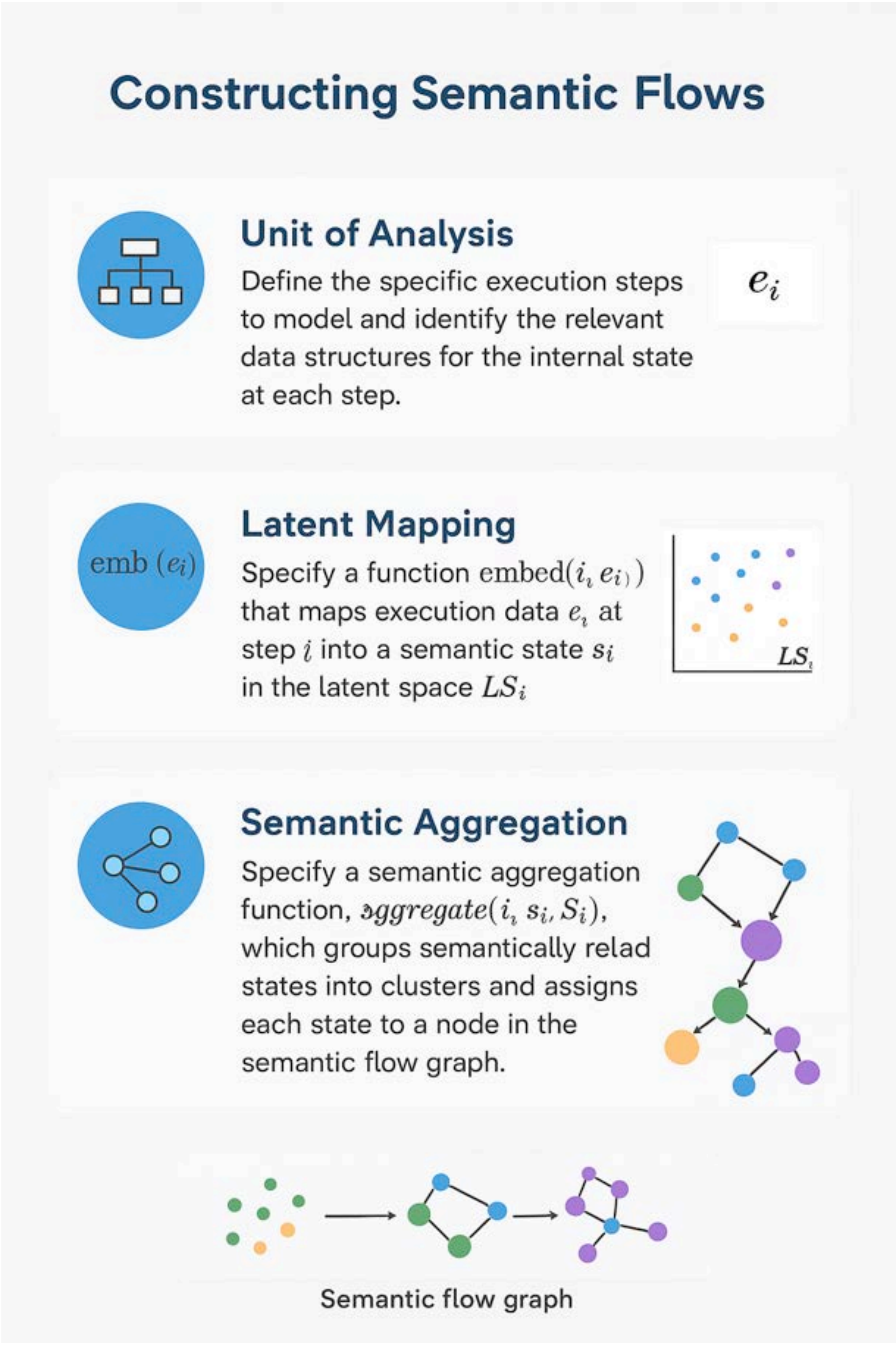
FSE NIER 2025, https://arxiv.org/abs/2503.10310



