

# From Reactive Prompts to a Proactive Knowledge Runtime

Evolving Perplexity's AI Agents to Select, Not Just Generate





# We propose evolving our AI agents to a Faceted Knowledge Runtime.

This architectural shift moves agent intelligence from brittle, monolithic XML prompts into a dynamic, queryable knowledge base.

Agents can **select** the best-proven action from thousands of scenarios in **50-150ms**, *before* they generate a response.

## For Support

A step-change in resolution speed, scale, and governance.

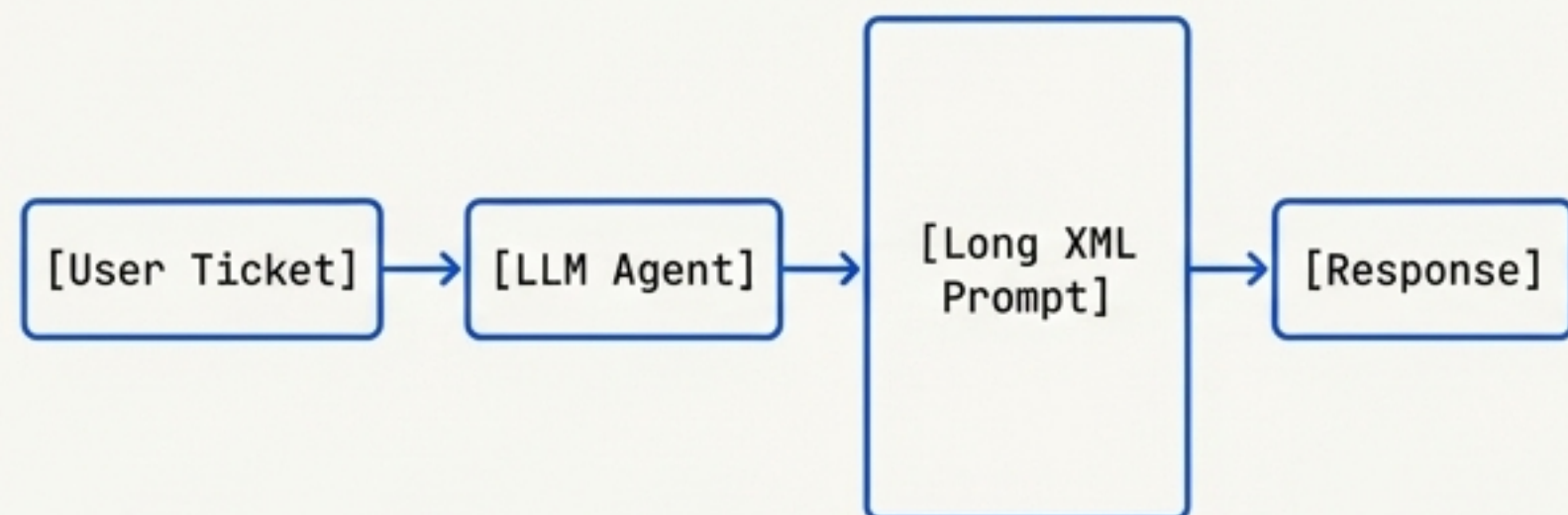
## For Product

Unlocks proactive, in-product user engagement and self-improving systems.



# Our current XML-based agents have been successful, but are reaching their scaling limits.

## The Current Model


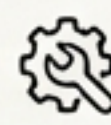
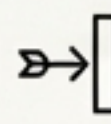
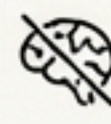


This model got us here, proving the value of AI-driven support.

## The Underlying Reality



### Key Problems

-  **Brittle:** A small change in one rule can have cascading, unpredictable effects.
-  **High Maintenance:** Adding a new scenario requires careful, time-consuming XML engineering and testing.
-  **Unscalable:** The prompt length and complexity grow linearly with each new scenario, hitting context window limits.
-  **Cannot Learn:** The system has no mechanism to identify and prioritize which rules perform best; it only executes.



