MSIS 549 HW2: Benchmark Appendix

1. Evaluation Methodology

Methods Used: Human Rubric Scoring (Method 1) + Baseline Comparison (Method 3)

Baseline: Single-prompt request to GPT-4: *"Write 6 LinkedIn posts about SQL Query Performance for Data Engineers and Business Stakeholders."*

Agentic System: Full 9-skill pipeline (Intent Discovery → Content Strategist → Draft Architect → Voice Refiner → Engagement Optimizer → Quality Review).

Scoring: All posts scored by the author (human rubric) on a 1-5 scale. Prompts and settings were frozen across all test cases.

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2. Scoring Rubric (Frozen)

Score	Anchor Description
5	Excellent — High-impact, strategically deep, sounds like a real senior leader. Specific, actionable, and well-formatted for LinkedIn.
4	Good — Professional and insightful, minor gaps in specificity or voice consistency.
3	Satisfactory — Clear and competent, but reads as generic thought leadership. Lacks personal anecdotes or unique strategic depth.
2	Below Average — Surface-level, uses AI cliches, could be about any topic. Weak hook or CTA.
1	Poor — Obviously AI-generated, no strategic depth, disconnected from audience needs.

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3. Metrics (5 Dimensions)

#	Metric	What It Measures
1	**Actionability**	Does the post give the reader something concrete to do?
2	**Voice Consistency**	Does this sound like the same leader across all 6 posts?
3	**Strategic Depth**	Does it demonstrate genuine expertise and insider knowledge?
4	**Narrative Cohesion**	Does it build on previous weeks and tease the next?
5	**LinkedIn Optimization**	Strong hook, clean formatting, hashtags, visual suggestion?

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4. Test Case 1: SQL Query Performance (Primary)

Input (Strategic Intent):

- **Topic**: Optimizing SQL Query Performance
- **Audience**: Data Engineers & Business Stakeholders
- **Core Message**: Continuous improvement in SQL is essential for AI-readiness
- **Anecdote**: Business team frustrated when data wasn't in sync with AI models; "near real-time" became a requirement

- **CTA**: Rethink your data platform strategy; follow for ongoing insights
- **Tone**: Provocative + Educational

4a. Baseline Output (Single-Prompt GPT-4)

Prompt: "Write 6 LinkedIn posts about SQL Query Performance for Data Engineers and Business Stakeholders."

Baseline Post 1 (excerpt):

> *"In today's data-driven world, SQL query performance is more important than ever. Here are 5 tips to optimize your queries: 1) Use indexes wisely 2) Avoid SELECT * 3) Optimize JOINs 4) Use query execution plans 5) Consider partitioning. What are your favorite SQL optimization tips? Drop them in the comments! #SQL #DataEngineering"*

Baseline Post 3 (excerpt):

> *"Let's dive into a common challenge: slow queries in production. Many teams struggle with this issue. Here are some best practices to address it: First, analyze your execution plan. Second, check for missing indexes. Third, consider caching strategies. What other approaches have worked for your team? #Database #Performance"*

Baseline Assessment: All 6 posts follow the same "here are X tips" pattern. No narrative arc, no personal anecdotes, no strategic depth. Generic hooks ("In today's..."), generic CTAs ("Drop in the comments"). Posts could be reordered without any loss of meaning.

4b. Agentic Output (This System)

Agentic Post 1 — "The Good Enough Trap" (excerpt):

> *"Is your data platform actually 'good enough,' or is it just holding you back? Traditional SQL performance is no longer a technical detail — it's a strategic bottleneck. Many teams settle for 'good enough' query speeds, but as business demands shift toward real-time insights, that complacency becomes a liability... Performance is the foundation of agility."*

Agentic Post 3 — "Near Real-Time is the New Baseline" (excerpt):

> *"The day 'near real-time' became a requirement, not a request. I remember a time when business teams were happy with daily reports. Those days are gone. Recently, I saw a business team's frustration when their data wasn't in sync with the AI models they were using for decision-making... Stakeholder expectations are driven by the fastest tool in their kit."*

4c. Scoring — Test Case 1

Baseline (Single-Prompt GPT-4):

Post	Actionability	Voice	Depth	Cohesion	LinkedIn	Avg
Post 1	3	2	2	1	3	2.2
Post 2	3	2	2	1	3	2.2
Post 3	2	3	2	1	2	2.0
Post 4	3	2	2	1	3	2.2
Post 5	2	2	2	1	2	1.8
Post 6	2	2	1	1	2	1.6
Avg	**2.5**	**2.2**	**1.8**	**1.0**	**2.5**	**2.0**

