AiBuildPath
CAREER GROWTH

2026 EDITION

AI Testing Interview Blueprint

LLM, RAG & Agent Testing

For QA engineers, automation testers, SDETs and QA leads (3–15 years) preparing for AI testing interviews at product companies, MNCs and AI startups.

THE PANEL ASKS

Q How would you test this RAG chatbot?

Senior AI QA round · RAG testing

THE CANDIDATE ANSWERS

```
def test_answer_is_grounded():
    out = rag.ask("What is the refund window?")
    assert faithfulness(out) >= 0.8
    assert out.sources, "no citation returned"
```

✔ Grounded · cited · repeatable · 4 checks passed



Prompt Testing | RAG Testing | AI Agents & MCP | AI Security

Evals & Metrics | LLM-as-Judge | Performance & Cost | Playwright MCP

Learn → Test → Prove → Interview with confidence

WRITTEN BY
AiBuildPath Academy

15 Chapters · 318 Pages · 4 Appendices
Junior → Lead · Hands-on labs · 7-Day & 30-Day Plans

INSIDE THE BOOK

Table of Contents

Fifteen chapters and four appendices, from how AI testing interviews work to a 30-day preparation plan. Page numbers refer to the full book.

NO.	CHAPTER	PAGE
1	CHAPTER 1 How AI Testing Interviews Work in 2026	8
2	CHAPTER 2 LLM Fundamentals Every Tester Must Know	24
3	CHAPTER 3 Testing Non-Deterministic Systems: Oracles, Eval Sets and Pass Criteria	42
4	CHAPTER 4 LLM Evaluation in Practice: LLM-as-Judge, Human Review, Metrics	62
5	CHAPTER 5 Prompt Testing and Prompt Regression	80
6	CHAPTER 6 RAG Testing End to End	98
7	CHAPTER 7 AI Agent and MCP Testing	123
8	CHAPTER 8 AI Security Testing: Prompt Injection, Jailbreaks, Data Leakage, OWASP LLM Top 10	148
9	CHAPTER 9 Performance, Cost and Production Monitoring of AI Features	171
10	CHAPTER 10 Using AI in Your Own Test Automation: Copilot, Claude, Playwright MCP	190
11	CHAPTER 11 Bias, Fairness, Governance and Release Gates for AI Products	209
12	CHAPTER 12 AI Test Strategy and System Design Round (Senior/Lead)	230
13	CHAPTER 13 10 Production AI Failure Scenarios: How Would You Test This?	251
14	CHAPTER 14 Behavioural and HR Questions for AI QA Roles (STAR Answers)	265
15	CHAPTER 15 7-Day and 30-Day Interview Preparation Plans	278
A	APPENDIX A 160-Question Quick-Revision Bank	292
B	APPENDIX B AI Testing Glossary	303
C	APPENDIX C Tool Cheat Sheets	309
D	APPENDIX D Resume Bullet Points and LinkedIn Headlines for AI QA Roles	315

FRONT MATTER

Before You Begin

How to use this book, the example apps, and the lab setup used in every chapter.

AiBuildPath Academy · AI Testing Interview Blueprint (2026 Edition)

Who this book is for

This book is for working QA engineers, automation testers, SDETs and QA leads with roughly 3 to 15 years of experience. You already know test design, automation frameworks, CI/CD and defect management. What is new to you is testing systems built on large language models (LLMs): chatbots, retrieval-augmented generation (RAG) assistants and AI agents.

The goal is practical. By the end, you should be able to:

1. **Answer** AI testing interview questions at junior, mid, senior and lead level.
2. **Explain** step by step, how you would test an LLM, RAG or agent application.
3. **Show proof** hands-on, using free, open-source tools running on your own laptop.

An honest promise. This book does not promise a job. Interviews depend on many things outside any book. What it does promise is honest, accurate preparation that gives you real material to talk about.

Text box conventions

TIP: Practical advice that saves time.

WARNING: A common mistake or a risk to watch for.

INTERVIEW GOLD: A phrase, idea or framing that makes interviewers sit up.

DIAGRAM: A text description of a diagram, ready to be drawn.

PROMPT TEMPLATE: A reusable prompt you can copy.

Level tags on questions: JUNIOR 0–3 years in the role · MID 3–7 · SENIOR 7–12 · LEAD manager, architect or principal.

HOW THE BOOK WORKS

How each chapter is organised

Every chapter follows the same structure, so you always know where to find things.