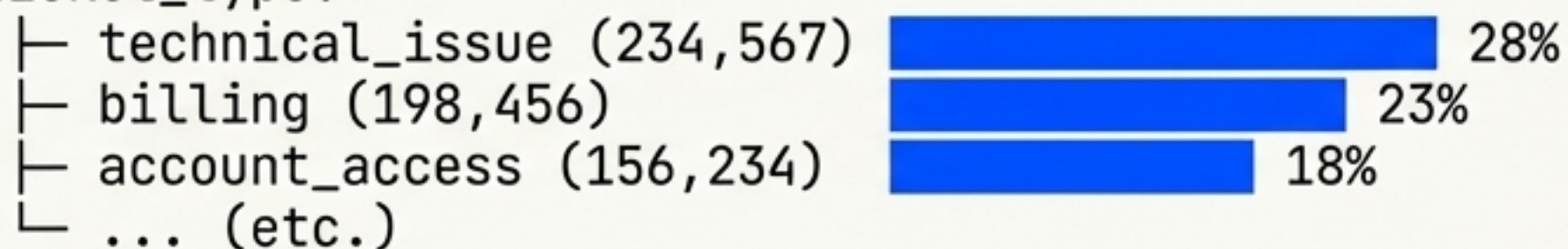
# The foundation of the new runtime is Facets: a metadata language for our entire support database.

THE DATABASE (847,293 tickets)

An LLM cannot read all 847K tickets.

But it CAN understand the database's structure via facets:

ticket\_type:



This IS the database content, expressed as queryable metadata. The agent now makes INFORMED choices.

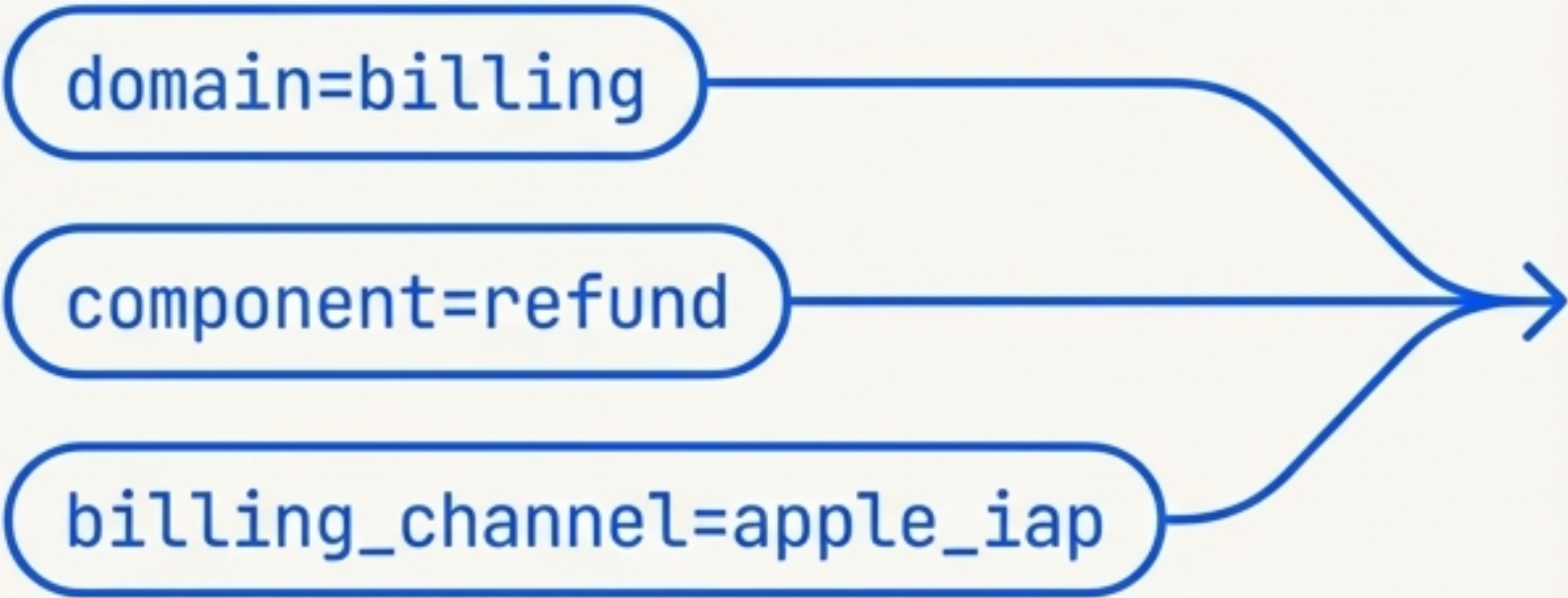
Instead of feeding the LLM raw text, we provide it a structured, hierarchical understanding of our entire knowledge space. The agent can now reason over distributions and correlations to find the most relevant context, just like faceted search.



# Playbooks are version-controlled, performance-scored recipes for resolution.

If Facets describe *what* a ticket is about, Playbooks define *how* to solve it. They are discrete, executable objects stored in our database, not embedded in a prompt.

