2026 NCP-AAI Reliable Test Guide 100% Pass | Valid NCP-AAI Practice Test Fee: Agentic AI

This is a NVIDIA NCP-AAI practice exam software for Windows computers. This NCP-AAI practice test will be similar to the actual NCP-AAI exam. If user wish to test the Agentic AI (NCP-AAI) study material before joining PassTorrent, they may do so with a free sample trial. This NCP-AAI Exam simulation software can be readily installed on Windows-based computers and laptops. Since it is desktop-based NCP-AAI practice exam software, it is not necessary to connect to the internet to use it.

NVIDIA NCP-AAI Exam Syllabus Topics:

Topic	Details
Topic 1	• Human-AI Interaction and Oversight: Focuses on designing systems that enable effective human supervision, control, and collaboration with AI agents.
Topic 2	• Knowledge Integration and Data Handling: Covers how agents integrate external knowledge sources and manage diverse data types to support informed decision-making.
Topic 3	• NVIDIA Platform Implementation: Focuses on leveraging NVIDIA's AI hardware and software stack to build and optimize agentic AI systems.
Topic 4	• Cognition, Planning, and Memory: Explores the reasoning strategies, decision-making processes, and memory management techniques that drive intelligent agent behavior.
Topic 5	• Safety, Ethics, and Compliance: Covers the principles and practices needed to ensure agents operate responsibly, ethically, and within legal and regulatory requirements.
Topic 6	• Evaluation and Tuning: Addresses methods for measuring agent performance, running benchmarks, and optimizing agent behavior.
Topic 7	• Deployment and Scaling: Covers operationalizing agentic systems for production use, including containerization, orchestration, and scaling strategies.
Topic 8	• Run, Monitor, and Maintain: Addresses the ongoing operation, health monitoring, and routine maintenance of agentic systems after deployment.

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NVIDIA Agentic AI Sample Questions (Q90-Q95):

NEW QUESTION # 90
A customer service agentic AI is designed to resolve billing inquiries. It consistently resolves inquiries accurately and efficiently. However, a significant number of customers are reporting frustration due to the agent's tendency to repeatedly ask for the same information (account number, address) during each interaction, even after it's already been provided.
Which evaluation method would be most effective for addressing this issue?

- A. Increasing the agent's processing speed to reduce the time it takes to handle each inquiry and increase customer satisfaction.
- B. Adjusting the agent's reward function to prioritize speed of resolution over customer satisfaction.
- C. Implementing a "conversational flow" analysis to optimize the order of questions asked during each interaction.
- D. Analyzing the agent's dialogue transcripts to identify patterns in its questioning techniques.

Answer: D

Explanation:
The best answer is Option B when the design is judged by reliability, latency budget, auditability, and maintainability rather than demo simplicity. Repeated questions are visible in transcripts. Dialogue analysis shows whether state is being stored, retrieved, or ignored across turns. The high-value engineering move is a tool boundary where every API has declared inputs, declared outputs, validation, retry behavior, and instrumentation. The selected option specifically B states "Analyzing the agent's dialogue transcripts to identify patterns in its questioning techniques.", which matches the operational requirement rather than a superficial wording match. The alternatives would look simpler in a prototype, but relying on the model to infer API behavior invites fabricated endpoints, malformed arguments, and brittle production behavior. The stack-level anchor is clear: NVIDIA's agent tooling favors explicit function specifications and observable execution paths instead of free-form API narration in the prompt. Anything less would make the agent fragile when traffic, schemas, policies, or user behavior shift.

NEW QUESTION # 91
After a series of adjustments in a supply chain agentic system, the agent has dramatically reduced shipping times and minimized costs, but the team is receiving a high volume of complaints from customers regarding delayed deliveries.
Which metric is MOST important to prioritize when investigating this situation?

- A. The percentage of delivery times that fall within the acceptable delay window, considering customer satisfaction as a key factor.
- B. The total cost savings achieved through the agent's optimization, which represents a significant financial benefit.
- C. The agent's adherence to the prescribed delivery schedules, as it's demonstrably improving efficiency.
- D. The agent's ability to predict future demand fluctuations, as accurate forecasting is crucial for effective logistics.

Answer: A

Explanation:
The NVIDIA implementation angle is not cosmetic here: the NVIDIA stack makes it possible to correlate model-serving metrics with workflow events and user-visible task failures. If complaints rise while cost falls, the optimization objective is misaligned with service quality. Delivery-window compliance connects logistics performance to customer experience. Option C wins because it optimizes the system boundary around the risky component rather than hoping the base model behaves consistently. The selected option specifically C states "The percentage of delivery times that fall within the acceptable delay window, considering customer satisfaction as a key factor.", which matches the operational requirement rather than a superficial wording match. That matters because repeatable benchmark suites that separate accuracy, cost, latency, reliability, and human satisfaction rather than blending them into one vague score. The losing choices mostly optimize for short-term convenience; offline benchmarks alone cannot expose live API failures, schema drift, queue saturation, or feedback-driven dissatisfaction. The result is a system that can be benchmarked, traced, and revised without destabilizing the whole agent fabric.

NEW QUESTION # 92
An AI engineer at an oil and gas company is designing a multi-agent AI system to support drilling operations.