Agentic System (This System):

Post	Actionability	Voice	Depth	Cohesion	LinkedIn	Avg
Week 1: Good Enough Trap	4	5	4	5	5	4.6
Week 2: Instant Satisfaction Gap	4	5	4	5	4	4.4
Week 3: Near Real-Time	5	5	5	5	4	4.8
Week 4: Technical Levers	5	4	5	4	5	4.6
Week 5: AI-Ready Infrastructure	3	4	4	5	4	4.0
Week 6: Strategic Pivot	4	5	4	5	4	4.4
Avg	**4.2**	**4.7**	**4.3**	**4.8**	**4.3**	**4.5**

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5. Test Case 2: Enhancing Data Cleanliness

Input (Strategic Intent):

- **Topic**: Enhancing Data Cleanliness
- **Audience**: Data Analysts & Product Managers
- **Core Message**: Data quality is the foundation of trustworthy AI — clean data isn't optional, it's strategic
- **Anecdote**: A product launch delayed by 2 weeks because the ML model was trained on dirty customer data
- **CTA**: Audit your top data sources for quality this quarter
- **Tone**: Educational + Empathetic

5a. Agentic Output Summary (Test Case 2)

The system generated a 6-week roadmap:

Week	Title
1	"The Dirty Data Tax" — cost of poor data quality
2	"The 80/20 Rule of Data Cleaning" — focus on highest-impact sources
3	"The Launch That Almost Wasn't" — personal anecdote
4	"5 Data Quality Checks Every Pipeline Needs" — tactical advice
5	"AI Can't Fix What You Won't Measure" — data quality for ML
6	"Building a Data Quality Culture" — organizational change CTA

5b. Scoring — Test Case 2

Post	Actionability	Voice	Depth	Cohesion	LinkedIn	Avg
Week 1	4	4	4	5	4	4.2
Week 2	5	4	4	4	4	4.2
Week 3	4	5	5	5	4	4.6
Week 4	5	4	4	4	5	4.4

Week 5	3	4	4	4	3	3.6
Week 6	4	4	3	5	4	4.0
Avg	**4.2**	**4.2**	**4.0**	**4.5**	**4.0**	**4.2**

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6. Edge Case: Highly Technical Topic

Input: "Implementing Write-Ahead Logging in Distributed Database Consensus Protocols"

- **Audience**: Database kernel engineers
- **Tone**: Data-driven

Result: The system handled this well through Skills 1-2 (the interview forced clarification of the audience and simplified the scope). However, Skill 4 (Voice Refiner) struggled — it over-simplified technical terminology that the audience would expect (e.g., replacing "WAL" with "write-ahead logging" every time, which felt condescending to kernel engineers).

6a. Edge Case Output Excerpts

Week 1 — Hook Post (excerpt — shows correct provocation for technical audience):

> *Most distributed databases claim durability. Few teams actually understand how their write-ahead log guarantees it.*
>
> *WAL isn't just a recovery mechanism — it's the contract between your database and your users that committed data will survive a crash. But the gap between "we have WAL" and "we understand our WAL implementation's failure modes" is where production incidents live.*

Week 5 — Vision Post (excerpt — shows the voice consistency failure, scored 2.0):

> *The future of distributed consensus is moving toward more intelligent write-ahead logging strategies. As organizations scale their data infrastructure, leadership teams will need to make strategic decisions about how their consensus protocols align with business objectives and operational efficiency goals.*
>
> *Forward-thinking database teams are already positioning themselves for this shift by investing in next-generation persistence layers.*

Note: Week 5 dropped into generic "leadership strategy" language ("strategic decisions," "operational efficiency goals," "forward-thinking teams") that is inappropriate for kernel engineers. This is the exact failure mode: Skill 4's Manager/Director voice profile replaced precise technical language with executive platitudes.

6b. Edge Case Scoring

Score: 3.4/5.0 average — acceptable but weaker on Voice Consistency (2.5) because the "senior leader" voice template doesn't fit highly specialized technical audiences well.

Lesson: The skill set is optimized for Manager/Director-level audiences. For deeply technical niche audiences, Skill 4 needs a "technical expert" mode that preserves jargon rather than simplifying it.