## FACET INPUTS



## PLAYBOOK: BILL-REFUND-APPLE-111

Playbook Name	Refund Request / Apple IAP
Match Clauses	domain=billing, billing_channel=apple_iap
Steps	1. (Tool Call) `lookup_subscription(user_id)` 2. (Policy Check) Explain that Apple manages IAP refunds directly. 3. (Response Template) Provide link and instructions for Apple's refund process.
Risk Ceiling	Low
Performance Score	<b>0.92</b> (success_rate_smoothed)

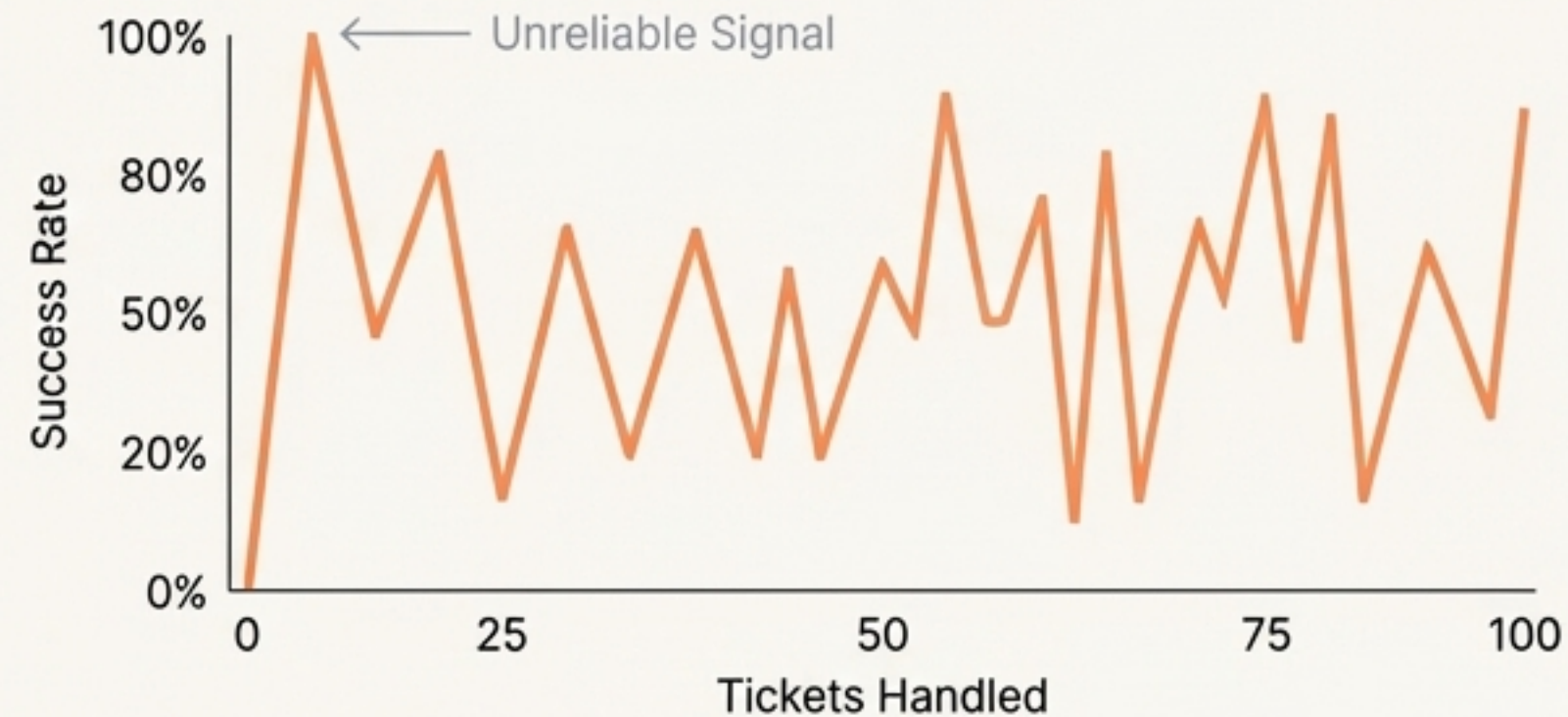


# The system self-improves by scoring Playbooks on performance, with statistical smoothing.

We don't just execute Playbooks; we measure their outcomes (success rate, resolution time, CSAT) and use that data to rank them for future tickets.