Different agents are responsible for subsurface modeling, risk analysis, and resource allocation. These agents must share operational context, reason through interdependent planning steps, and justify their collaborative decisions using structured, transparent logic. The architecture must support memory persistence, sequential decision-making and chain-of-thought prompting across agents. Which implementation best supports this design?

- A. Fine-tune separate NeMo models for each agent role using LoRA, with pre-scripted action flows deployed via TensorRT for latency reduction.
- B. Use stateless LLM endpoints behind an API gateway and pass shared prompts across agents to simulate context and reasoning.
- C. Orchestrate NeMo agents via Triton, use vector memory for shared context, ReAct planning, and NeMo Guardrails for reasoning.
- D. Use LangChain to coordinate third-party agent APIs and store shared information in external memory, with logic encoded in static prompt chains.

Answer: C

Explanation:
This is a lifecycle problem, not a wording problem, and Option A gives the team a controllable lifecycle for the agent behavior. For a production build, Triton dynamic batching and model configuration are where throughput and tail latency tradeoffs become controllable. The selected option specifically A states
"Orchestrate NeMo agents via Triton, use vector memory for shared context, ReAct planning, and NeMo Guardrails for reasoning.", which matches the operational requirement rather than a superficial wording match. The answer combines orchestration, vector memory, ReAct-style planning, and guardrails. That stack supports shared context, tool use, and controlled reasoning across specialized agents. The runtime should therefore be built around dynamic batching, model instance tuning, concurrency control, precision optimization, KV-cache-aware LLM serving, and end-to-end latency waterfalls. The distractors fail because sequential microservices can add avoidable hops and tail latency even when every individual model looks fast. The answer is therefore about engineered control planes, not simply model capability. For LLM systems, the bottleneck often shifts between compute kernels, KV cache memory, request queues, and guardrail/tool latency.

NEW QUESTION # 93
Which two optimization strategies are MOST effective for improving agent performance on NVIDIA GPU infrastructure? (Choose two.)

- A. Manually tuning kernel launch parameters to optimize individual operations while overlooking overall pipeline performance dynamics.
- B. Applying TensorRT-LLM optimizations to reduce inference latency by improving kernel efficiency and memory usage.
- C. Expanding GPU memory capacity to support larger models, assuming this alone guarantees meaningful performance improvements.
- D. Using multi-GPU coordination to distribute workloads, enabling higher throughput and efficiency for scaling agent tasks.

Answer: B,D

Explanation:
The best answer is the combination of Options A and B when the design is judged by reliability, latency budget, auditability, and maintainability rather than demo simplicity. Multi-GPU coordination increases throughput; TensorRT-LLM improves kernel efficiency and memory behavior. More memory alone does not guarantee speed. Operationally, the design depends on profiling the request path from ingress through guardrails, routing, Triton scheduling, TensorRT-LLM execution, and response assembly. Together, A states
"Using multi-GPU coordination to distribute workloads, enabling higher throughput and efficiency for scaling agent tasks."; B states "Applying TensorRT-LLM optimizations to reduce inference latency by improving kernel efficiency and memory usage.", so the answer covers both sides of the requirement instead of solving only the model or only the infrastructure layer. The alternatives would look simpler in a prototype, but overlarge batches may improve throughput while violating interactive latency targets. The stack-level anchor is clear: NVIDIA Perf Analyzer, GenAI-Perf, Nsight, and Triton metrics help isolate whether the bottleneck is batching, compute, memory, or request scheduling. It also creates clean evidence for audits, incident review, and root-cause analysis when behavior drifts.

NEW QUESTION # 94
In your RAG deployment, you've identified a performance bottleneck in the retrieval phase - specifically, the time it takes to access the vector database.

Which of the following optimization strategies is most aligned with micro-service best practices, considering your RAG architecture?

- A. Introduce a dedicated service responsible solely for querying the vector database and returning relevant chunks.
- B. Increase the size of the LLM model itself, because it will automatically accelerate the overall response time.
- C. Implement a "cache-and-check" mechanism where the retrieval microservice immediately returns the first matching chunk, regardless of relevance.
- D. Optimize the LLM prompt to be shorter and more concise, significantly reducing the computational load.

Answer: A

Explanation:
Operationally, the design depends on query transformation and fusion before generation so the model receives evidence-rich context rather than one brittle keyword match. At production scale, Option C preserves separability between reasoning, state, tools, and runtime operations. A dedicated retrieval service isolates the vector database bottleneck so it can be cached, scaled, profiled, and deployed separately from generation. For a production build, RAG quality depends on data handling as much as generation; vector retrieval and reranking must be validated with their own metrics. The selected option specifically C states "Introduce a dedicated service responsible solely for querying the vector database and returning relevant chunks.", which matches the operational requirement rather than a superficial wording match. The rejected options are weaker because stuffing raw chunks into prompts or relying on model priors makes answers stale, irreproducible, and difficult to debug. It also creates clean evidence for audits, incident review, and root-cause analysis when behavior drifts. The retrieval layer should be independently measured for recall, relevance, freshness, and latency before blaming the generator.

NEW QUESTION # 95
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