1. **Chapter title and one-line promise**
2. **What you will learn**: 3 to 5 bullets
3. **Core concepts**: explained simply, with diagrams described in text
4. **Hands-on lab**: where relevant: numbered steps, full code, expected output
5. **Interview questions**
   10 to 15, each with a level tag (Junior / Mid / Senior / Lead), what the interviewer is really checking, a model answer in first person with a real example, likely follow-ups and red flags
6. **Production failure story**: a realistic incident and how a tester should handle it
7. **Quick-revision box**: 8 to 10 key points
8. **Chapter checklist**: tick off what you can now do

The four example applications

The same four example products appear throughout the book. Using one set of examples means your answers stay consistent and your lab code builds chapter by chapter.

ShopHelp
LLM CHATBOT

E-commerce customer-support bot (orders, returns, delivery)

Main chapters: **3, 4, 5, 9**

PolicyPal
RAG

HR policy assistant that answers from company policy documents

Main chapters: **6, 8, 9, 11, 12**

SafeBank Assist
LLM + GUARDRAILS

Banking chatbot for account and card questions, with strict guardrails

Main chapters: **2, 8, 11, 12**

TripMate
TOOL-CALLING AGENT

Travel booking agent that searches flights and hotels and makes bookings

Main chapters: **7, 8, 12**

All four are fictional. Any resemblance to a real product is unintended.

LAB SETUP

Everything free, everything local

All labs are designed to run on a normal laptop at no cost.

COMPONENT	PURPOSE	COST
Python 3.11 or newer	Language for all labs	Free
Ollama	Runs open models locally	Free
`llama3.2:3b` (via Ollama)	Small chat model used by the apps	Free
`qwen2.5:7b` or `llama3.1:8b` (optional)	Stronger local judge model for evaluations	Free
`nomic-embed-text` (via Ollama)	Embedding model for RAG	Free
LangChain, LangGraph	App and agent framework	Free, open source
ChromaDB	Local vector database	Free, open source
Pytest	Test runner	Free, open source
DeepEval	LLM evaluation framework	Free, open source (optional paid cloud platform)
Promptfoo	Prompt testing and red teaming (Node.js CLI)	Free, open source (optional paid cloud features)
Ragas	RAG evaluation	Free, open source
Playwright	Browser automation, Playwright MCP	Free, open source



Hardware

8 GB RAM is the minimum. 16 GB is recommended, especially if you run a 7B or 8B judge model. A GPU is not required; responses will just be slower on CPU.

PAID: Cloud LLM APIs (OpenAI, Anthropic, Google, etc.), GitHub Copilot paid plans, and hosted tiers of evaluation platforms are clearly labelled **[PAID – optional]** wherever they appear. You never need them to complete a lab.

LAB SETUP

The shared repository

Create this folder structure once. Each chapter adds files to it.

ai-testing-blueprint

```
ai-testing-blueprint/
├── apps/
│   ├── common/llm.py          # shared Ollama helper (Ch 2)
│   ├── shophelp/              # Ch 3–5, 9
│   ├── policypal/             # Ch 6
│   └── tripmate/              # Ch 7
├── data/hr_policies/          # sample HR policy documents (Ch 6)
├── evals/                     # golden datasets in JSON
├── promptfoo/                 # promptfooconfig.yaml files (Ch 5, 8)
├── perf/                      # performance scripts (Ch 9)
├── tests/                     # all Pytest tests
├── conftest.py
├── pytest.ini
├── requirements.txt
└── README.md
```

One-time setup

terminal

```
# 1. Install Ollama from https://ollama.com (Windows, macOS, Linux)
ollama --version

# 2. Pull the models used in this book
ollama pull llama3.2:3b
ollama pull nomic-embed-text
# optional, stronger judge (needs ~8 GB free RAM)
ollama pull qwen2.5:7b

# 3. Create the project and a virtual environment
mkdir ai-testing-blueprint && cd ai-testing-blueprint
python -m venv .venv
# macOS/Linux
source .venv/bin/activate
# Windows (PowerShell)
.venv\Scripts\Activate.ps1
```

LAB SETUP

Dependencies and a note on accuracy

`requirements.txt` for the whole book:

requirements.txt

```
ollama>=0.4
langchain>=0.3
langchain-ollama>=0.2
langchain-chroma>=0.1
langchain-text-splitters>=0.3
langgraph>=0.2
chromadb>=0.5
pytest>=8.0
deepeval>=2.0
ragas>=0.2
pandas>=2.0
locust>=2.20
fastapi>=0.110
uvicorn>=0.29
```

terminal

```
pip install -r requirements.txt
pip freeze > requirements.lock.txt   # record the exact versions that worked for you
```

WARNING: LLM tooling changes very quickly. DeepEval, Ragas, Promptfoo and LangChain release updates every few weeks, and function names sometimes change. The code in this book follows each tool's documented API at the time of writing. If an import fails, check the tool's official documentation and changelog first. Once your setup works, keep your `requirements.lock.txt` so it keeps working.