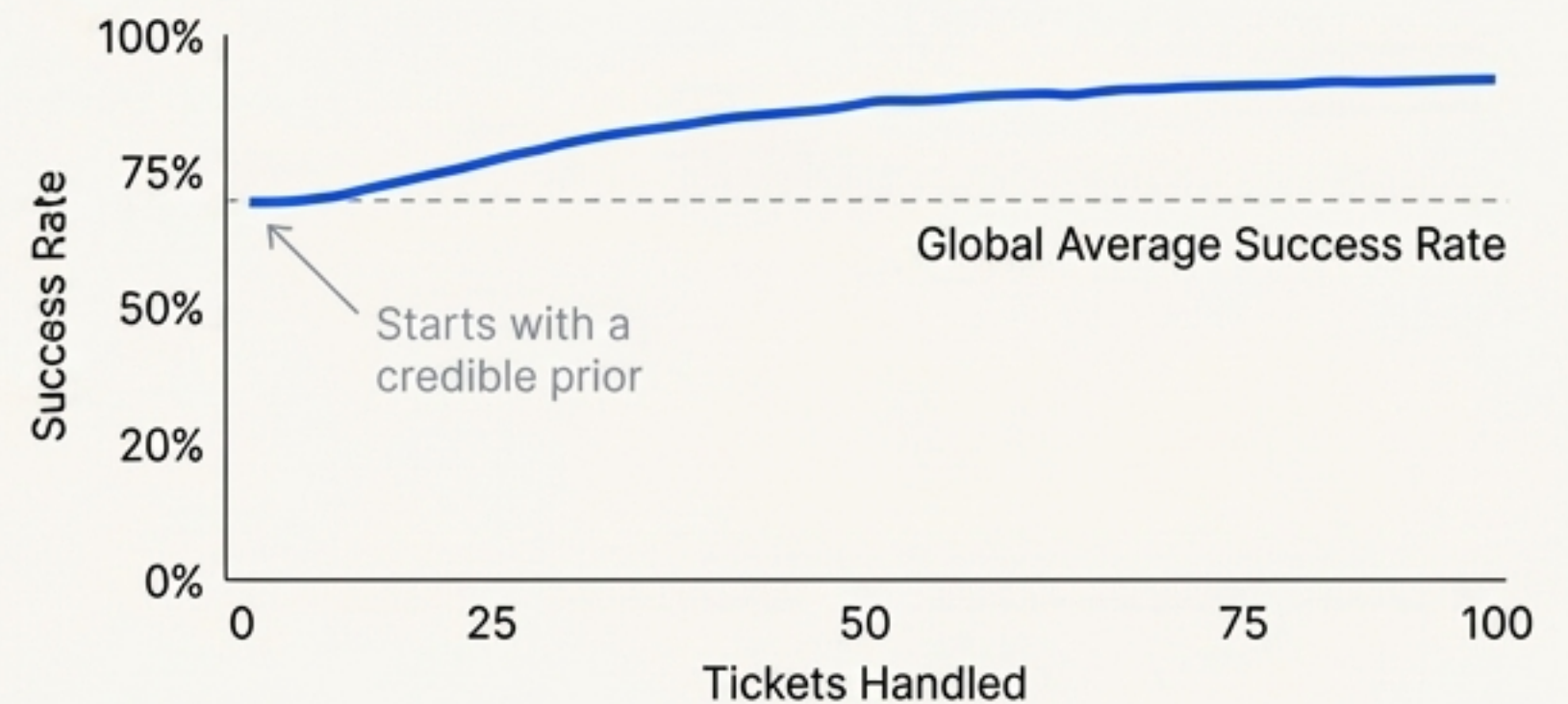
## Without Smoothing

A new Playbook with one lucky success gets a 100% score, unfairly promoting it.



## With Smoothing

Bayesian smoothing (Beta-Binomial) pulls the score of new or low-volume Playbooks towards the global average. This "shrinks" outlier results, ensuring only consistently high-performing Playbooks rise to the top.

