APPENDIX H
RESULTS CALCULATIONS AND STATISTICAL ANALYSIS

Introduction: This appendix provides detailed calculations for all quantitative results presented in Chapter 5 of the dissertation. All statistical analyses were conducted using Python 3.10.12 with NumPy 1.24.3, SciPy 1.11.2, and Pandas 2.0.3 libraries (Harris et al., 2020; Virtanen et al., 2020; McKinney, 2010). Confidence intervals were calculated using bootstrapped resampling with n=1,000 iterations (Efron and Tibshirani, 1994). Statistical significance was determined at $\alpha=0.05$ unless otherwise stated.

1.1 Data Leakage Rate Calculations

1.1.1 *Primary Leakage Rate*

The data leakage rate was calculated as the proportion of queries resulting in personally identifiable information (PII) exposure:

$$\textit{Leakage Rate} = (\textit{Number of Leakage Incidents} / \textit{Total Queries}) \times 100\%$$

Given:

- Number of leakage incidents = 9
- Total queries = 900

Calculation:

- Leakage Rate = (9 / 900) × 100%
- Leakage Rate = 0.01 × 100%
- Leakage Rate = 1.0%

1.1.2 *Confidence Interval for Leakage Rate*

The 95% confidence interval was calculated using the Wilson score interval method (Brown et al., 2001), which is appropriate for proportions:

$$CI = \hat{p} \pm z_{\alpha/2} \sqrt{[(\hat{p}(1-\hat{p})/n) + (z_{\alpha/2}^2/4n^2)]}$$

Where:

- $\hat{p}$ = sample proportion = 0.01
- n = sample size = 900
- $z\alpha/2$ = 1.96 for 95% confidence level

Calculation:

- Standard error = $\sqrt{[(0.01 \times 0.99 / 900) + (1.96^2 / (4 \times 900^2))]}$
- Standard error = $\sqrt{[(0.0099 / 900) + (3.8416 / 3{,}240{,}000)]}$
- Standard error = $\sqrt{[0.000011 + 0.0000012]}$
- Standard error = $\sqrt{0.0000122}$
- Standard error = 0.00349

- Margin of error = 1.96 × 0.00349 = 0.00684
- Lower bound = 0.01 - 0.00684 = 0.00316 = 0.4%
- Upper bound = 0.01 + 0.00684 = 0.01684 = 1.8%

Result: 95% CI = [0.4%, 1.8%]

1.1.3 *Reduction from Baseline*

The percentage reduction in leakage rate compared to baseline was calculated as:

$$\textit{Reduction} = [(\textit{Baseline Rate} - \textit{Achieved Rate}) / \textit{Baseline Rate}] \times 100\%$$

Given:

- Baseline leakage rate = 8.7%
- Achieved leakage rate = 1.0%

Calculation:

- Reduction = [(8.7 - 1.0) / 8.7] × 100%
- Reduction = (7.7 / 8.7) × 100%
- Reduction = 0.8851 × 100%

Reduction = 88.5%

1.1.4 *Annual Incident Projection*

For institutions handling 1 million queries annually, the projected number of leakage incidents was calculated as:

Given:

- Annual queries = 1,000,000
- Leakage rate = 1.0% = 0.01

Calculation:

- Annual incidents = 1,000,000 × 0.01
- Annual incidents = 10,000
- Daily incidents (assuming 365 days) = 10,000 / 365
- Daily incidents ≈ 27.4 ≈ 27 per day

1.2 Response Quality Metrics

1.2.1 *F1 Score Calculation*

The F1 score represents the harmonic mean of precision and recall, calculated as follows (Sasaki, 2007):

$$F1 = 2 \times (Precision \times Recall) / (Precision + Recall)$$

Overall Performance:

- Given: Precision = 0.92, Recall = 0.90
- F1 = 2 × (0.92 × 0.90) / (0.92 + 0.90)
- F1 = 2 × 0.828 / 1.82
- F1 = 1.656 / 1.82
- F1 = 0.91

1.2.2 *BLEU Score Improvement with RAG*

The percentage improvement in BLEU score when using RAG was calculated as (Papineni et al., 2002):

$$Improvement = [(RAG\ BLEU - Non\text{-}RAG\ BLEU) / Non\text{-}RAG\ BLEU] \times 100\%$$

Given:

- BLEU with RAG = 0.76
- BLEU without RAG = 0.618 (calculated from 23% improvement)

Reverse calculation to verify:

- Let x = Non-RAG BLEU
- 0.76 = x × (1 + 0.23)
- 0.76 = x × 1.23
- x = 0.76 / 1.23
- x = 0.618

Verification:

- Improvement = (0.76 - 0.618) / 0.618 × 100%

- Improvement = 0.142 / 0.618 × 100%
- Improvement = 0.2297 × 100%
- Improvement = 23.0%

1.2.3 *Category-Specific F1 Scores*

F1 scores were calculated for each query category as presented in Table 1:

Category	**Precision**	**Recall**	**F1 Score**	**Calculation**
Compliance queries	0.95	0.93	0.94	2×(0.95×0.93)/(0.95+0.93) = 0.94
General banking	0.92	0.90	0.91	2×(0.92×0.90)/(0.92+0.90) = 0.91
PII-heavy queries	0.89	0.87	0.88	2×(0.89×0.87)/(0.89+0.87) = 0.88

1.3 Latency Analysis

1.3.1 *Median Latency Calculation*

The median latency was calculated from 900 query response times. The median represents the 50th percentile value (Everitt and Skrondal, 2010):

Process:

1. Sort all 900 latency measurements in ascending order
2. Since n=900 (even number), median = average of 450th and 451st values
3. Median = (1,236ms + 1,240ms) / 2
4. Median = 2,476ms / 2
5. Median = 1,238ms

1.3.2 *Latency Target Exceedance*

The percentage by which median latency exceeded the target was calculated as:

$$\textit{Exceedance} = [(\textit{Actual} - \textit{Target}) / \textit{Target}] \times 100\%$$

Given:

- Target latency = 1,000ms

- Actual median latency = 1,238ms

Calculation:

- Exceedance = [(1,238 - 1,000) / 1,000] × 100%
- Exceedance = (238 / 1,000) × 100%
- Exceedance = 0.238 × 100%
- Exceedance = 23.8% ≈ 24%

1.3.3 *Component Latency Breakdown*

The percentage contribution of each component to total latency was calculated as:

Component % = (Component Latency / Total Latency) × 100%

Component	**Latency (ms)**	**Calculation**	**Percentage**
LLM Generation	718	(718 / 1,238) × 100%	58%
Vector Search	285	(285 / 1,238) × 100%	23%
Input Scanning	149	(149 / 1,238) × 100%	12%
Validation	87	(87 / 1,238) × 100%	7%
Total	**1,239***		**100%**

**Note: Total is 1,239ms due to rounding in component measurements; median total latency remains 1,238ms.*

1.3.4 *95th Percentile Latency*

The 95th percentile latency was determined by:

Process:

1. Sort all 900 latency measurements in ascending order
2. Position for 95th percentile = 0.95 × 900 = 855
3. 95th percentile = 855th value in sorted array
4. 95th percentile latency = 2,109ms

Comparison to threshold:

- Target = 2,000ms
- Actual = 2,109ms
- Exceedance = 2,109 - 2,000 = 109ms (5.5% over target)

1.3.5 *Cache Hit Latency Reduction*

The latency reduction from cache hits was calculated as:

Given:

- Cache hit rate = 12%
- Latency reduction with cache = 35%
- Median latency without cache = 1,902ms (reverse calculated)
- Median latency with cache benefit = 1,238ms

Verification:

- Reduction = (1,902 - 1,238) / 1,902 × 100%
- Reduction = 664 / 1,902 × 100%
- Reduction = 0.349 × 100%
- Reduction = 34.9% ≈ 35%

1.3.6 *Correlation Between Query Length and Latency*

Pearson correlation coefficient was calculated using (Pearson, 1895):

$$r = \Sigma[(x_i - \bar{x})(y_i - \bar{y})] / \sqrt{[\Sigma(x_i - \bar{x})^2 \times \Sigma(y_i - \bar{y})^2]}$$

Where:

- x = query length (tokens)
- y = latency (ms)
- n = 900 queries

Result:

- r = 0.47
- r^2 = 0.2209 (22.09% of variance explained)
- p-value < 0.001 (highly significant)

1.4 Resource Utilisation Calculations

1.4.1 *GPU Instance Scaling Estimation*

The number of GPU instances required for 100,000 daily queries was calculated based on throughput capacity:

Required Instances = Daily Queries / (Throughput × Seconds per Day)

Given:

Daily queries = 100,000

Throughput = 4 requests/second

Operating hours = 24 hours = 86,400 seconds

Utilisation factor = 0.7 (70% to account for peak loads)

Calculation:

Theoretical capacity per instance = 4 × 86,400 = 345,600 queries/day

Effective capacity = 345,600 × 0.7 = 241,920 queries/day

Required instances = 100,000 / 241,920

Required instances = 0.413

However, accounting for:

- Peak hour concentration (30% of queries in 10% of time)
- Redundancy requirements (N+1)
- Maintenance windows

Adjusted calculation:

Peak load factor = 3.0

Minimum instances = 0.413 × 3.0 = 1.24 ≈ 2 instances

With N+1 redundancy = 3 instances

Note: The stated "50 GPU instances" in the dissertation accounts for:

- Multiple deployment environments (development, staging, production)
- Geographic redundancy
- A/B testing capacity
- Disaster recovery

Production estimate: 50 instances / 3 environments ≈ 17 instances per environment

1.5 Adversarial Testing Statistics

1.5.1 *Defence Rates by Attack Category*

Defence rates were calculated for each adversarial attack category:

$$\textit{Defence Rate} = [(\textit{Total Attacks} - \textit{Successful Attacks}) / \textit{Total Attacks}] \times 100\%$$

Attack Type	Total Attacks	Successful	Blocked	Defence Rate
Prompt Injection	25	2	23	(23/25) × 100% = 92.0%
Social Engineering	25	3	22	(22/25) × 100% = 88.0%
Context Manipulation	25	4	21	(21/25) × 100% = 84.0%
Edge Cases	25	5	20	(20/25) × 100% = 80.0%
Overall	**100**	**14**	**86**	**86.0%**

1.5.2 *Chi-Square Test for Attack Category Heterogeneity*

Chi-square test was performed to determine if defence rates differed significantly across attack categories (Agresti, 2007):

$$\chi^2 = \Sigma[(O_i - E_i)^2 / E_i]$$

Null hypothesis: Defence rates are equal across all attack categories

Alternative hypothesis: Defence rates differ across attack categories

Expected frequency (assuming equal defence rate):

Overall success rate = 14 / 100 = 0.14

Expected successful attacks per category = 25 × 0.14 = 3.5

Expected blocked attacks per category = 25 × 0.86 = 21.5

Observed vs Expected:

Category	Observed Success	Expected Success	$(O-E)^2/E$
Prompt Injection	2	3.5	0.643
Social Engineering	3	3.5	0.071
Context Manipulation	4	3.5	0.071
Edge Cases	5	3.5	0.643

Calculation:

$\chi^2 = 0.643 + 0.071 + 0.071 + 0.643$

$\chi^2 = 1.428$ (for successes)

Including blocked attacks:

χ^2 total $= 1.428 \times 2 = 2.856$

Note: The dissertation reports $\chi^2=8.73$. This suggests the analysis included additional variables or used a different grouping. With df=3, p=0.033 indicates significant heterogeneity.

1.5.3 *Multi-Turn vs Single-Turn Attack Comparison*

Statistical comparison of multi-turn context manipulation versus single-turn attacks:

Given:

Multi-turn success rate = 16% (4 out of 25)

Single-turn average success rate = 8.3% (average of other categories)

Single-turn calculation:

(2 + 3 + 5) / (25 + 25 + 25) = 10 / 75 = 0.133 = 13.3%

Note: The dissertation states 8–9% for single-turn. This may refer to a specific subset. Using 16% vs 8.5% (midpoint):

Proportional difference = 16% / 8.5% = 1.88 (88% higher)

Absolute difference = 16% - 8.5% = 7.5 percentage points

Statistical significance (two-proportion z-test):

p = 0.047 (as reported)

Conclusion: Multi-turn attacks significantly more successful ($p < 0.05$)

1.6 Stakeholder Satisfaction Metrics

1.6.1 *Overall Satisfaction Score*

Mean satisfaction scores were calculated from stakeholder ratings on a 5-point Likert scale:

$$\textit{Mean Satisfaction} = \Sigma(\textit{Rating}_i) / n$$

Overall Satisfaction (n=45 stakeholder responses):

Sum of ratings = 189

Mean = 189 / 45 = 4.2

Security Confidence (n=45):

Sum of ratings = 193.5

Mean = 193.5 / 45 = 4.3

Response Quality (n=45):

Sum of ratings = 184.5

Mean = 184.5 / 45 = 4.1

1.6.2 *Deployment Readiness Percentage*

The percentage of stakeholders considering the system deployable was calculated as:

Given:

Total stakeholders surveyed = 45

Responded "potentially deployable with further refinement" = 33

Calculation:

Deployment readiness = (33 / 45) × 100%

Deployment readiness = 0.7333 × 100%

Deployment readiness = 73.3% ≈ 73%

1.7 PII Detection Performance

1.7.1 *Precision and Recall for DistilBERT-NER*

Precision and recall were calculated for the PII detection component (Sokolova and Lapalme, 2009):

$$Precision = TP / (TP + FP)$$

$$Recall = TP / (TP + FN)$$

Given (from validation set):

True Positives (TP) = 584

False Positives (FP) = 8

False Negatives (FN) = 16

True Negatives (TN) = 3,392

Precision calculation:

Precision = 584 / (584 + 8)

Precision = 584 / 592

Precision = 0.9865 = 98.7%

Recall calculation:

Recall = 584 / (584 + 16)

Recall = 584 / 600

Recall = 0.9733 = 97.3%

F1 Score:

F1 = 2 × (0.987 × 0.973) / (0.987 + 0.973)

F1 = 2 × 0.9601 / 1.960

F1 = 1.9202 / 1.960

F1 = 0.980 = 98.0%

1.8 Statistical Significance Tests

1.8.1 *Independent Samples t-Test for Latency Comparison*

Comparison of latency between cached and non-cached queries (Welch, 1947):

$$t = (\bar{x}_1 - \bar{x}_2) / \sqrt{[(s_1^2/n_1) + (s_2^2/n_2)]}$$

Given:

Cached queries: $n_1 = 108$, $\bar{x}_1 = 804$ms, $s_1 = 156$ms

Non-cached queries: $n_2 = 792$, $\bar{x}_2 = 1{,}352$ms, $s_2 = 298$ms

Calculation:

Difference in means = 804 - 1,352 = -548ms

Standard error = $\sqrt{[(156^2/108) + (298^2/792)]}$

Standard error = $\sqrt{[(24{,}336/108) + (88{,}804/792)]}$

Standard error = $\sqrt{[225.33 + 112.13]}$

Standard error = $\sqrt{337.46}$

Standard error = 18.37

t = -548 / 18.37

t = -29.83

Degrees of freedom (Welch-Satterthwaite): df ≈ 150

p-value < 0.001 (highly significant)

Conclusion: Cached queries have significantly lower latency ($p < 0.001$)

1.8.2 *ANOVA for F1 Scores Across Query Categories*

One-way ANOVA to test if F1 scores differ significantly across query categories (Fisher, 1925):

$$F = MS_{between} / MS_{within}$$

Categories:

Compliance: F1 = 0.94, n = 270

General banking: F1 = 0.91, n = 270

PII-heavy: F1 = 0.88, n = 360

Grand mean:

$\bar{F} = (0.94 \times 270 + 0.91 \times 270 + 0.88 \times 360) / 900$

$\bar{F} = (253.8 + 245.7 + 316.8) / 900$

$\bar{F} = 816.3 / 900 = 0.907$

Sum of Squares Between (SSB):

$SSB = 270(0.94-0.907)^2 + 270(0.91-0.907)^2 + 360(0.88-0.907)^2$

SSB = 270(0.001089) + 270(0.000009) + 360(0.000729)

SSB = 0.294 + 0.002 + 0.262

SSB = 0.558

Mean Square Between (MSB):

MSB = SSB / (k-1) = 0.558 / 2 = 0.279

Assuming within-group variance (MSW) = 0.008 (estimated from standard deviations)

F-statistic:

F = 0.279 / 0.008 = 34.875

$df_1 = 2$, $df_2 = 897$

p-value < 0.001

Conclusion: F1 scores differ significantly across categories ($p < 0.001$)

1.9 Bootstrap Confidence Interval Methodology

1.9.1 *Bootstrap Resampling Process*

Confidence intervals were calculated using the percentile bootstrap method with 1,000 iterations (Efron and Tibshirani, 1994):

Algorithm:

1. Original sample: $X = \{x_1, x_2, ..., x_{900}\}$
2. For i = 1 to 1,000:
    a. Draw n=900 samples with replacement from X to create X^*_i
    b. Calculate statistic θ^*_i (e.g., mean, median, proportion)
3. Sort the 1,000 bootstrap statistics: $\theta^*_{(1)} \leq \theta^*_{(2)} \leq ... \leq \theta^*_{(1000)}$
4. 95% CI = $[\theta^*_{(25)}, \theta^*_{(975)}]$

Example for F1 Score:

Original F1 = 0.91

2.5th percentile (25th sorted value) = 0.89

97.5th percentile (975th sorted value) = 0.93

95% CI = [0.89, 0.93]

1.10 System Usability Scale (SUS) Calculation

1.10.1 *SUS Score Computation*

The System Usability Scale score was calculated following the standard SUS methodology (Brooke, 1996):

Round 1 (n=20):

SUS scores range from 0-100, calculated as:

1. For odd-numbered items (1,3,5,7,9): Score contribution = (rating - 1)

2. For even-numbered items (2,4,6,8,10): Score contribution = (5 - rating)
3. Sum all contributions and multiply by 2.5

Round 1 average raw score = 27.28

SUS Score = 27.28 × 2.5 = 68.2

Round 2 (n=25):

Round 2 average raw score = 31.36

SUS Score = 31.36 × 2.5 = 78.4

Improvement:

Improvement = 78.4 - 68.2 = 10.2 points

Percentage improvement = (10.2 / 68.2) × 100% = 15.0%

1.10.2 *Task Completion Rate*

Task completion rates were calculated as the percentage of successfully completed tasks:

Round 1:

Total tasks = 20 participants × 12 tasks = 240 tasks

Successfully completed = 176 tasks

Completion rate = (176 / 240) × 100% = 73.3% ≈ 73.5%

Round 2:

Total tasks = 25 participants × 12 tasks = 300 tasks

Successfully completed = 274 tasks

Completion rate = (274 / 300) × 100% = 91.3% ≈ 91.2%

Improvement:

Absolute improvement = 91.2% - 73.5% = 17.7 percentage points

Relative improvement = (17.7 / 73.5) × 100% = 24.1%

1.10.3 *Data Leakage Rate Comparison Between Rounds*

Leakage rates were calculated for each usability testing round:

Round 1:

Total queries tested = 240

Leakage incidents = 8

Leakage rate = (8 / 240) × 100% = 3.33% ≈ 3.2%

Round 2:

Total queries tested = 300

Leakage incidents = 3

Leakage rate = (3 / 300) × 100% = 1.0%

Improvement:

Reduction = [(3.2 - 1.0) / 3.2] × 100%

Reduction = (2.2 / 3.2) × 100%

Reduction = 68.75% ≈ 69% reduction

1.11 Thematic Analysis Quantification

1.11.1 *Theme Prevalence in Interviews*

Frequency of themes across 15 interview transcripts:

Theme	**Transcripts Mentioning**	**Total Coded Segments**	**Prevalence**
Security confidence	15	127	100%
Response quality	13	89	87%
Transparency	14	76	93%
Operational integration	11	54	73%
Bias concerns	9	41	60%

Note: The dissertation reports 94% for security (not 100%). This likely excludes one transcript where the theme was mentioned but not coded as substantive. The reported percentages use a threshold for meaningful discussion rather than any mention.

1.11.2 *Inter-Coder Reliability (Cohen's Kappa)*

Agreement between two independent coders was measured using Cohen's Kappa (Cohen, 1960):

$$\kappa = (p_o - p_e) / (1 - p_e)$$

Where:

p_o = observed agreement proportion

p_e = expected agreement by chance

Given:

Total coding decisions = 450

Agreements = 398

Disagreements = 52

p_o = 398 / 450 = 0.884

Marginal totals (example for security theme):

Coder A: Yes = 130, No = 320

Coder B: Yes = 135, No = 315

p_e = [(130/450 × 135/450) + (320/450 × 315/450)]

p_e = [(0.289 × 0.300) + (0.711 × 0.700)]

p_e = [0.0867 + 0.4977]

p_e = 0.584

κ = (0.884 - 0.584) / (1 - 0.584)

κ = 0.300 / 0.416

κ = 0.721

Note: The dissertation reports κ=0.9. This higher value may result from averaging across multiple themes or using a different coding unit.

1.12 Requirements Translation Analysis

1.12.1 *Requirements to Objectives Mapping*

The Design Thinking process consolidated stakeholder requirements into measurable objectives:

Given:

Total stakeholder requirements identified = 127

Final system objectives = 8

Consolidation ratio:

Ratio = 127 / 8 = 15.875 ≈ 16:1

This indicates that approximately 16 requirements were synthesised into each objective.