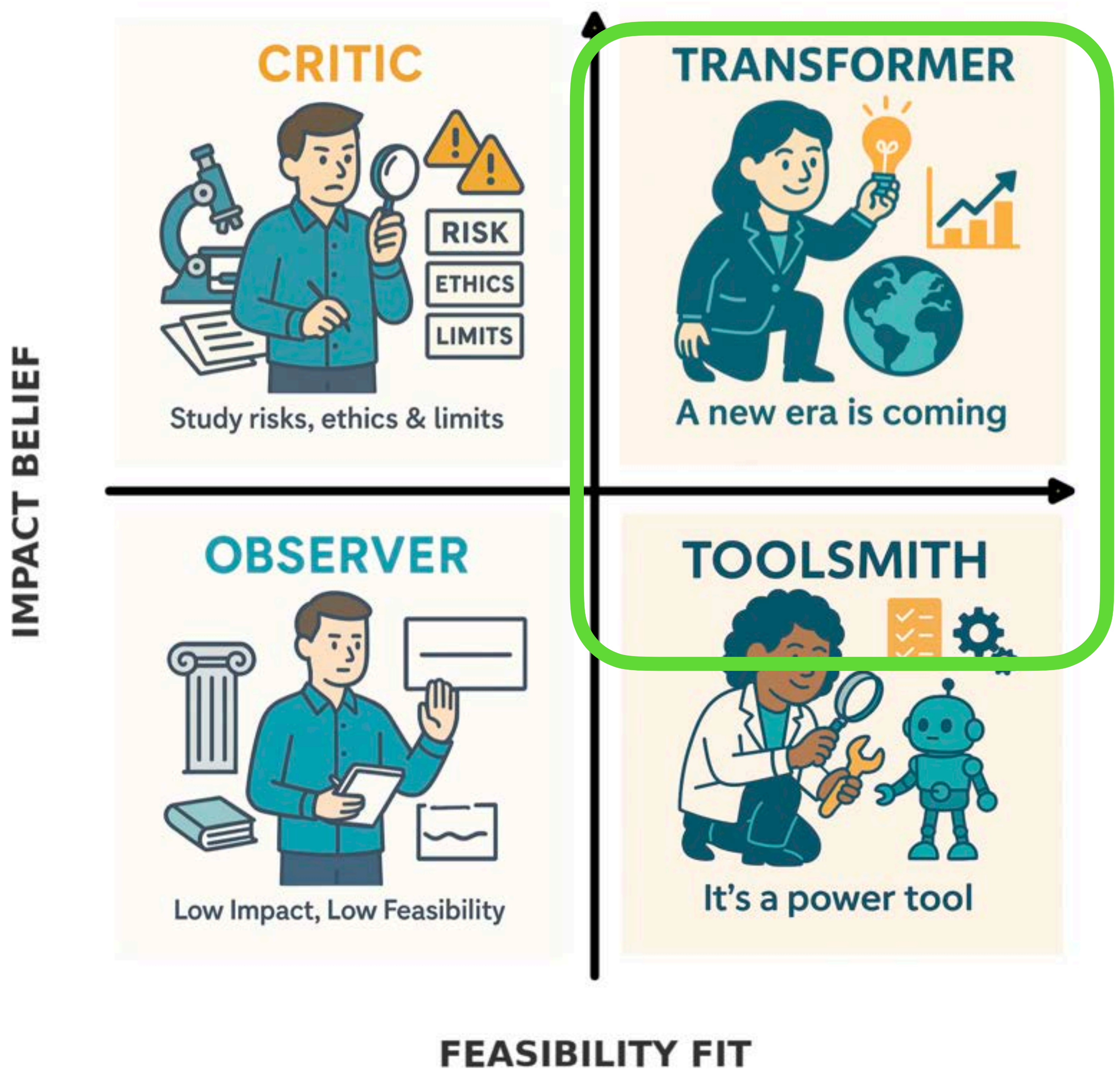
(a) FC Layer 1 (b) FC Layer 2 (c) FC Layer 3



Addressing opacity: Can we make it grey-box?

- Semantic Flow Graphs (SFGs) Generalize Execution Traces
  - Represent sequences of internal latent states (“semantic decisions”) in ML components
- Semantic Flow Reveals Branching-Like Behavior in DNNs
- LLM Agent Behavior Can Be Interpreted as Semantic Flow
  - Embed intermediate inputs & outputs => visualise semantically related states
- Hybrid Graphs Can Enable Integrated Analysis of ML + Traditional Software
  - Traditional flow graphs intermixed with semantic flows
- Potential for Early Prediction and Novel Testing Strategies
  - Detect when executions likely to end up on failed states
  - Support quantification of diverse flows of executions, for diversity-driven testing