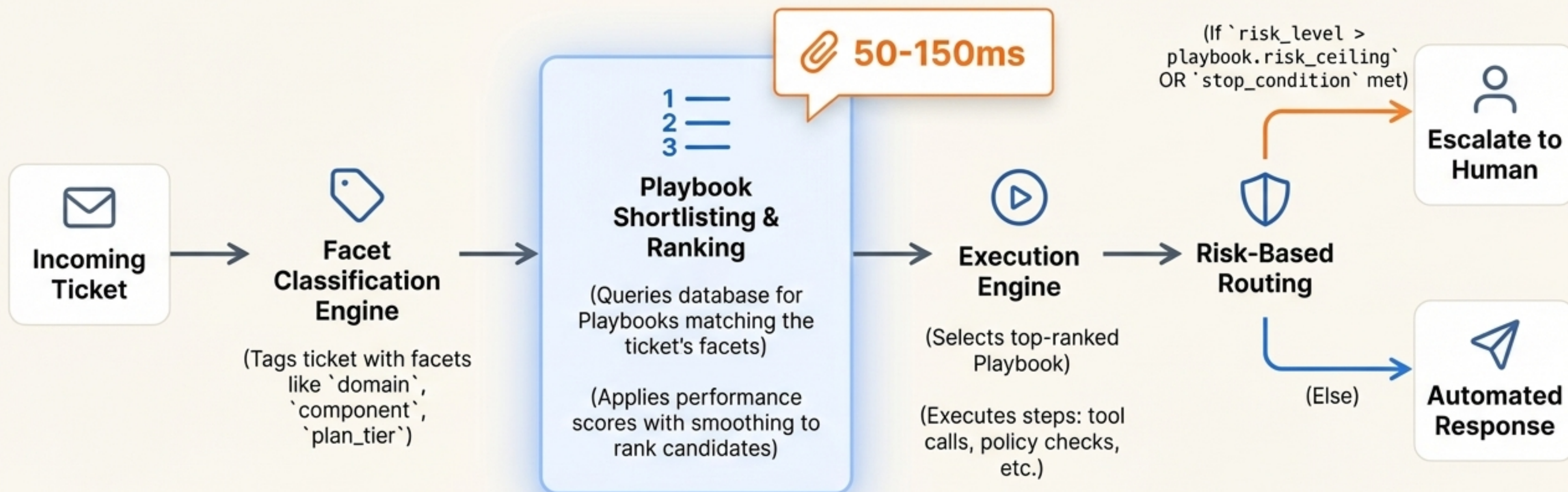


This mechanism prevents volatility and ensures the agent reliably selects paths that are proven to work at scale.



# The Faceted Knowledge Runtime:

## A high-level view.





# The system's logic is governed by a central Facet Registry.




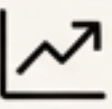

The registry is the “source of truth” that defines every facet, its hierarchy, its data source, and its relationship to other entities. This ensures consistency and allows the agent to reason about the data model itself.

```
{
  "facet_name": "component",
  "description": "Granular component inside domain",
  "kind": "categorical",
  "allowed_values_by_parent": {
    "parent_facet": "domain",
    "map": {
      "billing": [ "payment_failed", "refund", ... ],
      "account_access": [ "google_signin", ... ]
    }
  },
  "sources": [{ "type": "classifier", "from": "ticket.text" }],
  ...
},
{
  "facet_name": "risk_level",
  "description": "Computed risk for escalation decisions",
  "kind": "categorical",
  "sources": [{
    "type": "computed",
    "expression": "risk_model_v1(...)",
    "depends_on": [ "domain", "customer_segment", ... ]
  }]
}
```

- **Definitions & Hierarchies:** Defines parent-child relationships (e.g., `domain` -> `component`).
- **Source Mapping:** Specifies where each facet's value comes from (e.g., a classifier, a DB join, or a computed rule).
- **Join Policy:** Defines which data entities can be connected, ensuring security and performance.
- **Exploration Policy:** Guides the agent on which facets provide the most information gain.