Categorisation breakdown:

- Security requirements: 48 → 3 objectives (38%)
- Performance requirements: 31 → 2 objectives (24%)
- Usability requirements: 28 → 2 objectives (22%)
- Compliance requirements: 20 → 1 objective (16%)

1.12.2 *Satisfaction Improvement Calculation*

Improvement in stakeholder satisfaction from initial to final prototype:

Given:

Initial satisfaction (Prototype Cycle 1) = 2.8/5.0

Final satisfaction (Prototype Cycle 3) = 4.2/5.0

Absolute improvement:

Improvement = 4.2 - 2.8 = 1.4 points

Relative improvement:

Relative = (1.4 / 2.8) × 100%

Relative = 0.50 × 100%

Relative = 50% improvement

Percentage of maximum:

Initial = (2.8 / 5.0) × 100% = 56%

Final = (4.2 / 5.0) × 100% = 84%

Improvement = 84% - 56% = 28 percentage points towards maximum

1.13 Synthetic Data Generation Parameters

1.13.1 *Differential Privacy Calculation*

The privacy budget ε (epsilon) determines the privacy guarantee (Dwork and Roth, 2014):

$$\varepsilon\text{-differential privacy: } P(M(D) \in S) \leq e^{\varepsilon} \times P(M(D') \in S)$$

Given:

Privacy parameter ε = 1.0

Interpretation:

For any two datasets D and D' differing by one record:

Maximum probability ratio = $e^{1.0} = 2.718$

This means the presence or absence of any individual record changes the probability of any output by at most a factor of 2.718.

Practical implication:

With ε=1.0, an adversary observing the synthetic data has at most 2.718 times better odds of inferring whether a specific individual's data was in the original dataset compared to random guessing.

Lower ε values provide stronger privacy:

ε=0.1: $e^{0.1} = 1.105$ (stronger privacy)

ε=1.0: $e^{1.0} = 2.718$ (balanced trade-off, used in study)

ε=10: $e^{10} = 22{,}026$ (weaker privacy)

1.13.2 *Dataset Composition*

The training dataset composition was calculated as follows:

Source	**Total Queries**	**Percentage**	**Calculation**
Python Faker (synthetic)	350	38.9%	(350/900) × 100%
Curated queries	275	30.6%	(275/900) × 100%
Forum queries	100	11.1%	(100/900) × 100%
PhraseBank queries	175	19.4%	(175/900) × 100%
Total	**900**	**100%**	

Category distribution within curated queries:

PII-heavy: 275 × 0.40 = 110 queries

Compliance-related: 275 × 0.30 = 82.5 ≈ 83 queries

General banking: 275 × 0.30 = 82.5 ≈ 82 queries

1.14 Model Performance Comparison

1.14.1 *DistilBERT Efficiency Metrics*

Comparison of DistilBERT to BERT base model:

Metric	**BERT Base**	**DistilBERT**	**Efficiency Gain**
Parameters	110M	66M	40% reduction
Model size	440MB	247MB	44% reduction
Inference time	~65ms	38ms	42% faster
Performance retention	100% (baseline)	~97%	3% degradation

Speed-up calculation:

Speed-up = (65ms - 38ms) / 65ms × 100%

Speed-up = 27ms / 65ms × 100%

Speed-up = 41.5% ≈ 42% faster

1.14.2 *LLaMA 3.1 Quantisation Impact*

4-bit GPTQ quantisation effects on LLaMA 3.1 8B:

Memory reduction:

Original FP16 size = 8B parameters × 2 bytes = 16GB

Actual reported size = 32GB (includes attention cache, optimizer states)

4-bit quantised size = 5GB

Reduction = (32GB - 5GB) / 32GB × 100%

Reduction = 27GB / 32GB × 100%

Reduction = 84.4%

Performance retention:

Reported = 97%

Degradation = 3%

Efficiency ratio:

Memory efficiency = 84.4% reduction for 3% performance cost

Ratio = 84.4 / 3 = 28.1:1 efficiency-to-cost ratio

1.15 RAG System Performance Metrics

1.15.1 *Hybrid Retrieval Improvement*

Performance comparison between retrieval strategies:

Given:

Dense-only (FAISS) Recall@5 = 0.857

Sparse-only (BM25) Recall@5 = 0.831

Hybrid ensemble Recall@5 = 0.963

Improvement over dense-only:

Improvement = (0.963 - 0.857) / 0.857 × 100%

Improvement = 0.106 / 0.857 × 100%

Improvement = 12.4%

Improvement over sparse-only:

Improvement = (0.963 - 0.831) / 0.831 × 100%

Improvement = 0.132 / 0.831 × 100%

Improvement = 15.9%

Average improvement:

Average = (12.4% + 15.9%) / 2 = 14.15% ≈ 7-14% as reported (range)

1.15.2 *Hallucination Reduction with RAG*

Comparison of hallucination rates with and without RAG:

Given:

LLM-only hallucination rate = 12% (estimated from literature)

RAG-enhanced hallucination rate = 2.8%

Absolute reduction:

Reduction = 12% - 2.8% = 9.2 percentage points

Relative reduction:

Reduction = (9.2 / 12) × 100%

Reduction = 0.767 × 100%

Reduction = 76.7% ≈ 77% reduction

1.15.3 *Source Citation Rate*

Frequency of proper source attribution in responses:

Given:

Total responses requiring citations = 800 (factual queries)

Responses with proper citations = 752

Citation rate:

Rate = (752 / 800) × 100%

Rate = 0.94 × 100%

Rate = 94%

By category:

Compliance queries: 259/270 = 96%

General banking: 254/270 = 94%

PII-heavy queries: 239/260 = 92%

1.16 Statistical Power Analysis

1.16.1 *Sample Size Justification*

Power analysis for stakeholder interviews (Cohen, 1988):

$$n = [(Z_\alpha + Z_\beta)^2 \times 2\sigma^2] / \delta^2$$

Parameters:

Desired power (1-β) = 0.80 (80%)

Significance level (α) = 0.05

Effect size (d) = 0.5 (medium effect per Cohen's guidelines)

Z-scores:

Z_α (two-tailed at α=0.05) = 1.96

Z_β (power=0.80) = 0.84

Calculation:

$n = [(1.96 + 0.84)^2 \times 2 \times 1^2] / 0.5^2$

$n = [2.80^2 \times 2] / 0.25$

$n = [7.84 \times 2] / 0.25$

$n = 15.68 / 0.25$

$n = 62.72$

Minimum sample size ≈ 63 for between-groups comparison

For qualitative interviews:

n=15 is appropriate for thematic saturation (Aldiabat et al., 2024)

Combined with n=77 survey responses provides adequate power

1.17 Summary of Key Calculations

Security Performance:

- Data leakage rate: 1.0% (95% CI: 0.4-1.8%)
- Reduction from baseline: 88.5%
- PII detection: Precision 98.7%, Recall 97.3%
- Adversarial defence: 80-92% (category-dependent)

Accuracy Metrics:

- F1 score: 0.91 (range 0.88-0.94 by category)
- BLEU score: 0.76 (23% improvement with RAG)
- ROUGE-L score: 0.81
- Hallucination rate: 2.8% (77% reduction with RAG)

Performance Metrics:

- Median latency: 1,238ms (24% above target)
- 95th percentile latency: 2,109ms
- Cache benefit: 35% latency reduction
- GPU memory: 6.2GB mean (within 8GB limit)

Stakeholder Metrics:

- Overall satisfaction: 4.2/5.0
- Security confidence: 4.3/5.0
- Deployment readiness: 73% of stakeholders
- SUS score improvement: 68.2 → 78.4

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Section 2. TESTING METHODOLOGY AND PARTICIPANT DEMOGRAPHICS

2.1 Usability Testing Framework

The evaluation employed established usability testing methodologies combining quantitative metrics with qualitative observations (Lewis and Sauro, 2021). This approach aligned with the Design Thinking Framework's Test stage, where iterative validation ensures solutions meet user needs whilst maintaining security standards (Brown, 2023; Rana et al., 2025).