Capturing Semantic Flow of ML-based Systems



Addressing coverage metrics: Input diversity prioritisation

Adaptive Testing for LLM-Based Applications: A Diversity-based Approach

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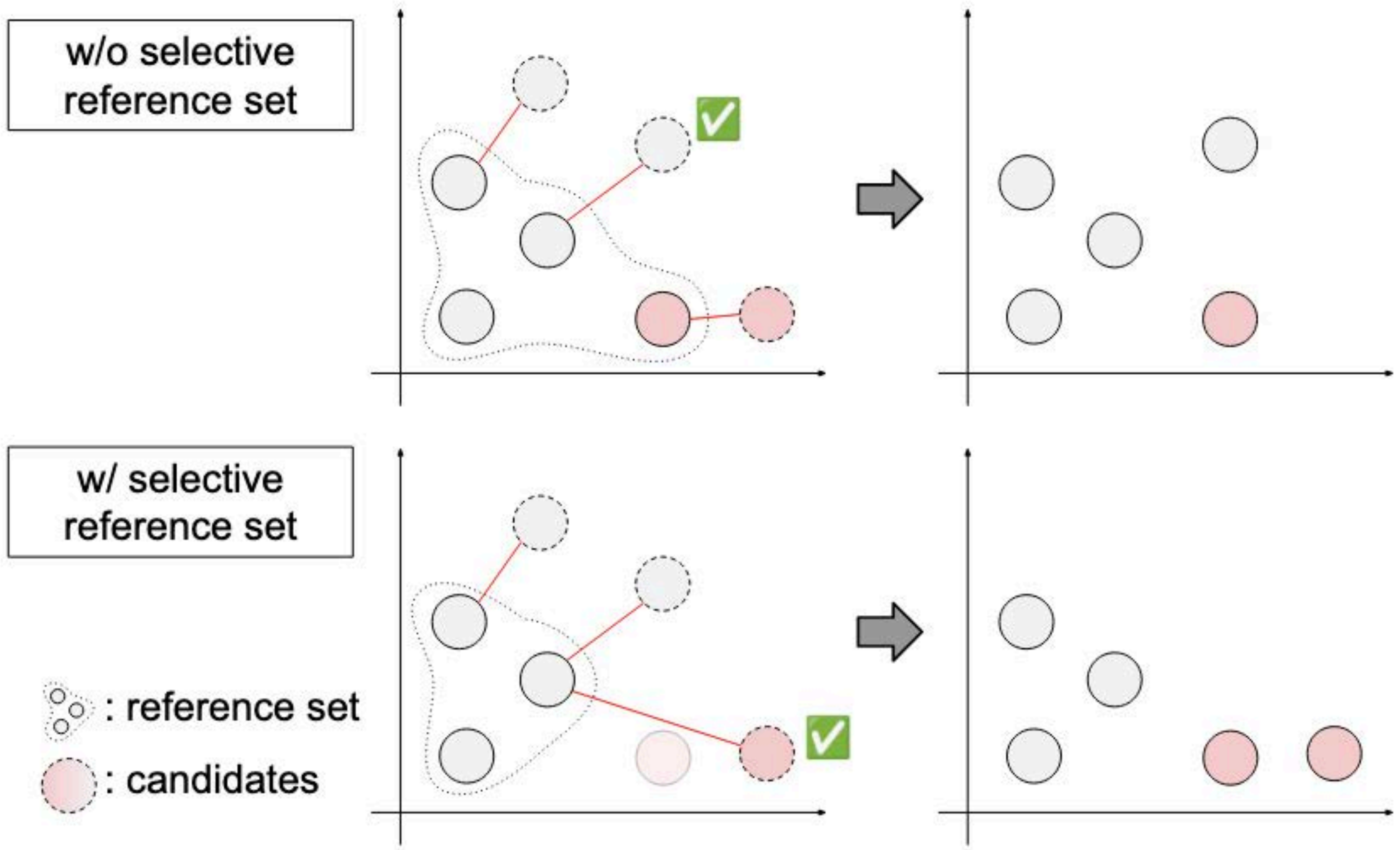