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7. Ambiguous Case: Vague Business Goal

Input: "I want to write about making things better with data"

- No specific audience, message, anecdote, or tone provided initially.

Result: Skill 1 (Intent Discovery) handled this well — the 5-question interview forced the user to clarify:

- Audience: "Mid-level managers in retail"
- Core message: "Data-driven decision making reduces operational waste"
- Anecdote: Prompted user to share one; user provided a story about inventory forecasting
- Tone: Educational

7a. Ambiguous Case Output Excerpts

Week 1 — Hook Post (excerpt — shows Skill 1 successfully rescued a vague topic):

> *Every retailer has data. Dashboards, spreadsheets, weekly reports. But here's the uncomfortable question: when was the last time a data point actually changed a decision your team made?*
>
> *Most mid-level managers I talk to have more data than they know what to do with — and less clarity than they had before the dashboards existed. The problem isn't access. It's action.*

Week 4 — Tactics Post (excerpt — shows where shallow input led to shallow advice, scored 3.0 on Strategic Depth):

> *Here are five ways to start making more data-driven decisions in your retail operations:*
>
> 1. *Pick one KPI per department and review it weekly — not monthly.*
> 2. *Ask "what would change our approach?" before opening the dashboard.*
> 3. *Track decisions, not just metrics — log what you decided and why.*
> 4. *Start small: one category, one store, one quarter.*
> 5. *Share results openly — wins and failures.*

Note: The advice is reasonable but generic — it could apply to any industry, not specifically retail. The vague initial input ("making things better with data") meant Skill 2's roadmap lacked the specificity to drive deep, industry-specific tactical advice. Compare this to the SQL Performance series (TC1), where the specific topic produced Week 4 advice about execution plans, index strategies, and partitioning.

7b. Ambiguous Case Scoring

The downstream skills produced a reasonable series, scoring 3.6/5.0 average. The weakest area was Strategic Depth (3.2) — because the initial topic was so broad, the series stayed at a high level rather than diving deep.

Lesson: The interview (Skill 1) is the most critical skill. Vague inputs can be rescued but result in shallower content. A possible improvement would be adding a "topic sharpening" step between Skills 1 and 2.

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8. Aggregate Results

Test Case	Actionability	Voice	Depth	Cohesion	LinkedIn	Overall
TC1: SQL Performance	4.2	4.7	4.3	4.8	4.3	**4.5**
TC2: Data Cleanliness	4.2	4.2	4.0	4.5	4.0	**4.2**
TC3: AI Chatbot to Dev Tool	4.2	4.7	4.3	4.8	4.7	**4.5**
TC4: Agentic AI for Data Eng.	4.2	4.4	4.2	4.7	4.3	**4.35**
Edge: WAL Protocol	3.5	2.5	4.0	3.8	3.2	**3.4**
Ambiguous: Vague Input	3.5	3.8	3.2	4.0	3.5	**3.6**
Baseline: Single-Prompt	2.5	2.2	1.8	1.0	2.5	**2.0**

Key Findings

- **Agentic system outperformed baseline by +2.1 points** on the primary test case (4.5 vs 2.0).
- **Biggest improvement**: Narrative Cohesion (+3.8 over baseline) — the 6-week roadmap ensures posts build on each other, which a single prompt cannot achieve.
- **Strongest metric**: Narrative Cohesion (avg 4.3 across all agentic runs) — the structured arc from Skill 2 is consistently effective.
- **Weakest metric**: Voice Consistency on edge cases (2.5) — the voice refiner needs audience-specific modes.

Worst Failure

Edge Case, Week 5: The post on "consensus protocol implications for AI workloads" scored 2.0 on Voice Consistency. The Skill 4 refiner replaced precise technical terminology with strategic business language, which felt patronizing to the target audience of database kernel engineers. The anecdote about "leadership decisions" felt forced in a deeply technical series.

Root Cause: Skill 4 is hard-coded to a "Manager/Director" voice. It needs a configuration parameter to select between voice profiles (e.g., `executive`, `technical-expert`, `practitioner`).

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9. Reproducibility Notes

- **LLM**: Manus AI (Claude-based) for primary runs; GPT-4 for baseline
- **Prompts**: Frozen as documented in each skill's `.md` file
- **Settings**: Default temperature, no custom parameters
- **Evaluator**: Human scoring by the author (single rater)
- **Limitation**: Single rater introduces subjective bias. An improvement would be inter-rater reliability with 2+ evaluators.