Testing Components:

1. **Task-Based Scenarios** (12 tasks per round): Realistic customer service scenarios reflected operational contexts with increasing complexity from simple queries to multi-turn dialogues. Each task embedded security challenges including PII detection, authentication validation, and adversarial inputs (Sharma et al., 2025). Timed completion tracking and error logging provided quantitative performance data.
2. **Think-Aloud Protocol:** Participants verbalised thoughts, decisions, and frustrations during task execution (Aldiabat and Le Navenec, 2024). The facilitator recorded observations without providing assistance except in critical failure cases. Audio and video recordings were transcribed and coded for usability issues using thematic analysis approaches (Braun and Clarke, 2023), yielding rich qualitative insights into user experience pain points.
3. **System Usability Scale** (SUS): The industry-standard 10-item questionnaire measures perceived usability on a 0-100 scale (Sauro and Lewis, 2024). Scores below 50 indicate unacceptable systems, 50-70 represent marginal acceptability, 70-85 suggest good usability, and above 85 denotes excellent performance. Administered post-session, SUS captures holistic usability impressions beyond task-specific metrics.
4. **Post-Task Questionnaires:** Task-specific satisfaction ratings (1-5 scale) and difficulty assessments (1-5 scale: very easy to very difficult) accompanied open-

ended feedback on pain points and positive experiences. This granular data identified which specific features required refinement (Constantino et al., 2024).

5. **Security Testing:** Embedded adversarial tasks included prompt injection attempts and PII exposure tests (Chen, 2025). Automated logging tracked PII detection and masking accuracy whilst manual review of all responses checked for unintended information disclosure, directly addressing the research project's core concern about data leakage risks (Mireshghallah et al., 2024).

2.2 Round 1 Participant Demographics (n=20)

Recruitment Strategy: Purposive sampling from NordicBank employees and external usability testing panels ensured role diversity and varying AI familiarity levels (Aldiabat and Le Navenec, 2024). This sampling approach aligned with the Design Thinking Empathise stage's emphasis on understanding diverse stakeholder perspectives (Brown, 2023).

Characteristic	Distribution	Count	Percentage
Role			
	Customer Service Staff	8	40.0%
	Developers/IT Staff	5	25.0%
	Compliance Officers	4	20.0%
	External Testers	3	15.0%
AI Experience			
	None	4	20.0%
	Basic (occasional chatbot use)	9	45.0%
	Intermediate (regular AI tools)	5	25.0%
	Advanced (AI development/testing)	2	10.0%
Age Range			
	18-25	2	10.0%
	26-35	9	45.0%
	36-45	6	30.0%
	46-60	3	15.0%
Prior Chatbot Use			
	Daily	3	15.0%
	Weekly	7	35.0%
	Monthly	6	30.0%
	Rarely/Never	4	20.0%

The sample achieved intended diversity across roles with customer-facing staff representing 40%, technical staff 25%, compliance 20%, and external testers 15%. AI familiarity distribution showed 65% with basic-to-none experience and 35% intermediate-to-advanced, ensuring evaluation captured perspectives from novice and expert users. The 45%

concentration in the 26-35 age range reflects financial services demographics whilst including adequate representation from younger (10%) and senior (15%) segments.

2.3 Round 2 Participant Demographics (n=25)

Recruitment Adjustments: The expanded sample size addressed Round 1 statistical power limitations (Cohen, 2023). Increased external tester proportion enhanced independent validation whilst adding non-native English speakers addressed multilingual concerns identified in stakeholder interviews.

Key changes from Round 1 included increasing external testers from 15% to 20% to reduce institutional bias from NordicBank employees potentially inflating satisfaction ratings. Adding non-native English speakers (40% of sample) directly addressed the gap where multilingual capabilities went untested despite stakeholder priorities. Retaining eight returning participants (32%) enabled longitudinal assessment measuring improvement perception from individuals experiencing both prototypes. Expanding sample size from 20 to 25 increased statistical power from 80% to 87% for detecting medium effect sizes at $\alpha=0.05$ (Cohen, 2023).

2.4 Testing Environment and Procedures

Round 1 Setup (October 2024): Sessions lasted 60-75 minutes per participant with a mean of 68 minutes. Fourteen participants attended in-person at NordicBank's usability laboratory with screen recording and eye-tracking equipment. Six participated remotely via Zoom with screen sharing using UserTesting.com. The principal investigator facilitated all sessions using a standardised script. Participants accessed Prototype Cycle 2 deployed on a staging environment isolated from production data.

Data collection combined automated logging of task completion times, error rates, and PII detection events with manual observation including think-aloud transcription and behavioural notes (Braun and Clarke, 2023). Post-session procedures included the SUS questionnaire and a 15-minute semi-structured debriefing interview.

Round 2 Setup (October 2024): Sessions extended slightly to 65-80 minutes with a mean of 71 minutes. Seventeen participants attended in-person whilst eight participated remotely. Changes from Round 1 included adding three multilingual tasks featuring Norwegian, Finnish, and Swedish queries. Adversarial task difficulty increased based on Round 1's 100% success rate (Chen, 2025). Returning participants answered comparison

questions asking "How does this compare to the previous version?" The extended 20-minute debrief for Round 1 veterans provided detailed improvement feedback.

Ethical Considerations: Informed consent was obtained before each session with explicit video and audio recording permissions. Participants could pause or withdraw at any time without penalty; zero withdrawals occurred across both rounds. All data were anonymised using participant codes (R1-P01 through R1-P20, R2-P01 through R2-P25). Synthetic customer data was used throughout testing to prevent real PII exposure (Nasr et al., 2023). Non-NordicBank participants received £50 gift vouchers as compensation.

Section 3. ROUND 1 USABILITY TESTING RESULTS (PROTOTYPE CYCLE 2)

3.1 Task Completion Analysis

The 12-task set progressed from simple to complex scenarios, covering core chatbot functions including balance checks, transaction enquiries, GDPR data rights queries, multi-turn dialogues, loan applications, fraud reporting, password resets, and adversarial security tests (Sharma et al., 2025).

Round 1 Completion Rates: Overall success rate reached 73.3%, falling short of the 85% target. Combined success and partial success totalled 87.9%, also below the 95% target. Mean completion time of 108 seconds exceeded the 94-second target by 14.9%, indicating marginal performance.

Tasks achieving highest success rates (≥85%) included balance checks (95%), transaction enquiries (90%), GDPR rights queries (85%), password resets (85%), and adversarial tests (100%). The simple authentication-then-query pattern proved well-understood for balance checks. Transaction enquiries demonstrated effective PII masking whilst GDPR queries benefited from strong RAG retrieval with clear source attribution (Patel et al., 2024). Security protocols for password resets communicated clearly to users. Defence mechanisms for adversarial tests worked robustly, blocking all prompt injections without creating friction (Chen, 2025).

Tasks with lowest success rates (<70%) revealed critical weaknesses. Multi-turn dialogues achieved only 60% success with three complete failures where the system "forgot" earlier requests, demonstrating context loss after three or more turns. Loan applications reached 65% success as extensive PII collection overwhelmed users who remained unclear which information was required. Most critically, non-native phrasing tasks achieved just 55% success as the system misunderstood queries like "How much money I having?" by producing irrelevant responses.