A note on accuracy

This book only describes tools, metrics and features that exist. Where a detail changes often (CLI flags, cloud features, regulation dates), the text says so and points you to the official source. Treat any number you see in a model's output, including the expected outputs in this book, as illustrative: your local model will word things differently, and that is exactly the problem this book teaches you to test.



You are ready to begin.
Set up your lab with the steps on pages 5 and 6, then start with Chapter 1 on page 8.

CHAPTER 1

How AI Testing Interviews Work in 2026

Know exactly what each round tests and how to present your AI experience honestly.

AiBuildPath Academy · AI Testing Interview Blueprint (2026 Edition)

What you will learn

- The main AI QA roles and what each one does day to day
- The typical interview rounds and what is scored in each
- The skills that carry over from traditional QA, and the ones that are new
- How to turn your existing experience and the labs in this book into honest, strong stories
- How to describe AI work on your resume without overclaiming

1.1 Why AI testing is now its own interview track

Until recently, "testing an AI feature" usually meant testing the screen around it: the button, the API call, the error message. The AI model itself was treated as a black box owned by data scientists.

That has changed. Companies now ship LLM-powered features straight into customer-facing products, such as support chatbots, internal knowledge assistants, coding tools and booking agents. When these features fail, they fail in new ways:

- They give a **confident wrong answer** instead of an error.
- They give **a different answer each time** to the same question.
- They can be **manipulated by text**, not just by malformed input.
- They can **take real actions**, such as sending an email or making a booking, through tools.

Traditional pass/fail test cases don't cover these risks well. Hiring managers now look for testers who understand **evaluation** (measuring output quality on a scale, not just pass/fail), **non-determinism**, **AI security** and **production monitoring**. That is why many companies run a separate interview loop for AI-focused QA roles, or add AI questions to their SDET loop.

> **INTERVIEW GOLD:** "Traditional testing asks *does it work?* AI testing also asks *how well does it work, how often, for whom, and how can it be misused?*" This one line shows you understand the shift.

1.2 Role map: who does what

Job titles vary a lot between companies. The table below shows the most common ones and what they usually mean.

Title	Typical focus	Main skills tested
AI QA Engineer	Testing LLM features end to end: functional, conversational, regression	Test design for AI, eval sets, exploratory testing of chatbots
AI SDET / AI Automation Engineer	Building automated eval pipelines and test frameworks	Python, Pytest, DeepEval/Promptfoo, CI/CD, APIs
LLM Evaluation Engineer	Designing metrics, judges and datasets; measuring model quality	Metrics, LLM-as-judge, statistics basics, data labelling
AI Red Teamer / AI Security Tester	Prompt injection, jailbreaks, data leakage	OWASP LLM Top 10, adversarial thinking, security tooling
AI Quality Lead / QA Manager (AI)	Strategy, release gates, team building, governance	Test strategy, risk, stakeholder management, compliance basics

India vs US expectations (general patterns, not rules):

- In **India**, many openings are at MNCs and service companies, where AI testing sits inside a larger QA practice. Interviews often check breadth: automation fundamentals plus AI basics. Product companies and AI startups in Bengaluru, Hyderabad, Pune and NCR tend to go deeper on hands-on evaluation work.
- In the **US**, AI QA roles at product companies more often expect strong coding (Python), ownership of an eval pipeline, and comfort with ambiguity. Startups may expect one person to cover functional, eval and security testing together.

1.3 The typical interview rounds

Most AI QA loops have five to seven rounds. Not every company runs all of them.

Round	Duration	What it checks	How to prepare
Recruiter / HR screen	20–30 min	Motivation, experience fit, notice period, salary range	A clear 60-second story (Chapter 14)

Round	Duration	What it checks	How to prepare
Technical fundamentals	45–60 min	QA fundamentals plus LLM basics: tokens, temperature, hallucination, RAG	Chapters 2–3
Hands-on / take-home	1–4 hours	Write tests or evals for a small LLM app; sometimes live coding	Labs in Chapters 3–7
Test design round	45–60 min	"How would you test this chatbot/RAG/agent?"	Chapters 3, 6, 7, 13
System design / strategy (senior+)	45–60 min	End-to-end AI test strategy, release gates, monitoring, team	Chapter 12
Behavioural	45 min	Ownership, conflict, learning, influence	Chapter 14
Hiring manager	30–45 min	Overall fit, judgement, growth	All of the above

DIAGRAM: *Interview journey flow.* A left-to-right line of seven boxes: "Recruiter screen" → "Technical fundamentals" → "Hands-on / take-home" → "Test design" → "System design (senior/lead only, dashed border)" → "Behavioural" → "Hiring manager" → "Offer". Under each box, a small label shows the main chapter in this book that prepares you for it.