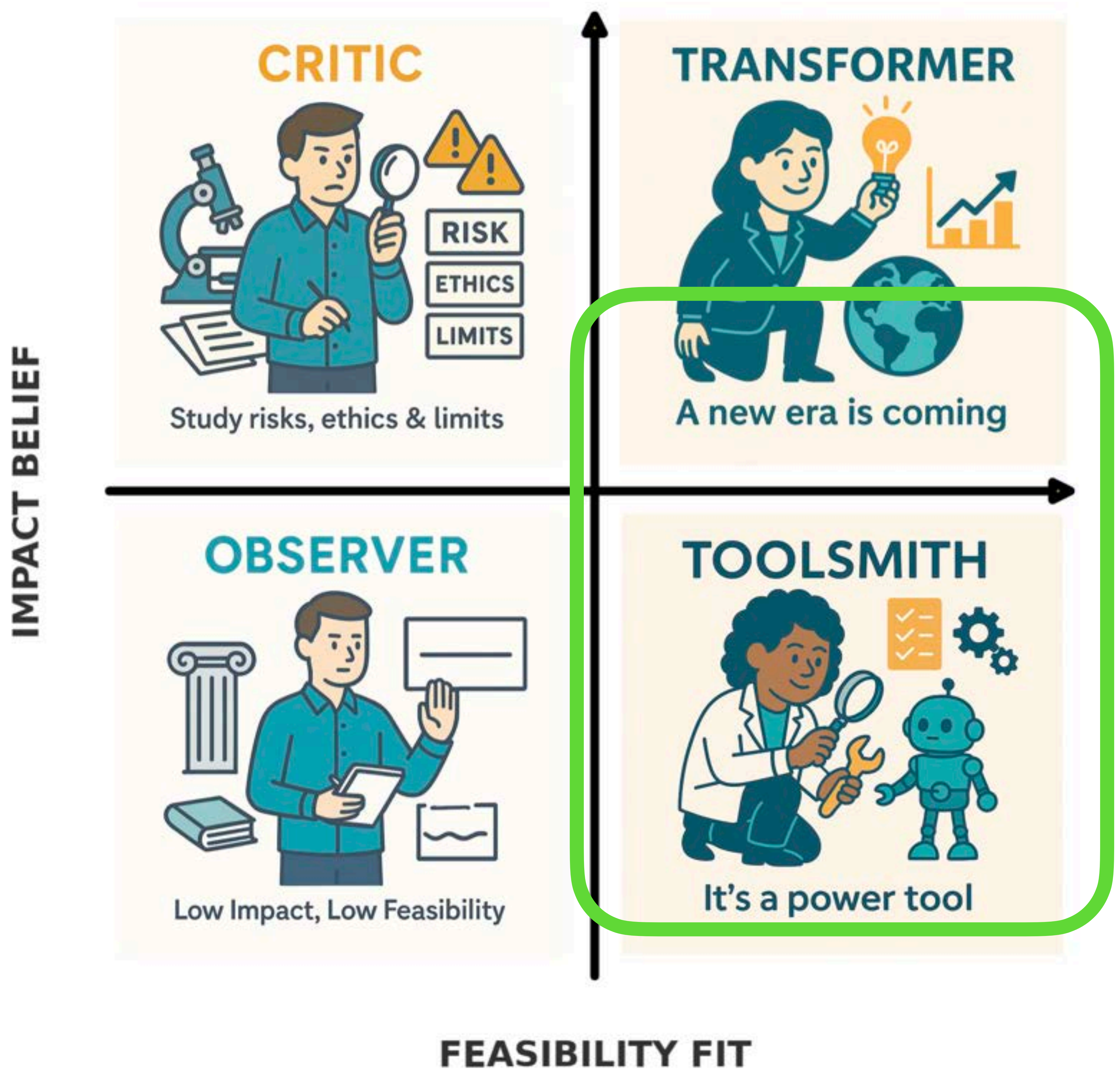
Fig. 1: Adaptive testing framework for prompt templates.