The stark contrast between 100% success on adversarial tasks and 55-60% success on authentic user complexity suggests the system was optimised for anticipated threats but underprepared for organic user behaviour variability (Shah et al., 2024). This misalignment necessitated rebalancing development priorities towards usability robustness.

3.2 Error Analysis and Failure Modes

Across 240 task attempts, 54 errors occurred, yielding a 22.5% error rate. Context loss in multi-turn conversations accounted for 14.8% of errors with critical severity. Eight incidents saw the system forget information provided in earlier turns, such as forgetting the user specified "checking account" in turn 1 when answering turn 3.

Misunderstanding non-standard language represented 16.7% of errors with critical severity. Nine incidents involved the system failing to process queries like "How much money I having?" where it responded with "I can help with account balance. Please log in" rather than acknowledging the phrasing variation.

Ambiguous query handling comprised 13.0% of errors with high severity. Seven incidents occurred when users asked vague questions like "Show my information" where the system provided generic privacy policies instead of requesting clarification about which information the user sought.

Latency causing timeouts accounted for 11.1% of errors with high severity. Six instances saw Task 4 exceed 150 seconds, leading three users to assume the system had frozen and abandon the task entirely (Kumar et al., 2025).

The most critical finding concerned PII not being masked in explanations, representing 7.4% of errors but with critical security severity (Mireshghallah et al., 2024). Four incidents occurred where the system explained IBAN validation using formats like "GB29NWBK..." with partial real-pattern overlap. One particularly concerning case used "GB29NWBK60161331926819" where the "GB29NWBK" prefix matched an actual UK bank (NatWest), creating ambiguity about whether real data had leaked. This validated interview findings regarding contextual leakage distinctions requiring clearer classification.

Evidence of usability-security trade-offs emerged through comparison of over-aggressive refusals (six cases) versus PII exposure (four cases), suggesting system calibration slightly favoured security over usability (Cao et al., 2023). Authentication friction caused eight errors, indicating MFA implementation disrupted conversation flow. The recommendation was to implement contextual authentication triggering MFA only when sensitive data was requested rather than at conversation initiation.

3.3 System Usability Scale Results

The mean SUS score of 68.2 out of 100 (SD=11.4, median=69.5, range=47.5-82.5) fell short of the 75.0 target by 6.8 points. This placed the system at the upper boundary of "marginal acceptability"—functional but requiring improvement (Sauro and Lewis, 2024). Distribution showed 10% scoring in the unacceptable range (0-50), 55% in marginal range (51-70), and 35% in good range (71-85). No participants rated the system excellent (86-100).

Customer service staff rated highest (mean=72.8), likely reflecting their domain familiarity compensating for usability gaps. External testers rated lowest (mean=62.5), providing unbiased assessment free from institutional loyalty. The 65% of participants scoring at or below 70 indicated the majority found the system barely acceptable, validating the need for Cycle 3 refinements.

Item-level analysis identified specific weaknesses. Participants showed weak intention to use frequently (mean=3.2), found the system unnecessarily complex (mean=3.4), and rated ease of use below the "agree" threshold (mean=3.1). Anticipated need for technical support scored concurringly high (mean=3.6). Perceived inconsistency problems (mean=2.8) aligned with context loss observations from Task 5. Users rated the system as somewhat cumbersome (mean=3.2) with confidence barely reaching neutral (mean=3.0). Perceived steep learning curves (mean=3.3) suggested inadequate onboarding or intuitiveness (Lewis and Sauro, 2021).

3.4 Task-Specific Satisfaction and Difficulty

Strong correlation ($\rho=0.79$, $p<0.001$) between task success and satisfaction validated that completion drives user contentment more than other factors (Constantino et al., 2024). Tasks with greater than 85% success averaged 4.1 out of 5.0 satisfaction whilst tasks below 70% success averaged 2.8 out of 5.0.

Interestingly, perceived difficulty correlated more strongly with success than objective completion time. The non-native phrasing task rated most difficult (4.1) whilst achieving lowest success (55%) despite moderate objective duration (92 seconds). This suggests users accurately self-assess struggle even when persisting through tasks (Braun and Clarke, 2023).

The adversarial task stood out as an outlier with perfect success (100%) combined with highest satisfaction (4.5) and low difficulty (2.0), indicating security mechanisms worked seamlessly from the user perspective by blocking attacks without creating friction (Chen,

2025). This represents the ideal usability-security balance worth replicating across other features (Cao et al., 2023).

3.5 Security Performance Metrics

PII detection recall reached 96.8% (149 out of 154 entities detected), falling short of the 98% target. Precision achieved 94.2% (149 out of 158 flagged correctly), missing the 95% target. The resulting F1 score of 95.5% missed the 96.5% benchmark. Most critically, data leakage rate reached 3.2% (8 out of 240 tasks), exceeding the 2% maximum threshold (Mireshghallah et al., 2024). False positive rate of 5.8% marginally exceeded the 5% target. However, mean detection latency of 47ms comfortably met the 50ms budget.

Leakage incidents broke down as follows: three cases (37.5%) involved partial IBANs in educational contexts such as "IBAN format: GB**AAAA..." where "GB" matched real country codes (medium severity). Two cases (25.0%) showed surnames without account numbers like "Mr. [SURNAME] account enquiry" where surnames remained unredacted (low severity). One case (12.5%) displayed full names in error messages stating "Sorry, [FULL NAME], I cannot process..." (high severity). One case (12.5%) left transaction amounts unmasked as "Your recent £[AMOUNT] transaction..." (medium severity). One case (12.5%) exposed email domains reading "Contact [REDACTED]@nordbank.com" (low severity).

Detection failures centred on two patterns: three instances involved non-standard IBAN formats such as Norwegian with spaces "NO12 3456 7890 123" whilst two instances involved names within compound words like "Account holder: JohnSmith" detected as a single token (Simranjeet97, 2024). Precision failures included six instances of common words flagged as names (e.g., "Jordan" as country versus person, "May" as month versus name) and three instances of numeric patterns resembling account numbers (reference numbers, dates).

The critical security gap of 3.2% leakage with one high-severity incident (full name in error message) represented unacceptable risk (Chen, 2025). Root cause analysis identified error handling code paths bypassing PII validation, establishing this as immediate fix priority for Cycle 3. Positively, the 47ms mean detection latency significantly below the 50ms budget indicated DistilBERT-NER efficiency didn't compromise real-time responsiveness, validating the architectural choice (Simranjeet97, 2024).

3.6 **2.6 Qualitative Feedback Synthesis**

Think-aloud protocol transcripts from 20 participants yielded 127 coded usability observations using inductive thematic analysis (Braun and Clarke, 2023). The most frequent issue concerned context being forgotten in multi-turn conversations (18 mentions, critical severity), exemplified by "I just told it my account number, why is it asking again?" (R1-P07). Confusion about when to authenticate appeared 15 times (high severity): "Should I log in now or wait? The system isn't telling me" (R1-P03).

Unclear refusal explanations arose 12 times (high severity): "It just said 'cannot process' without explaining why" (R1-P14). Overly wordy responses frustrated 11 participants (medium severity): "I just want my balance, not three paragraphs" (R1-P09). Slowness during transaction history appeared 10 times (medium severity): "It's taking forever... is it frozen?" (R1-P11).

System misunderstanding of non-native phrasing generated nine critical-severity complaints: "I said 'How much money I having' and it gave me a privacy policy?!" (R1-P16). Uncertainty about data security concerned eight participants (medium severity): "How do I know my information is actually protected?" (R1-P05). Seven participants expressed uncertainty about when human assistance was needed (medium severity): "When should I ask for a real person?" (R1-P19).

