Literature Review Outline: Generative AI's Impact on Software Security in Automated Code Review

This outline details the plan for structuring and executing the literature review on how generative AI influences software security, specifically within automated code review (ACR). The review will be framed by a socio-technical lens, synthesising academic and industry findings to provide a comprehensive analysis.

1. Introduction

- **Background:** Introduce the growing integration of generative AI, particularly Large Language Models (LLMs), into the Software Development Lifecycle (SDLC). Acknowledge the traditional reliance on Static Application Security Testing (SAST) tools and their limitations, such as high false positives (Cheah, 2021; Piskozub et al., 2024).
- **Problem Statement:** Outline the core security concerns that this new trend introduces. This includes the potential for LLMs to generate insecure code and the risks associated with adversarial misuse in ACR pipelines (Siddiqi et al., 2024; Perry et al., 2024).
- **Scope & Purpose:** Clearly define the objective of the review: to synthesise and evaluate the current literature on generative AI's impact on software security in ACR. This will cover capabilities, empirical evidence, risks, mitigation strategies, and governance.

2. Foundational Framework & Methodology

- **Socio-Technical Lens:** Adopt a socio-technical framework to analyse the literature. This approach considers not only the technical behaviour of LLMs but also the human factors and organisational governance that influence security outcomes (Saxe et al., 2018).
- **Thematic Organisation:** Structure the review around four key thematic areas to ensure a focused and comprehensive analysis:
    - **Outputs:** Examine what LLMs generate, including insecure code patterns and their proposed fixes (Svyatkovskiy et al., 2020).
    - **Threats:** Investigate the specific adversarial risks to LLMs, such as data poisoning, prompt injection, and data leakage (Hossen et al., 2024; OWASP Foundation, 2023).

    - **Mitigations:** Review proposed solutions and hybrid approaches, including Retrieval-Augmented Generation (RAG) and integration with CI/CD gates (Zhou et al., 2024; Zhang et al., 2025).
    - **Methodology & Governance:** Discuss the ethical and methodological considerations present in the literature, such as benchmark realism and intellectual property (IP) concerns (NIST, 2025).

3. Key Findings & Discussion

- **LLMs as Probabilistic Advisors:** Discuss the literature's view of LLMs as tools for semantic reasoning that improve triage but are inherently probabilistic and lack explainability (Ma, 2024).
- **Empirical Evidence:** Evaluate empirical studies, noting the mixed results on vulnerability detection and repair. Highlight the discrepancy between performance on curated datasets and real-world benchmarks like CVE-Bench, where repair rates remain low (SakiRinn et al., 2024; Wang et al., 2025; Veracode, 2025).
- **Risks: The Case of Over-Reliance:** Address the significant risk of developer over-reliance on AI outputs, which can lead to the widespread propagation of insecure code. Use key studies, such as the one on GitHub Copilot, as a cautionary example (Pearce et al., 2022).
- **Hybrid Systems & Mitigations:** Focus on the promising direction of hybrid frameworks that combine the semantic power of LLMs with the deterministic rigour of traditional tools. Discuss how these systems, often using RAG, can reduce hallucinations and improve patch quality (Hu et al., 2024; Zhou et al., 2024).

4. Synthesis & Conclusion

- **Strengths & Limitations of Existing Literature:** Critically assess the current body of work. Acknowledge its strengths (e.g., rapid empirical progress, diverse methods) and its limitations (e.g., benchmark realism, heterogeneity in evaluation, lack of longitudinal studies) (Wang et al., 2025).
- **Future Directions:** Propose clear directions for future research and practice. This will include advocating for the use of realistic

benchmarks (NAACL, 2025), implementing layered security controls, and developing human-in-the-loop governance models (NIST, 2025).

- **Concluding Statement:** Conclude by summarising that while generative AI significantly augments ACR, its secure and responsible integration depends on robust hybrid systems, ethical frameworks, and a continued focus on human oversight (Negri-Ribalta et al., 2024).

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