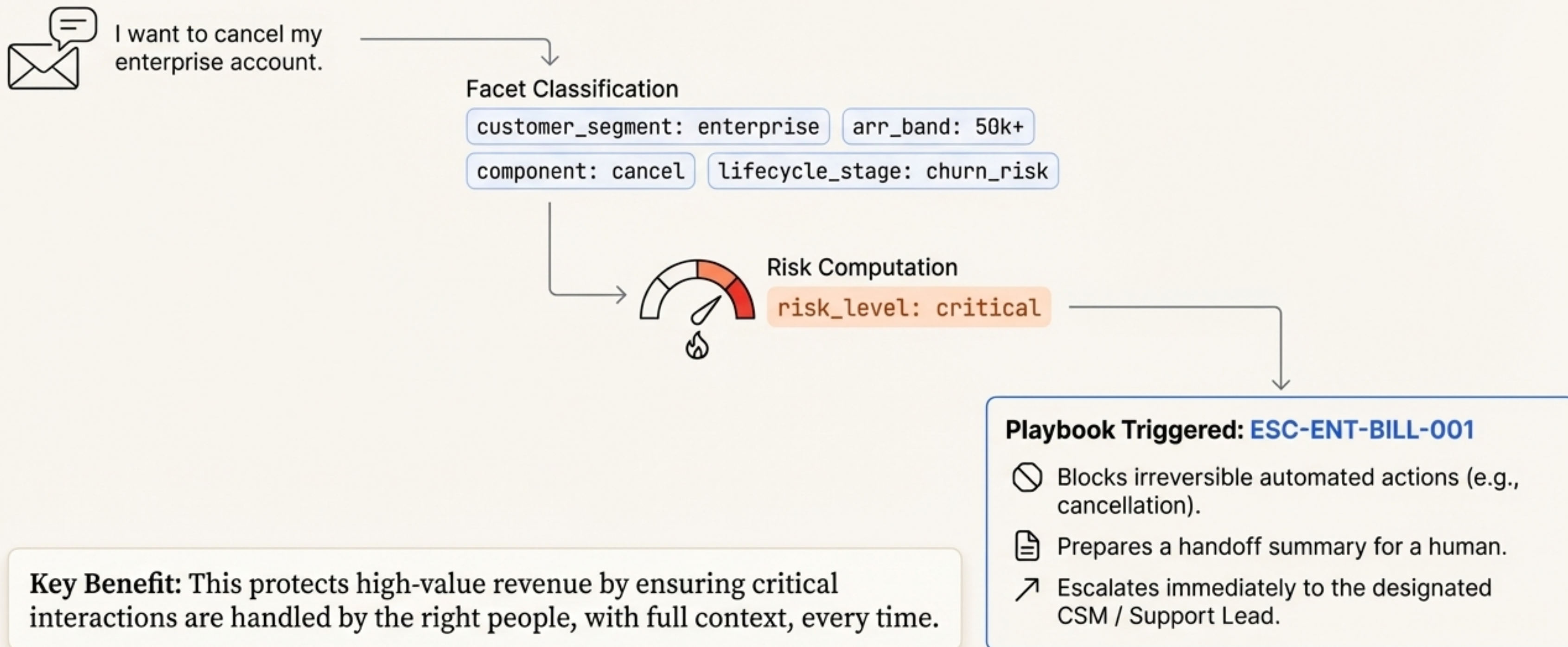
# The runtime delivers quantifiable gains in speed, scale, and quality.

Dimension	Current State (XML Prompts)	Faceted Knowledge Runtime
 <b>Speed (TTR)</b>	LLM must parse long prompt context before acting.	Agent selects a proven, optimized Playbook <b>instantly</b> .
 <b>Scalability</b>	High cost: Add 1 scenario = engineer & test complex XML logic.	<b>Low cost:</b> Add 1 scenario = insert a new Playbook object into a DB.
 <b>Maintenance</b>	High overhead. Prompts are monolithic and difficult to debug.	<b>Low overhead.</b> Playbooks are modular, versioned, and individually testable.
 <b>Quality</b>	Static. Quality depends on initial prompt engineering.	<b>Self-Improving.</b> Performance smoothing automatically promotes effective Playbooks.
 <b>Risk Mgmt.</b>	Implicit. Risk rules are buried in complex conditional logic.	<b>Explicit.</b> Risk is a computed facet ( <code>risk_level</code> ) used for routing.



# Explicit risk modeling enables intelligent, revenue-aware governance

Instead of treating all tickets equally, the runtime computes a `risk\_level` for each interaction based on a combination of facets.