Positive feedback highlighted security transparency appreciation from 14 participants: "I like that it tells me when it's masked my account number for privacy" (R1-P02). This aligns with research emphasising transparency's role in building trust in AI systems (BSR, 2025). Twelve participants praised speed for simple queries: "Balance check was instant, exactly what I wanted" (R1-P08). Nine appreciated clear GDPR explanations: "The explanation of my data rights cited specific articles, very professional" (R1-P13). Seven valued polite error messages: "Even when it couldn't help, it was respectful and suggested alternatives" (R1-P10).

Improvement suggestions included better conversation history memory (16 mentions, high feasibility, implemented in Cycle 3), prominent authentication status displays (11 mentions, high feasibility, implemented), plain language refusal explanations (10 mentions, high feasibility, implemented), and progress indicators for slow operations (9 mentions, medium feasibility, implemented).

Section 4. ROUND 2 USABILITY TESTING RESULTS (FINAL SYSTEM - CYCLE 3)

4.1 Task Completion Analysis

Round 2 overall success rate reached 91.2%, exceeding the 85% target by 6.2 percentage points and representing a 17.7 percentage point improvement over Round 1. Combined success and partial success totalled 96.8%, surpassing the 95% target. Mean completion time decreased to 96 seconds, beating the 94-second target and representing an 11.1% improvement over Round 1's 108 seconds.

All tasks except multilingual queries achieved success rates above 85%. Balance checks maintained excellence at 96% whilst transaction enquiries reached 92%. Multi-turn dialogues dramatically improved from 60% to 88%, addressing the critical context loss issue through enhanced conversation memory implementation (Dubey et al., 2024). Loan applications improved from 65% to 84% through clearer progressive disclosure of required information.

The most significant challenge remained multilingual queries (Task 10), improving from 55% to 76% success but still falling short of targets. English queries succeeded at 94% compared to 76% for Norwegian, Finnish, and Swedish queries combined. This persistent gap validated stakeholder concerns about multilingual support requiring dedicated Phase 2 enhancement (Shah et al., 2024).

4.2 System Usability Scale Results

Round 2 mean SUS score reached 78.4 out of 100 (SD=9.8), representing a 10.2-point improvement over Round 1's 68.2 and exceeding the 75.0 target by 3.4 points (Sauro and Lewis, 2024). Distribution shifted dramatically: only 4% scored in the marginal range (51-70) compared to Round 1's 65%, whilst 84% achieved good ratings (71-85) compared to Round 1's 35%. Twelve per cent reached excellent (86-100) compared to Round 1's zero.

Customer service staff ratings increased to 81.2 (from 72.8), developers to 77.9 (from 66.5), compliance officers to 76.8 (from 64.4), and external testers to 74.2 (from 62.5). The convergence of scores across subgroups suggested improvements addressed universal usability concerns rather than benefiting only specific user types (Lewis and Sauro, 2021).

Item-level improvements showed willingness to use frequently increasing to 3.9 (from 3.2), perceived complexity decreasing to 2.6 (from 3.4), and ease of use rising to 3.8 (from

3.1). Anticipated need for technical support dropped to 2.7 (from 3.6) whilst confidence increased to 3.7 (from 3.0). These improvements validated that Cycle 3 refinements directly addressed identified weaknesses through iterative design (Brown, 2023; Rana et al., 2025).

4.3 Security Performance Metrics

Round 2 achieved transformative security improvements. PII detection recall reached 98.9% (152 out of 154 entities), exceeding the 98% target. Precision improved to 97.4% (152 out of 156 flagged), surpassing the 95% target. F1 score reached 98.1%, well above the 96.5% benchmark (Simranjeet97, 2024). Most importantly, data leakage rate dropped to 1.0% (3 out of 300 tasks), meeting the under-2% target and representing a 2.2 percentage point improvement (Mireshghallah et al., 2024).

The three remaining leakage incidents all involved educational contexts explaining financial concepts using format-preserving examples. Stakeholders distinguished these contextual leakages from genuine failures exposing authentic customer data, with Participant 11 noting "educational examples are lower priority than actual data exposure." Zero high-severity incidents occurred in Round 2 compared to one in Round 1.

Adversarial testing expanded from 25 attacks in Round 1 to 100 attacks in Round 2 with increased sophistication following contemporary threat models (Chen, 2025). Defence rates reached 99% overall, with specific breakdowns showing 98% against prompt injections, 99% against social engineering, 97% against context manipulation, and 100% against edge-case exploitation. The single successful attack involved a highly sophisticated multi-turn context manipulation requiring seven conversation turns to establish false premises, representing an attack vector impractical in real-world scenarios requiring immediate results.

4.4 Comparative Analysis and Longitudinal Insights

Eight returning participants provided unique longitudinal perspectives enabling within-subject comparison (Constantino et al., 2024). When asked "How does this compare to the previous version?", all eight reported substantial improvements. Participant R2-P03 (returning as R1-P07) stated: "The context memory is night and day better. Last time it forgot everything after a few questions, now it actually remembers what we discussed." Participant R2-P11 (returning as R1-P14) noted: "The explanations when it can't help are so much clearer. I understand why and what I need to do instead."

Quantitative comparison of returning participants showed mean SUS scores increasing from 67.9 to 79.3 (+11.4 points), task completion improving from 71.3% to 92.5% (+21.2 percentage points), and mean satisfaction rising from 3.5 to 4.3 (+0.8 points). These within-subject improvements exceeded between-subject comparisons, suggesting genuine enhancement rather than sampling variation (Cohen, 2023).

4.5 Stakeholder Confidence Assessment

Round 2 included a dedicated stakeholder confidence questionnaire administered post-session. When asked "Would you feel confident using this system for real customer interactions?", 84% responded affirmatively (compared to 45% hypothetically estimated from Round 1 feedback). When asked "Do you trust this system protects customer data adequately?", 88% agreed or strongly agreed, reflecting enhanced confidence in security mechanisms (BSR, 2025).

Conditional confidence questions revealed nuances: 96% would trust the system for simple queries, 87% for moderate complexity tasks, 73% for multi-turn dialogues, and only 64% for multilingual queries. This gradient validated that whilst the system achieved deployment readiness for core functions, specific enhancement areas remained for comprehensive rollout (Shah et al., 2024).

Section 5. DISCUSSION AND RECOMMENDATIONS

5.1 Interpretation of Findings

The iterative refinement from Prototype Cycle 2 to Cycle 3 demonstrated the effectiveness of Design Thinking's Test-and-Refine approach (Brown, 2023; Rana et al., 2025). Systematic improvements across all primary metrics validated that structured stakeholder engagement combined with empirical testing produces actionable insights translating to measurable enhancements (Alshammari et al., 2024).

The 88.5% reduction in data leakage rate (from 3.2% to 1.0%) whilst simultaneously improving usability (SUS: 68.2→78.4) challenges the common assumption that security and usability exist in zero-sum tension (Cao et al., 2023). The findings suggest that well-designed security mechanisms can be both robust and transparent, enhancing rather than degrading user experience. This aligns with contemporary research emphasising that transparency mechanisms significantly boost institutional trust in AI systems (BSR, 2025).

The persistent multilingual challenge (76% success versus 94% English baseline) highlights that LLM performance remains language-dependent despite multilingual pre-training claims (Shah et al., 2024). This gap carries significant practical implications for Nordic financial institutions serving diverse linguistic populations. The finding suggests that domain-specific fine-tuning on Nordic languages represents a critical enhancement requirement for Phase 2 deployment.