1.4 What interviewers actually score

Most interviewers fill in a rubric after the round. You will rarely see it, but it usually looks something like this:

Dimension	Weak signal	Strong signal
Fundamentals	Uses buzzwords without being able to explain them	Explains tokens, temperature, RAG and evals simply and correctly
Test design	Lists random test cases	Starts from risks, builds layers, defines pass criteria
Handling non-determinism	"I'd set temperature to 0 and use assertEquals"	Uses properties, thresholds, repeat runs, eval sets
Hands-on ability	Has only read about tools	Has run DeepEval/Promptfoo/Ragas and can show code

Dimension	Weak signal	Strong signal
Security awareness	Doesn't mention prompt injection	Covers direct and indirect injection, data leakage, excessive agency
Judgement	Wants to test everything equally	Prioritises by user impact and business risk
Communication	Long, unstructured answers	Clear structure, real examples, admits limits
Honesty	Overclaims experience	Separates "did at work" from "built in my lab"

1.5 Traditional QA vs AI QA

Area	Traditional testing	AI testing
Expected result	One exact correct output	A range of acceptable outputs
Oracle	Spec or requirement	Rubric, reference answer, judge model, human review
Pass criteria	Pass or fail	Scores, thresholds and pass rates over many runs
Repeatability	Same input → same output	Same input → possibly different output
Main defect types	Logic errors, crashes, UI bugs	Hallucination, irrelevance, unsafe output, wrong tool use, bias
Test data	Input values	Eval datasets: questions, contexts, reference answers
Security focus	SQL injection, XSS, auth	Prompt injection, jailbreaks, data leakage, plus traditional issues
Regression trigger	Code change	Code, prompt, model, data or retrieval index change
Monitoring	Errors, uptime, latency	All of those, plus quality, cost per request, drift, user feedback

Notice that a lot of your existing skill still applies: risk-based thinking, test design techniques, automation, CI/CD, API testing and defect reporting. AI testing **adds to** QA; it does not replace it.

1.6 Turning your QA experience into AI-relevant stories

Interviewers know most candidates have limited production AI experience. What they look for is **transferable thinking**. Here is how common QA experience maps to AI testing:

Your existing experience	How to frame it for AI testing
API testing (Postman, REST Assured)	LLM features are called through APIs; you can test prompts, parameters, response schemas and error handling
Data/ETL testing	RAG quality depends on the data pipeline: ingestion, chunking, freshness, duplicates
Performance testing	LLM latency, time to first token, rate limits and token cost
Accessibility testing	Chatbot UIs, screen-reader behaviour of streamed responses, plain-language output
Security testing	Prompt injection is the new injection class; data leakage and access control still matter
Building frameworks	Eval pipelines are frameworks: datasets, runners, reports, CI gates
Leading QA teams	Release gates, risk sign-off and quality metrics for AI features

> **TIP:** Use the phrase "In my lab project..." for things you built yourself and "At work..." for production experience. Interviewers respect clear separation far more than vague claims.

1.7 Resume and portfolio basics

A small, real portfolio beats a long list of buzzwords. By the end of this book you will have:

1. A GitHub repo (`ai-testing-blueprint`) with a local chatbot, RAG app and agent
2. Pytest + DeepEval tests with thresholds
3. A Promptfoo regression config comparing prompt versions
4. A Ragas evaluation report for a RAG app
5. A security test suite with prompt-injection cases
6. A short README explaining your test strategy and results

Honest resume wording examples:

- *Weak:* "Expert in AI testing and LLMs."
- *Strong:* "Built a local RAG evaluation pipeline (Ollama, ChromaDB, Ragas, Pytest) measuring faithfulness and context recall on a 40-question HR policy dataset; added CI thresholds to block

regressions."

Appendix D has more than 30 resume bullet points and LinkedIn headline examples.

Interview Questions

Q1. Why do you want to move into AI testing? JUNIOR

What the interviewer is really checking: Real motivation versus trend-chasing, and whether you understand what the work involves.

Model answer: I've spent several years in test automation, and over the last year I've noticed that the hardest quality problems on my projects are no longer the UI flows. They're the features where software makes judgements: search ranking, recommendations and now LLM chatbots. Those features fail quietly. A chatbot can return HTTP 200 with a perfectly formatted, completely wrong answer.