**This architecture is the key to unlocking the next strategic horizon for AI at Perplexity.**

From **Reactive Agents** that *answer questions...*



**...to Proactive Agents** that *prevent questions.*

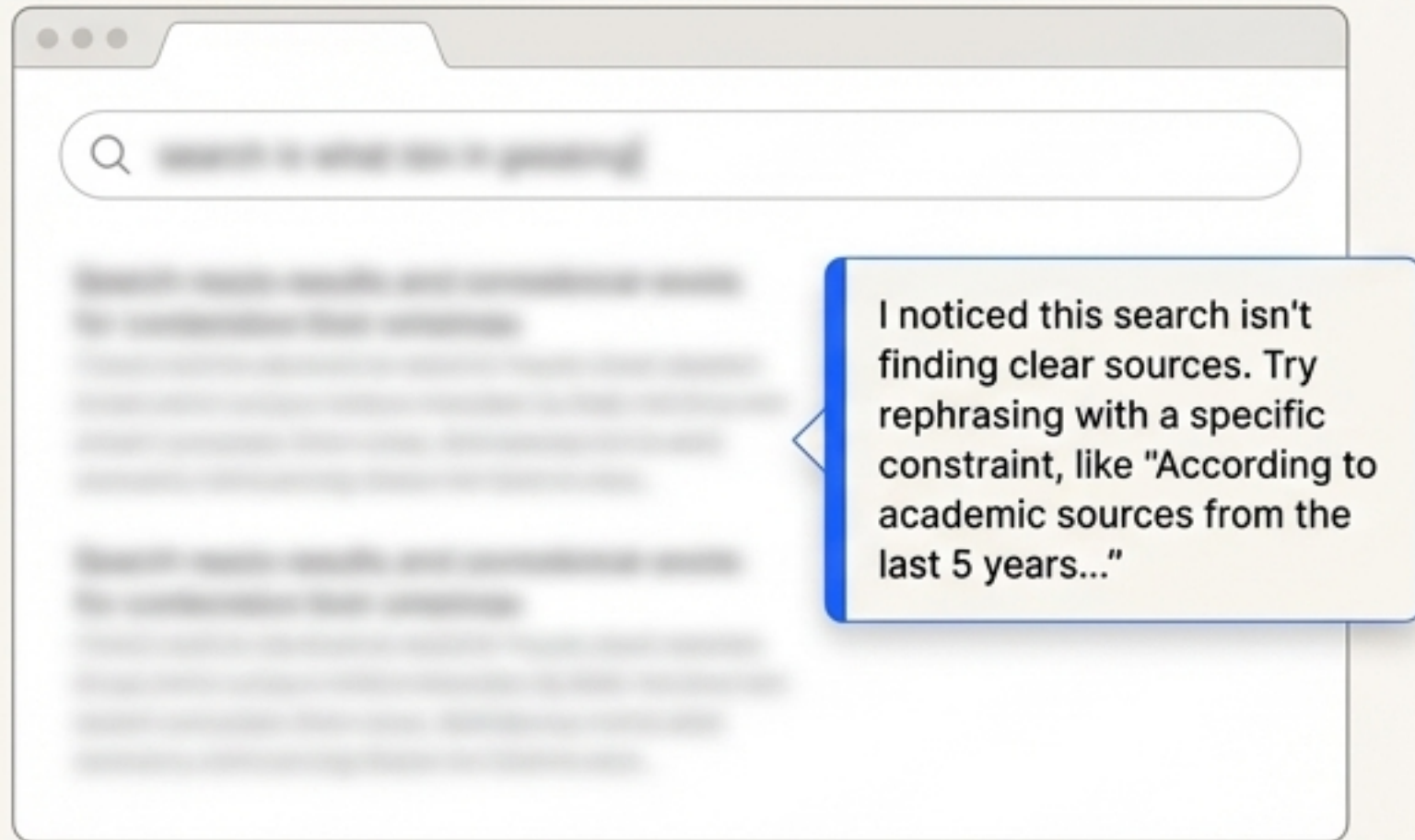
With a deep, faceted understanding of the user (`lifecycle_stage`, `usage_band`) and their context (component, symptom), our agents can move beyond the support queue and become an integrated part of the product experience. They can anticipate needs, guide users, and actively improve engagement.