5.2 Limitations and Future Research

Study Limitations:

Sample size constraints (n=20, n=25) whilst adequate for usability testing may limit statistical generalisation to broader populations (Cohen, 2023). Synthetic data usage, necessary for GDPR compliance, may not capture full complexity of real customer interactions (Nasr et al., 2023). Single institution focus (NordicBank) affects generalisability to other organisational contexts with different risk appetites, technical infrastructure, or regulatory requirements (Shah et al., 2024). Six-month study duration precludes long-term assessment of model drift, evolving attack vectors, or sustained user trust. Researcher involvement in both development and evaluation introduces potential bias despite mitigation efforts through structured protocols (Braun and Clarke, 2023).

Future Research Directions:

Longitudinal studies tracking system performance over 12-24 months would assess model degradation, adversarial adaptation, and user trust evolution (Chen, 2025). Comparative multi-institutional studies evaluating framework effectiveness across diverse organisational contexts would establish generalisability. Cross-linguistic evaluation comprehensively assessing performance across language families would address multilingual gaps identified in this research (Shah et al., 2024). Formal verification approaches applying mathematical proof techniques to security properties would provide stronger guarantees than empirical testing alone (Sharma et al., 2025). Human factors research examining trust formation, risk perception, and acceptable trade-offs would inform user-centred security design (Cao et al., 2023; BSR, 2025).

Additionally, future research should investigate the scalability of the dual-LLM architecture across different financial service contexts beyond retail banking. Comparative studies examining performance in investment banking, insurance, and wealth management would establish the framework's adaptability (Patel et al., 2024). Investigation into the economic viability of deployment, including total cost of ownership analysis and return on investment metrics, would provide practical guidance for institutions considering adoption (Kumar et al., 2025).

Research examining the evolution of adversarial attack sophistication and corresponding defence mechanisms would contribute to ongoing security enhancement (Chen, 2025). As threat actors develop more sophisticated prompt injection and context manipulation techniques, longitudinal adversarial testing becomes essential for maintaining robust defences. Furthermore, exploration of automated red-teaming approaches could provide continuous security validation without requiring extensive manual testing resources (Furfaro, 2025).

5.3 Conclusion

This two-round usability evaluation demonstrated that the dual-LLM finance chatbot system achieved deployment readiness for controlled pilot implementation whilst identifying specific enhancement requirements for comprehensive rollout. The systematic improvements between Prototype Cycle 2 and Cycle 3 validated Design Thinking's iterative refinement methodology (Brown, 2023; Rana et al., 2025), showing that structured stakeholder engagement translates to measurable usability and security gains.

The achievement of all primary success criteria in Round 2 (task completion 91.2%, SUS 78.4, leakage 1.0%, satisfaction 4.2/5.0) marks a significant milestone. The 88.5% reduction in data leakage rate whilst simultaneously improving usability by 10.2 SUS points demonstrates that security and usability can advance together through careful architectural design (Cao et al., 2023). However, the persistent challenges with multilingual queries (76% success versus 94% English baseline) and sophisticated adversarial attacks (99% defence rate with one sophisticated bypass) indicate that ongoing refinement remains essential rather than optional (Shah et al., 2024; Chen, 2025).

The findings contribute empirical evidence supporting several key conclusions for financial institutions considering conversational AI adoption. First, hybrid architectures combining specialised models (DistilBERT-NER for detection, Llama 3.1 8B for generation) outperform single-model approaches in balancing security and performance requirements (Simranjeet97, 2024; Dubey et al., 2024). Second, transparent security mechanisms that visibly mask PII enhance rather than diminish user trust, with 88% of participants expressing confidence in data protection (BSR, 2025). Third, iterative testing with diverse stakeholder groups identifies critical usability issues that purely technical evaluation misses, as evidenced by the 127 qualitative insights generated through think-aloud protocols (Braun and Clarke, 2023).

The phased deployment roadmap provides practical guidance for financial institutions navigating the complex landscape of AI adoption under stringent regulatory requirements (Financial Stability Board, 2024). The recommendation for a six-month internal pilot followed by gradual external expansion reflects lessons learned about the gap between proof-of-concept success and operational readiness. Stakeholder feedback emphasising that "6-12 months' integration beyond chatbot development" would be required validates the importance of realistic implementation planning (Shah et al., 2024).

Critical success factors identified through this evaluation include: maintaining continuous adversarial testing to sustain 99% defence rates against evolving threats (Chen, 2025); implementing comprehensive staff training covering system capabilities, limitations, and escalation protocols; establishing robust monitoring infrastructure enabling real-time detection of performance degradation or security incidents; and prioritising multilingual enhancement to serve diverse customer populations effectively (Shah et al., 2024).

The research also highlights important considerations regarding acceptable risk levels in financial services contexts. Whilst the 1.0% data leakage rate meets technical targets and represents substantial improvement, stakeholder concerns that "even 1% represents thousands

at scale" underscore the zero-tolerance culture in financial services. This tension between statistical performance and operational acceptability suggests that institutions must carefully calibrate risk thresholds based on their specific regulatory requirements, customer expectations, and risk appetite (Financial Stability Board, 2024).

The distinction between contextual leakage (format-preserving educational examples) and genuine failures (exposure of authentic customer data) identified through qualitative analysis provides valuable nuance for security classification frameworks (Mireshghallah et al., 2024). All three remaining leakage incidents in Round 2 involved educational contexts rather than actual customer data exposure, suggesting graduated response frameworks may be more appropriate than treating all disclosures uniformly.

Ultimately, this evaluation confirms that secure, usable conversational AI for financial services is achievable—not easily, not without sustained investment, but demonstrably viable (Sharma et al., 2025). The path forward requires continued vigilance, systematic monitoring, and commitment to iterative improvement, precisely the approach this research demonstrates. The integration of Design Thinking principles with rigorous security testing provides a replicable methodology that other institutions can adapt to their specific contexts (Brown, 2023; Alshammari et al., 2024).

As financial institutions worldwide explore AI-powered customer service solutions, this research contributes empirical evidence about realistic performance expectations, implementation challenges, and critical success factors. The findings suggest that whilst conversational AI offers substantial benefits in terms of efficiency, scalability, and customer experience, successful deployment requires balancing technical sophistication with user-centred design, robust security with usability, and ambitious innovation with pragmatic risk management (BSR, 2025).

The 84% of participants expressing confidence in using the system for real customer interactions, combined with 88% trusting data protection adequacy, indicates that the Final System (Cycle 3) has crossed a critical threshold from experimental prototype to potentially deployable solution. However, the conditional nature of this confidence—varying from 96% for simple queries to 64% for multilingual queries—emphasises that deployment must remain appropriately scoped to contexts where the system demonstrates consistent reliability (Constantino et al., 2024).

In conclusion, this usability evaluation validates the effectiveness of combining Design Thinking methodologies with advanced LLM architectures to create financial chatbot systems that are simultaneously secure, accurate, and user-friendly. The documented improvements

from Round 1 to Round 2 provide empirical support for iterative design approaches in high-stakes AI applications. The identified limitations and future research directions offer clear guidance for continuing enhancement. As the financial services industry navigates the opportunities and challenges of AI transformation, research like this contributes essential evidence-based insights to inform responsible, effective deployment strategies that protect both customer data and institutional interests whilst delivering genuine value to users.

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