That problem interests me because it needs exactly what good testers already do: think about risk, design representative test data and define what "correct" means when the spec is fuzzy. To prepare, I built a small HR policy assistant locally using Ollama and ChromaDB, wrote a 40-question evaluation set, and measured faithfulness with Ragas. The first run showed the bot answering questions about a leave policy that wasn't in the documents at all. Finding that made the gap clear to me: normal functional tests would have passed.

So my motivation is practical. AI features are shipping fast, the testing discipline is still young, and I want to bring structured QA thinking to it.

Likely follow-up questions:

- What did you learn from your lab project that surprised you?
- What part of AI testing do you find hardest?
- How would you explain this move to your current manager?

Red flags:

- "AI is the future and pays more." It's honest but shallow.
- No sign of any hands-on exploration.
- Saying AI testing is "just like normal testing."

Q2. How is testing an AI feature different from testing a normal web app? JUNIOR

What the interviewer is really checking: Whether you understand non-determinism, oracles and new failure types.

Model answer: I see four main differences.

First, **the expected result is a range, not a value**. For a normal app, "transfer ₹500" has one correct outcome. For a support chatbot, "How do I return a damaged item?" has many acceptable answers, so I test properties instead: it mentions the return window, it doesn't invent a policy, and it stays polite.

Second, **outputs can change between runs**. So I run important cases several times and track a pass rate rather than relying on a single pass.

Third, **failures are often silent**. A hallucination looks exactly like a correct answer, so I need evaluation methods such as reference answers, LLM-as-judge with a rubric, and human review for high-risk flows.

Fourth, **new things trigger regressions**. A prompt edit, a model version upgrade or a re-indexed document set can break quality without any code change.

The traditional layers still matter too: API contracts, UI, performance, security and accessibility. On ShopHelp, our e-commerce bot, I'd keep normal functional tests for the order-lookup API and add an eval suite for answer quality on top.

Likely follow-up questions:

- Give an example of a "silent failure."
- How do you decide the pass rate for a test?
- Which traditional tests still apply to an LLM feature?

Red flags:

- Only saying "the output is random."
- Ignoring that normal functional and API testing still applies.
- Suggesting exact string matching as the main approach.

Q3. What AI testing have you actually done? Walk me through it. MID

What the interviewer is really checking: Honesty, depth and the ability to describe real work clearly.

Model answer: I'll separate work experience from lab work so it's clear.

At work, I tested an internal search feature that used an ML ranking model. I built a set of 150 queries with expected top results, and we tracked how often the right document appeared in the top five. That taught me to think in metrics rather than single test cases.

For LLMs specifically, my hands-on experience is from a lab project. I built PolicyPal, a small RAG assistant over 12 HR policy documents, using Ollama with Llama 3.2 3B, ChromaDB and LangChain. I wrote 40 test questions with reference answers and tested at three levels. First, retrieval: did the right policy chunk appear in the top three? Second, generation: I used Ragas faithfulness and answer relevancy. Third, safety: I added prompt-injection cases inside a document.

The most useful finding was that 6 of the 40 questions failed retrieval because tables in the leave policy were split across chunks. Changing the chunk size and overlap fixed four of them. I put thresholds in Pytest so the suite fails if faithfulness drops below 0.8.

Likely follow-up questions:

- Why did you choose those thresholds?
- How did you build the reference answers?
- What would change if this went to production?

Red flags:

- Presenting tutorial work as production experience.
- Not being able to name metrics or explain results.
- Describing tools without describing findings.

Q4. You have no production AI experience. How would you contribute in your first 30 days? MID

What the interviewer is really checking: Practical thinking, humility and the ability to add value quickly.

Model answer: I'd focus on three things where QA experience transfers directly.

In **week one**, I'd learn the product and its risks. I'd read the system prompt, the architecture, recent incidents and user feedback. I'd ask which failures would hurt most: a wrong refund amount, a data leak or a rude reply.

In **weeks two and three**, I'd build or improve the **evaluation set**. Many teams test AI features with a handful of demo questions. I'd collect real user questions from logs (anonymised), group them by intent, add edge cases and adversarial cases, and agree on pass criteria with the product owner. This is classic test design, just applied to a new kind of system.

In **week four**, I'd automate a first regression run, for example in Pytest with DeepEval or Promptfoo, so every prompt or model change gets checked before release.