# Imagine proactive agents embedded directly within Comet and the core product.

## Proactive Prompt Engineering Tip

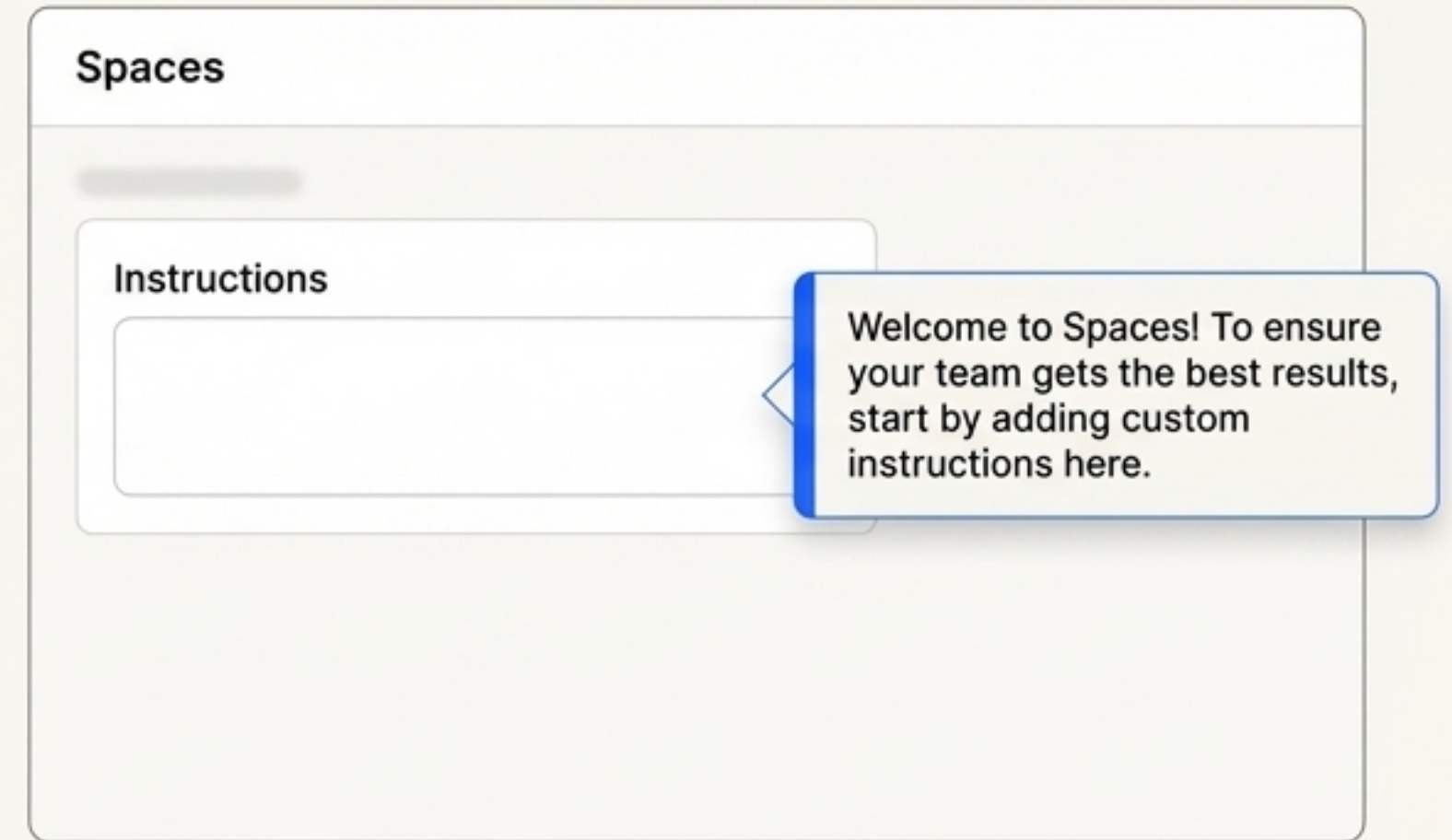
Source Serif Pro



Triggered by (domain=content\_quality, symptom=poor\_sources, usage\_band=high)

## Intelligent Onboarding

Source Serif Pro



Triggered by (lifecycle\_stage=onboarding, component=spaces, user\_role=org\_admin)



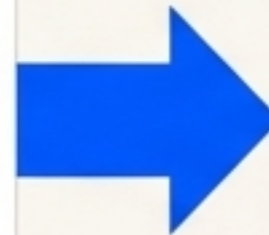
# We can achieve this vision through a phased, iterative rollout.

## Phase 1: Minimum Viable Facets (MVF) & Core Routing

**Goal:** Prove the core architecture and handle top-volume tickets.

- Implement 6 core facet dimensions: request\_type, domain, component, plan\_tier, customer\_segment, billing\_channel.
- Define 15-25 Playbooks for the highest volume and highest risk scenarios.
- Build simple, rules-based escalation triggers.

**Outcome:** A robust foundation for routing and resolving the majority of tickets, with safer escalation.



## Phase 2: Advanced Intelligence & Proactive Engagement

**Goal:** Activate the self-improving loop and begin in-product pilots.

- Add advanced context facets: lifecycle\_stage, usage\_band, arr\_band, symptom.
- Fully activate performance smoothing for Playbook ranking.
- Develop and pilot the first proactive agent interventions inside Comet.

**Outcome:** A self-improving system that actively enhances the product experience.



This is not an upgrade to our support system.

**It is the foundation for an  
in-product intelligence layer that  
understands user context and  
actively improves their experience.**