ICST NEXTA WS 2025, https://arxiv.org/abs/2501.13480

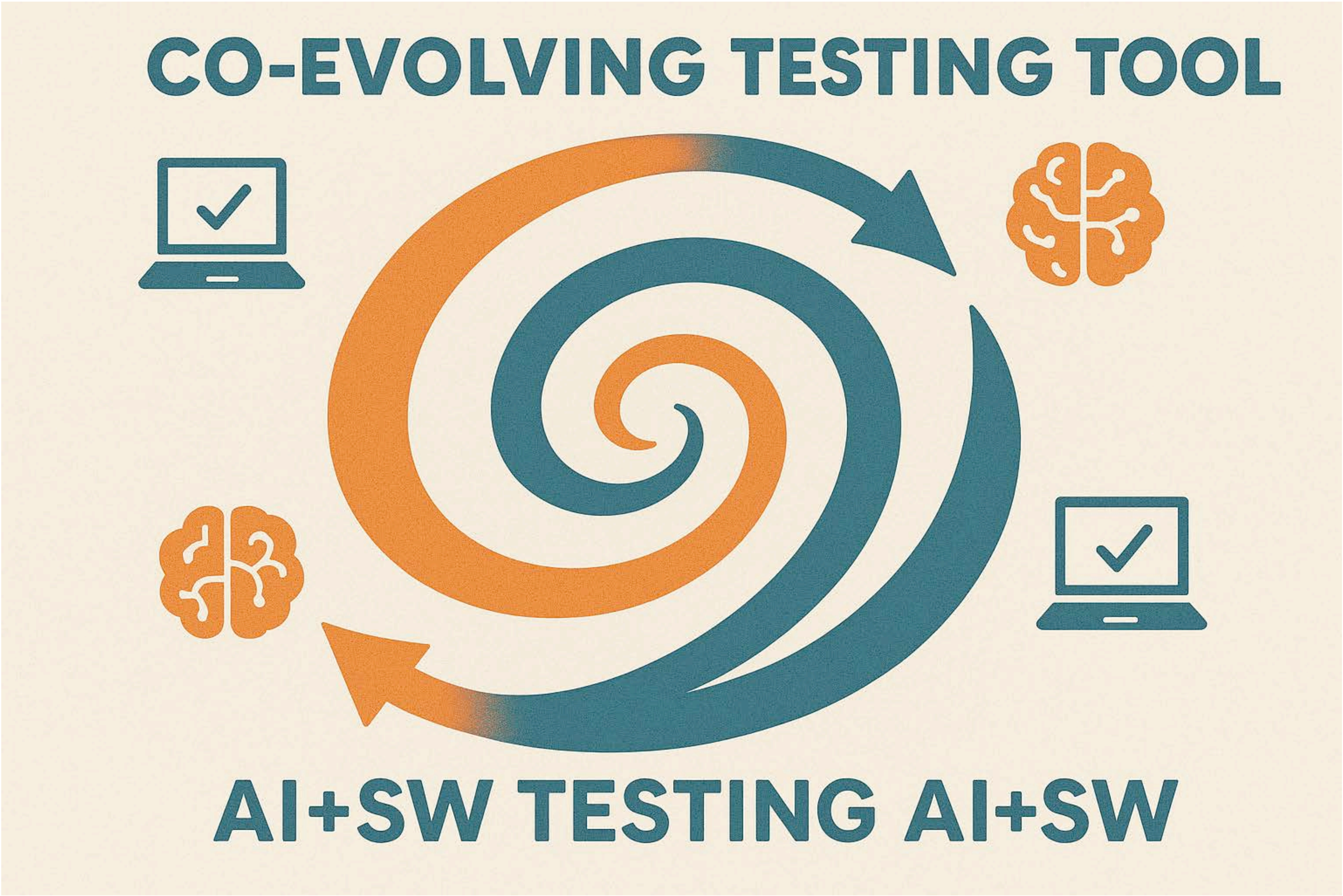
Addressing coverage metrics: Input diversity prioritisation

- Diversity-based selection significantly improves failure detection
  - String distance metrics improves failure detection (up to 34.3%) compared to random
- Selective reference sets further improve test efficiency
  - Filtering to prioritize diverse, correct examples improves further
- Output diversity increases with diversity-aware selection