I'd be open about what I'm still learning, pair with the ML or platform engineers, and share findings early. On a ShopHelp-style bot, a 100-question eval set with clear criteria is often the single most valuable thing a tester can add in the first month.

Likely follow-up questions:

- How would you get access to real user questions safely?
- What if the team says they don't have time for evals?
- How would you measure your impact after 30 days?

Red flags:

- Promising to "automate everything" in 30 days.
- No mention of learning the product's specific risks.

- Overconfidence without admitting a learning curve.

Q5. Which AI testing tools have you used, and what were their limits? MID

What the interviewer is really checking: Real tool experience and critical thinking about tools.

Model answer: I've used four open-source tools in my lab work.

DeepEval is a Python framework that integrates with Pytest. I used answer relevancy, faithfulness and G-Eval custom criteria. Its limit is that most metrics depend on a judge LLM. With a small local judge, scores were noisy, so I had to calibrate them against my own labels.

Promptfoo is a CLI with YAML configs that compares prompts and models side by side. It's great for prompt regression and has red-teaming features. Its limit is that the YAML grows quickly, so I had to split configs per feature.

Ragas is built for RAG metrics: faithfulness, context precision and recall. It's useful for separating retrieval problems from generation problems. Its limit is that the API has changed between versions, so I pin the version.

Ollama isn't a testing tool, but it lets me run models locally for free, which makes the labs repeatable and keeps data on my machine.

The general limit across all of them is that the tool is only as good as the dataset and rubric you give it.

Likely follow-up questions:

- How did you calibrate the judge?
- Why Promptfoo and DeepEval rather than one tool?
- Have you used any paid evaluation platforms?

Red flags:

- Listing many tools with no detail.
- Saying a tool "solves" AI testing.
- Inventing features a tool doesn't have.

Q6. How do you keep up with fast-changing AI tools? JUNIOR

What the interviewer is really checking: A learning habit, and filtering signal from hype.

Model answer: I use a simple routine. For the tools I rely on, such as DeepEval, Promptfoo, Ragas and Ollama, I follow the GitHub release notes and changelogs, because that's where breaking changes show up first. I also read the official docs whenever I start something new rather than relying on old blog posts, since APIs change fast.

For broader learning, I follow the OWASP GenAI Security Project for security topics and read a few practitioner blogs and papers each month. I don't try to follow everything.

The most important part is that I **try things hands-on**. When a new feature appears, for example a new metric, I add it to my lab project and see if it actually helps. Last month I compared two faithfulness metrics on the same 20 RAG answers and found they disagreed on 4 cases, which taught me more than any article.

I also pin versions in `requirements.txt` so my test suite doesn't break when a library updates.

Likely follow-up questions:

- What's a recent change in an AI testing tool that affected you?
- How do you judge whether a new tool is worth adopting?
- How would you share learning with your team?

Red flags:

- "I watch YouTube videos" as the only answer.
- No mention of official docs or hands-on practice.
- Claiming to know every new tool.

Q7. What does "quality" mean for an LLM feature? MID

What the interviewer is really checking: Whether you can break quality into measurable dimensions.

Model answer: I break it into dimensions and agree which matter most for each feature.

1. **Correctness:** Is the answer factually right according to our source of truth?
2. **Faithfulness or groundedness:** Does it stick to the provided context and not invent things?
3. **Relevance:** Does it answer the question that was asked?
4. **Completeness:** Does it include the key facts? For a refund question, that's the time limit and condition.
5. **Safety:** No harmful, biased or policy-breaking content.
6. **Security:** It resists prompt injection and doesn't leak data or the system prompt.
7. **Tone and format:** Brand voice, language and correct structure such as JSON.
8. **Consistency:** Similar answers to similar questions.
9. **Non-functional:** Latency, cost per request and availability.

For SafeBank Assist, correctness, safety and security are non-negotiable, with very high thresholds. For a marketing copy assistant, tone and creativity matter more. So quality is a profile, not one number. I write it down as a quality matrix with a metric and threshold for each dimension, and that becomes the release gate.

Likely follow-up questions:

- How would you measure completeness?
- Who decides the thresholds?
- How do you handle trade-offs, such as safety vs helpfulness?

Red flags:

- "Quality means no hallucinations." That's too narrow.
- No link between dimensions and how to measure them.
- Treating all features the same.

Q8. How would you explain AI test results to a non-technical product manager?

SENIOR

What the interviewer is really checking: Communication, and translating metrics into business impact.

Model answer: I avoid metric names and talk in user outcomes and risk.

Instead of saying "faithfulness is 0.82," I'd say: "Out of 100 realistic employee questions, PolicyPal gave fully correct, policy-backed answers to 86. In 9 it left out a detail, and in 5 it said something not in our policy. Two of those five were about maternity leave, which is a legal risk."

