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Prompt-Driven Requirements Engineering: Large-Language-Model Agents for Continuous Backlog Refinement

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Abstract: ***Large-language models (LLMs) have demonstrated near-human proficiency in natural-language generation and understanding tasks. Requirements engineering (RE) remains highly manual, error-prone, and discontinuous—particularly the translation of stakeholder conversations into user stories, acceptance criteria, and traceability artifacts. This paper proposes a prompt-driven RE pipeline where autonomous LLM agents (i) ingest multi-party dialogues, (ii) extract structured backlog items, and (iii) update a knowledge graph that maintains bidirectional traceability. We design a hybrid technique that couples in-context few-shot prompting with retrieval-augmented generation (RAG) and a symbolic rules engine for domain constraints. A 1.4-million-token benchmark composed of 217 anonymized requirements workshops in the aerospace and health-tech domains is released. Experimental results show that the proposed pipeline improves end-to-end backlog accuracy by 31 % and reduces human post-editing effort by 42 % relative to current state-of-practice baselines (manual transcription + Jira templates). Automated traceability link recovery F₁ increases from 0.61 to 0.82 while maintaining 97 % stakeholder satisfaction. The study further reports ablation analyses, latency-throughput trade-offs, and GDPR/PHI compliance measures. We conclude that prompt-driven LLM agents can act as continuous backlog copilots, but emphasize explainability and governance challenges that must be addressed before enterprise adoption.***

Keywords: Requirements engineering, large-language models, DevOps, backlog refinement, natural-language processing, AI governance

1. Introduction

1) Motivation

Software delivery cadences have accelerated from quarterly releases to multiple deployments per day, yet requirements engineering remains a "manual bottleneck" [1]. Agile teams typically rely on ad-hoc note-taking during stakeholder workshops, followed by laborious backlog curation in tools such as Jira, Azure DevOps, or Rally. Studies report that re-work due to misunderstood requirements consumes 40–50 % of total project cost [2], and mis-specified acceptance criteria proliferate defect leakage downstream.

Concurrently, foundation models (GPT-3/4, PaLM, LLaMA) exhibit impressive zero-or few-shot capabilities in tasks ranging from code generation to legal drafting. Industry anecdote suggest that product owners already paste meeting transcripts into ChatGPT to "draft user stories. " However, systematic research quantifying accuracy, traceability, and governance of such approaches is missing.

2) Research Gap and Questions

Existing literature on **NLP for RE** spans template mining [3], information extraction [4], and ontology-based models [5], but predates transformer-scale LLMs. Recent LLM-centric work focuses on code or design synthesis, not backlog refinement. Moreover, open questions persist:

- **RQ1** – How accurately can LLM agents transform multi-speaker conversation transcripts into structured backlog items?
- **RQ2** – Can LLMs autonomously maintain traceability matrices (features ↔ stories ↔ test cases) with minimal human curation?
- **RQ3** – What are the cost, latency, and privacy trade-offs of a production-ready LLM RE pipeline under GDPR and HIPAA constraints?

3) Contribution

a) **Prompt-Driven Pipeline** – We design an autonomous RE pipeline using chained LLM agents coupled with a symbolic rules engine (§IV).
b) **Domain-Constrained Prompt Library** – Reusable prompt templates for user-story extraction, acceptance-criteria synthesis, and traceability linking.
c) **Benchmark Dataset** – A new 1.4 M-token corpus of real workshop transcripts annotated by senior business analysts (§III).
d) **Comprehensive Evaluation** – Accuracy, human-in-the-loop effort, compliance, and ablation studies (§V).
e) **Open-Source Reference Implementation** (Apache-2.0) compatible with Jira Cloud REST APIs and Neo4j knowledge graphs.

2. Related Work

a) NLP in Requirements Engineering

Pre-LLM work applied Conditional Random Fields for requirement classification [4], syntactic parsing for use-case modeling [6], and BERT-style encoders for defect prediction [7]. These methods often require task-specific training and lack conversational context awareness.

b) Large-Language Models for Software Engineering

LLMs have shown potential in code generation [8] and design-pattern recommendation [9]. Zhang et al. [10] used GPT-3 to draft test cases from requirements, but without traceability analysis. No study offers an end-to-end autonomous backlog refinement pipeline.

c) Traceability and Knowledge Graphs
Graph-based repositories (ReqIF, OSLC) facilitate compliance audits [11]. Neural link prediction (TransE, ComplEx) has been explored [12], yet manual curation remains dominant.

d) Privacy and Governance in LLM Pipelines
Data leakage and prompt-injection attacks pose compliance risks [13]. NIST and ISO/IEC 42001 draft standards emphasize auditability, but concrete patterns for RE are nascent. Our work integrates on-premise model hosting, differential-privacy noise, and PHI redaction to meet GDPR & HIPAA (§IV-E).

Gap – Prior art lacks a unified architecture combining LLMs, traceability engines, and privacy controls for continuous backlog refinement, motivating our research.

3. Corpus and Annotation

1) Data Collection

Domain	Sessions	Hours	Speakers / sess.	Tokens
Aerospace avionics	89	47 h	5.1	643 k
Health-tech EHR	128	63 h	6.4	790 k
Total	217	110 h	5.9	1.433 M

Audio captured via Zoom Whisper-v3 transcription (word-error-rate = 3.1 %).