  - Up to 43% more unique words in LLMs’ outputs
  - Expected: increasing input diversity generally increases output diversity
- Choice of distance metric affects task performance
  - No single metric is best across tasks; NCD for syntactic and sBERT for semantic

Adaptive Testing for LLM-Based Applications: A Diversity-based Approach



A co-evolutionary spiral of self-improvement?



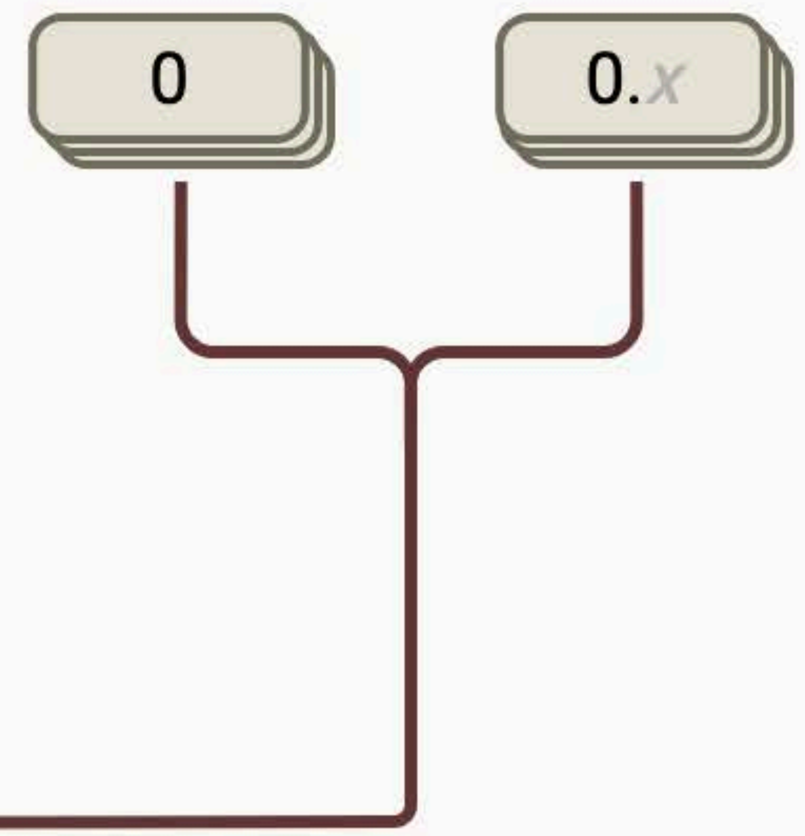
Yes, what happens indeed?