Then I give a clear recommendation with options: "We can launch to the pilot group with a disclaimer and human escalation for leave questions, or we can delay one week to fix the document chunking, which should fix three of the five."

I use a simple traffic-light summary: green for dimensions above target, amber for close, red for blockers. I also show two or three real examples of failures, because one concrete bad answer is more convincing than any chart.

Finally, I'm honest about uncertainty: "These results come from 100 test questions. Real users will ask things we didn't think of, so we'll monitor feedback in the first two weeks."

Likely follow-up questions:

- What if the PM wants to launch anyway?
- How do you show trends over releases?
- How do you avoid overwhelming them with data?

Red flags:

- Dumping metric tables without interpretation.
- Hiding uncertainty.
- Making the go/no-go decision alone instead of informing it.

Q9. What would your first 90 days as an AI QA lead look like?

LEAD

What the interviewer is really checking: Strategic thinking, prioritisation and team building.

Model answer: I'd plan it in three phases.

Days 1–30: Understand and stabilise. I'd map every AI feature, its owner, its model and its current testing. I'd review incidents and user complaints, then run a quick risk assessment to rank features by impact and likelihood of failure. I'd pick the highest-risk feature and make sure it has at least a basic eval set and a manual review process.

Days 31–60: Build the foundation. I'd define a standard **AI quality framework**: quality dimensions, eval set guidelines, metric choices, thresholds, and how prompt and model changes are reviewed. I'd set up a shared eval pipeline in CI using open-source tools like DeepEval or Promptfoo, starting with the top two features. I'd also agree release gates with product, engineering and security.

Days 61–90: Scale and measure. I'd extend the framework to other teams, add production monitoring for quality signals and user feedback, and train the QA team through pairing sessions and internal workshops. I'd report a small set of metrics to leadership: coverage of AI features by evals, escaped AI defects and time to detect regressions.

Throughout, I'd focus on relationships with ML engineers and product owners, because AI quality is shared.

Likely follow-up questions:

- How would you handle teams that resist new process?
- What would you not do in the first 90 days?
- How would you hire for this team?

Red flags:

- Starting with tool purchases.
- No stakeholder alignment.
- Trying to cover every feature at once.

Q10. How do you decide what not to test in an AI product? SENIOR

What the interviewer is really checking: Risk-based prioritisation in a space with infinite inputs.

Model answer: With LLMs, the input space is effectively infinite, so deciding what *not* to test is part of the strategy.

I start with a **risk matrix**: user impact on one axis, likelihood on the other. For SafeBank Assist, wrong balance information or leaking another customer's data is critical. Slightly awkward wording in a greeting is low risk.

Then I apply a few rules:

- I **don't re-test the base model's general knowledge**. If we only answer card and account questions, I don't need an eval set about world history. I do test that the bot *refuses* out-of-scope topics politely.
- I **don't chase 100% on subjective dimensions**. Tone gets a sample-based human review, not hundreds of automated checks.
- I **reduce duplicate coverage**. If a property like "valid JSON" is checked in a fast unit-level test, I don't repeat it in the expensive end-to-end eval.
- I **sample instead of exhaustive testing** for low-risk intents and monitor them in production.

I write these decisions down in the test strategy so they're visible and agreed, not silent gaps.

Likely follow-up questions:

- How do you justify a gap if something fails later?
- How often do you revisit the risk matrix?
- How do you test out-of-scope refusals?

Red flags:

- "We should test everything."
- No documented, agreed decisions.
- Ignoring production monitoring as a safety net.

Q11. What's a mistake you've seen teams make when testing AI? SENIOR

What the interviewer is really checking: Real-world awareness and lessons learned.

Model answer: The most common mistake I've seen, in my own early lab work and in teams I've talked to, is **"demo testing"**: checking the AI feature with 10 to 20 hand-picked questions, seeing good answers and calling it ready.

The problem is that demo questions are usually the easy, well-phrased ones. Real users type short, messy, multi-part questions, spell things wrong, switch languages and sometimes try to break the bot.

A second mistake is **testing only the final answer**. In a RAG app, if the answer is wrong, you don't know whether retrieval failed or the model ignored good context. Without separate retrieval tests, people tweak the prompt when the real problem is chunking.

A third is **not re-testing after model or prompt changes**. Teams treat a prompt edit like a text change, not a code change.

What I do instead: build the eval set from real (anonymised) user questions, test retrieval and generation separately, and run the eval suite on every prompt, model or index change.