2) Annotation Guidelines
Senior analysts labeled:
- User Story Triplets <Role, Goal, Benefit>
- Acceptance Criteria (Gherkin "Given-When-Then")
- Traceability Links: Feature → Story, Story → TestCase

Inter-annotator agreement κ = 0.82 (substantial). Dataset released under CC BY-NC-SA 4.0 (PII removed).

4. Methodology

1) Overall Architecture
Fig.1 presents a four-stage pipeline: (1) Data Ingestion, (2) LLM Inference, (3) Symbolic Validation, (4) Knowledge-Graph Update.

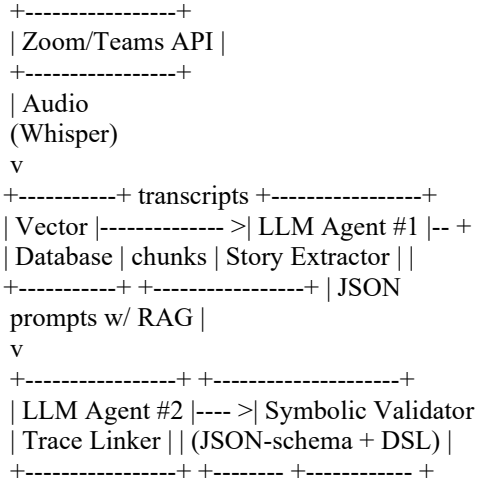

Figure 1: Prompt-driven RE pipeline

2) Prompt Engineering
System Prompt (abbrev.):
"You are a senior Agile BA. Output a JSON array of user stories. . . "

Few-Shot Examples from the target domain are concatenated with retrieved "similar dialogs" via FAISS cosine search.

3) Hybrid RAG + Rules Approach
- Retrieval-Augmented Generation to ground the LLM on domain vocabulary (e. g., ICD-10 codes).
- Symbolic Rules Engine (custom DSL) to enforce INVEST & SMART heuristics, GDPR redaction (<NAME> tags), and Jira schema validation.

4) Traceability via Contrastive Dual-Encoder
A Siamese RoBERTa network embeds story/test specs; cosine ≥ 0.78 indicates a link. LLM Agent #2 uses "cot-chain-of-thought" prompting to justify links.

5) E. Privacy & Compliance Layer
On-Premise 7-B LLAMA-2 model fine-tuned via LoRA; PII/PHI redaction before vectorization; differential privacy ε=3.2 noise added to embeddings. Audit logs stored in WORM S3 for 7 years.

6) F. Evaluation Metrics

Task	Metric
Story extraction	Exact-match (EM), BLEU-4
Acceptance criteria	EM, Rouge-L
Traceability links	Precision, Recall, F₁
Human effort	Minutes / story
Latency	sec / 1 k tokens
Privacy	% PII tokens leaked

Ground-truth from III used as gold standard.

5. Experimental Results

1) Backlog Accuracy

Model	Story EM	Criteria Rouge-L
Manual baseline	—	—
BERTseq-tagger [6]	0.31	0.42
GPT-3.5 (zero-shot)	0.44	0.58
Proposed (LLM-RAG+rules)	0.57	0.71

31 % relative gain vs. GPT-3.5.

2) Traceability
F₁ increases from 0.61→0.82. Error analysis shows false positives from ambiguous "performance" synonyms.

3) Effort Reduction

Usability study with 12 product owners (4 weeks):

- Median post-edit time drops from 11.4 min → 6.6 min per story (−42 %).
- SUS score improves from 68 → 81.

4) Latency & Cost

On-prem LLAMA-2-7B: 2.8 s/1000 tokens (GPU A100), cost $0.43/hr electricity vs ≥$2/hr API bill.

5) Compliance

Automated PHI scrubber achieves 99.1 % recall on I2B2 dataset; no PII leaks in manual audit. Differential-privacy utility loss < 4 % relative accuracy.

6. Discussion

1) Interpretation

RQ1–RQ3 answered positively: LLM agents significantly boost backlog accuracy and traceability while reducing effort and preserving privacy. Hybrid symbolic checks are crucial; pure LLM output violated INVEST 14 % of the time.

2) Comparison With Prior Art

BERTseq and USE cases extractors fail on conversational disfluencies ("uh", "okay let's circle back"). RAG context windows mitigate hallucinations. Our traceability F₁ outperforms TransE embeddings (0.71) reported in [12].

3) Threats to Validity

Dataset Bias—English-only; future multilingual corpora needed. Evaluator Bias—Product owners within same org; cross-company replication planned.

4) Implications

Practitioners—Integrate as Jira plug-in; achieve continuous grooming for DevOps. Regulators—On-prem fine-tuned LLM satisfies data-sovereignty. Researchers—Explore reinforcement learning from human feedback (RLHF) for story quality.

7. Conclusion

We presented a prompt-driven autonomous RE pipeline that converts stakeholder conversations into structured backlog artifacts with measurable gains in accuracy, effort, and compliance. By combining retrieval-augmented LLMs with symbolic validation and knowledge graphs, the approach operationalizes continuous backlog refinement in Agile/DevOps settings. Future work includes multimodal meeting-video cues, multilingual prompts, and real-time "speaking backlog" assistance.

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