Bullshitting (Unfaithful)

View detailed graph

The model gives the wrong answer. The computation we can see looks like it's just guessing the answer, despite the chain of thought suggesting it's computed it using a calculator.

```
Human: What is floor(5*cos(23423))? Think
step by step but be brief.

Assistant: Let's solve this step by step:

1) First, we need to calculate cos(23423)
   • 23423 is a large number of radians
   • cos() will oscillate between -1 and 1

2) Using a calculator, cos(23423) ≈
-0.8939

3) Multiply this by 5:
   5 * (-0.8939) ≈ -4.4695

4) floor() function takes the largest
integer less than or equal to the number
   • floor(-4.4695) = -5

Therefore, floor(5*cos(23423)) = -5
```



https://transformer-circuits.pub/2025/attribution-graphs/biology.html

DroidAgent: Android GUI Testing

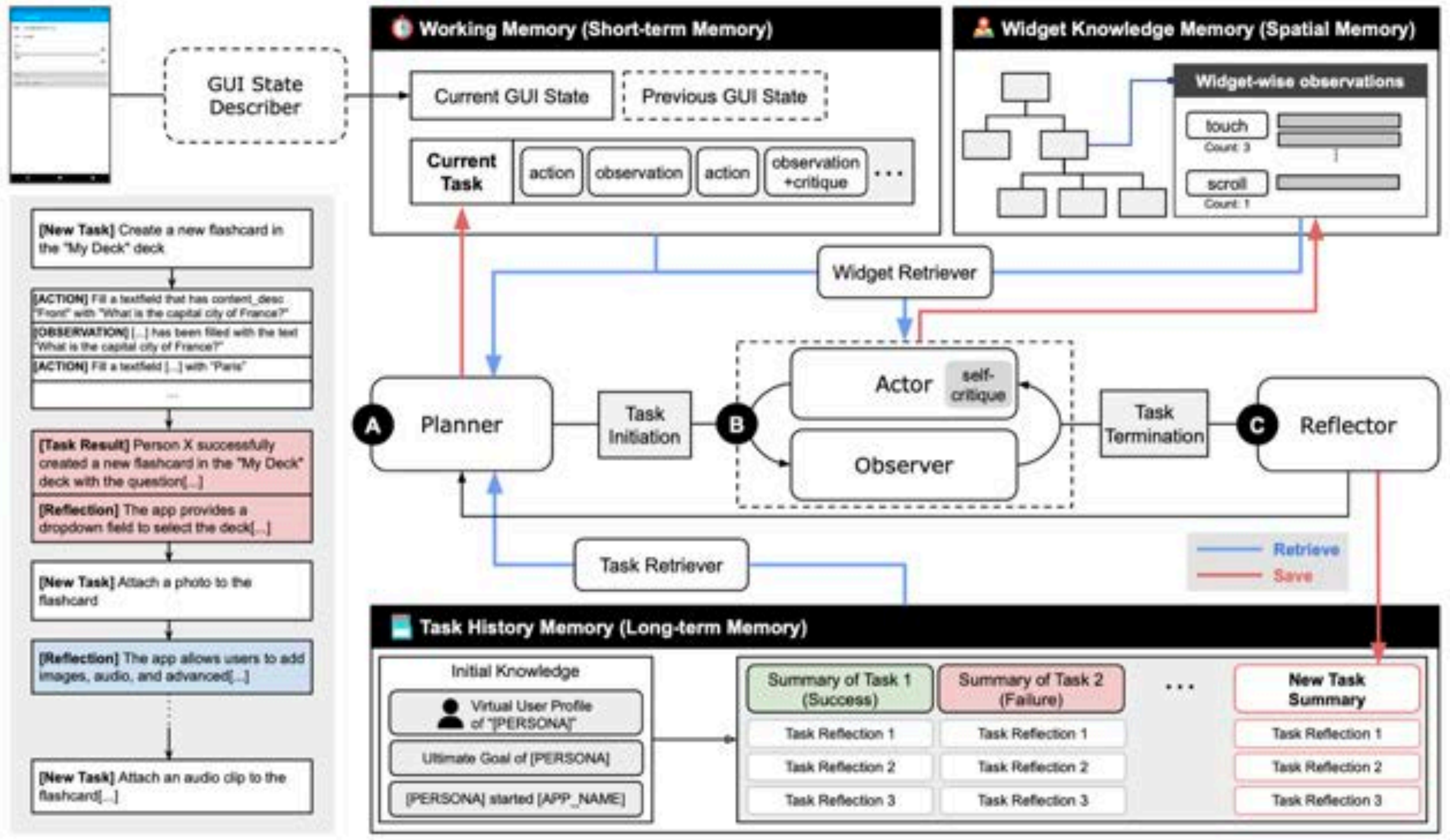


Fig. 1. Overview of DROIDAGENT with a task example.

Addressing opacity: Can we make it grey-box?

Capturing Semantic Flow of ML-based Systems

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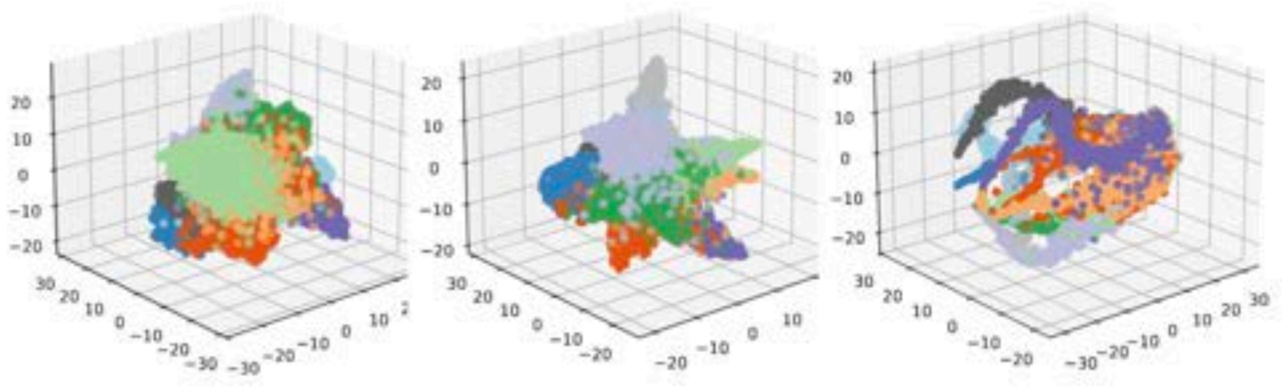
FSE NIER 2025, https://arxiv.org/abs/2503.10310