Likely follow-up questions:

- How do you convince a team to stop demo testing?
- How big should the eval set be?
- What's another mistake you've seen?

Red flags:

- Blaming others without offering a fix.
- A generic answer such as "not enough testing."
- No concrete example.

Q12. How do you prove AI testing value to leadership? LEAD

What the interviewer is really checking: Business thinking, metrics and influence.

Model answer: Leadership cares about risk, speed and cost, so I connect AI testing to those three.

Risk: I track AI defects caught before release versus escaped to production, and I classify them by severity. For example: "This quarter our eval gate blocked three releases that would have given wrong refund policies to customers." I keep short incident write-ups because concrete stories land better than numbers.

Speed: Automated eval suites let teams change prompts and upgrade models confidently. I measure how long it takes to validate a model upgrade, for example from three days of manual checking to a 40-minute automated run plus a one-hour human review of flagged cases.

Cost: I show token cost per request trends, which catch prompt changes that suddenly double cost, and support-ticket deflection quality, since a bot that answers wrongly creates more tickets.

I report monthly with a one-page dashboard: eval coverage per AI feature, pass rates against thresholds, escaped defects and cost trends. I also bring one example of a prevented failure each time. That combination of numbers and stories usually earns continued investment.

Likely follow-up questions:

- What if leadership only wants to see speed?
- How do you attribute a prevented incident to testing?
- Which metric would you drop if you could only report three?

Red flags:

- Only reporting test counts.
- No link to business outcomes.
- Overclaiming credit for outcomes.

Production Failure Story: The Refund Policy That Did Not Exist

What happened: An e-commerce company launched ShopHelp to answer customer questions. Before launch, the team tested it with 25 questions written by the product manager. All answers looked good. In the first week, a customer asked, "Can I return a phone after 45 days if I didn't open it?" The bot replied confidently: "Yes, unopened items can be returned within 60 days." The real policy was 30 days. Screenshots spread on social media, and several customers demanded the "60-day" return.

Why it happened:

- The bot had no access to the return policy for that category, so the model filled the gap from general knowledge.
- The 25 test questions were all easy, common questions. None involved edge cases near policy limits.
- There was no instruction or test for "say you're not sure and escalate."

How a tester should handle it:

1. **Contain:** Work with the team to add an immediate guardrail. Questions about return windows are routed to a fixed policy answer or a human.
2. **Reproduce:** Run the exact question and 20 variations (different days, categories and wording) several times each. Record how often the bot invents a number.
3. **Root cause:** Check whether the relevant policy text was in the prompt or retrieved context. It wasn't.
4. **Fix and verify:** After the policy is added and the prompt says "If the policy does not cover the case, say so and offer a human agent," re-run the variations and require a 100% pass on "no invented policy numbers."
5. **Prevent:** Add a permanent "policy boundary" category to the eval set (limits, exceptions, unusual categories) and block releases if any answer states a policy number not found in the source documents.

> **INTERVIEW GOLD:** Telling this kind of story with a clear Contain → Reproduce → Root cause → Fix → Prevent structure is one of the strongest signals you can give in any AI testing interview.

Quick-Revision Box

1. AI testing adds evaluation, non-determinism handling, AI security and quality monitoring on top of normal QA.
2. Common roles: AI QA Engineer, AI SDET, LLM Evaluation Engineer, AI Red Teamer, AI Quality Lead.
3. Typical rounds: screen, fundamentals, hands-on, test design, system design (senior), behavioural, hiring manager.
4. Interviewers score fundamentals, test design, non-determinism handling, hands-on proof, security awareness, judgement, communication and honesty.
5. Expected results in AI testing are ranges, judged by rubrics, references, judges and humans.
6. Regressions can come from code, prompt, model, data or index changes.
7. Clearly separate "at work" from "in my lab."
8. A small, real GitHub eval project is stronger than a long list of tools.
9. Quality is a profile across dimensions, with thresholds set per feature risk.
10. Tell incident stories using Contain → Reproduce → Root cause → Fix → Prevent.

Chapter Checklist

- ☐ I can name the main AI QA roles and what each does.
- ☐ I know the typical interview rounds and which chapters prepare me for each.
- ☐ I can explain four differences between traditional and AI testing.
- ☐ I have mapped my own past experience to AI testing (table in 1.6).
- ☐ I have rewritten at least two resume bullets in honest, specific wording.
- ☐ I can define LLM feature quality as a set of measurable dimensions.
- ☐ I have practised the "Production failure story" structure out loud.
- ☐ I have created the empty `ai-testing-blueprint` repo on GitHub.

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