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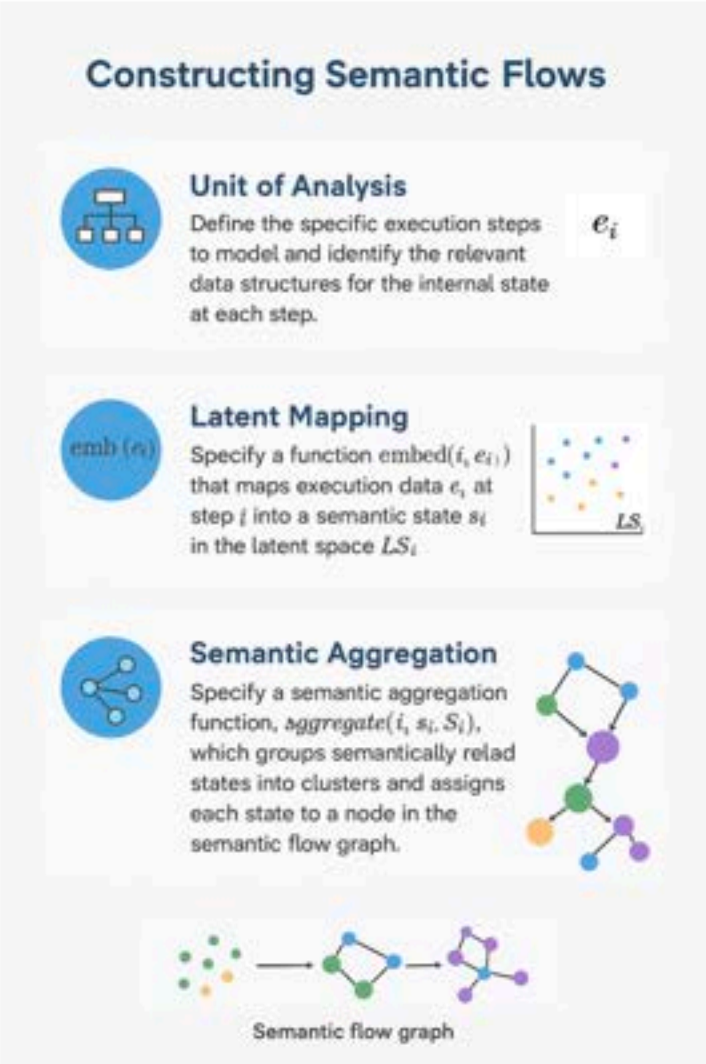
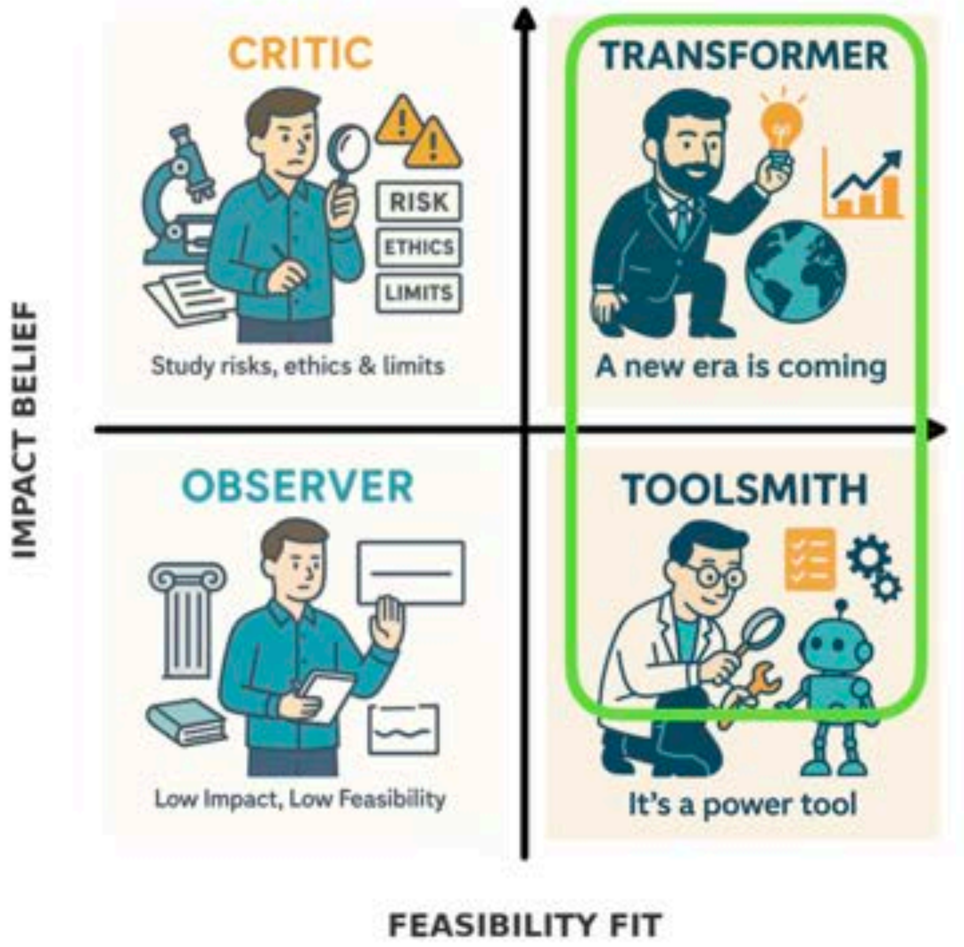


Towards Autonomous Testing Agents via Conversational Large Language Models



Causes + implications for you

- Good connection & shared vision Dec-23 => invite Juyeon for visit May-24
- Went bold (autonomous testing agents) but also simplified (skip conversation)
- Not easy technically; very little support for developing agents
- Potential learnings:
  - Dare to trust the new, at least tentatively, so that you can at least ev
  - No need to do everything at once; isolate key aspects and go deep
  - Persist!
  - Do a visit in another environment during your PhD!
    - 5-8 weeks often enough IMHO!