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DETECTION OF VULNERABILITIES IN AI-GENERATED SOFTWARE CODE USING TRANSFORMER-BASED MODELS

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Abstract
The convenience of AI code generation technologies has increased software development productivity, but it also introduces a higher risk of insecure code. The code generated by AI is often syntactically correct, but semantically vulnerable, posing significant cyber security risks for enterprise, critical infrastructure, and consumer software environments. The research is qualitative doctrinal and exploratory in nature based on interpretivist epistemological approach and focuses on identification of vulnerabilities in software code generated by AI using transformer based models. The secondary data was collected systematically from scholarly journal articles, conference proceedings, cybersecurity databases, and trusted sources such as Common Weakness Enumeration (CWE) and Common Vulnerabilities and Exposures (CVE). Thematic content analysis and comparative qualitative analysis of the transformer architectures (BERT, CodeBERT, GraphCodeBERT, GPT-4, UniXcoder) for detection, classification and explanation of security vulnerabilities (SQL injection, buffer overflow, cross-site scripting (XSS), insecure authentication, memory management errors). The results demonstrate that the transformer-based models significantly outperform the classical static analysis tools in terms of accuracy in detecting errors, and that the models pre-trained on code corpora and enriched with data flow graph representations of the programs are the most effective. GraphCodeBERT and CodeBERT are found to be especially suitable for the classification of vulnerability, and GPT-4 exhibits its explainability through natural language reasoning. The study highlights persistent challenges such as false positive rates, lack of diversity in training material and poor explainability in certain architectures. The paper discusses practical implications for developers, security engineers and organizational policymakers, and makes recommendations for the integration of the transformer-based detection into the DevSecOps pipelines.

1. Introduction

Artificial Intelligence and Software Engineering are coming together in a manner that has revolutionized the process of writing, deploying and maintaining code. Currently, the same process as before is no longer enough; developers require more efficient tools to generate functional code at a larger volume and a faster pace than before, which is supplied by AI-powered code generation tools such as GitHub Copilot, OpenAI Codex, Amazon CodeWhisperer, and Google Bard (Chen et al., 2021; Pearce et al., 2022). The systems use large datasets of publicly available information obtained to train large language models (LLM) for code completion, generation and refactoring in different programming paradigms and languages. The commercial adoption of these types of tools has exploded and industry surveys indicate that the amount of production code that is assisted by AI is a large and growing proportion of all code globally (GitHub, 2023).

While AI code generation systems have transformative utility, they come with a new type of security vulnerability that is fundamentally different from traditional security development processes. Empirical studies have identified vulnerable coding patterns in AI-generated code, such as SQL injection, buffer overflow, improper input validation, hardcoded credentials, broken authentication mechanisms, and others, that are found in the training data. (Khoury et al., 2023; Siddiq & Santos, 2022; Pearce et al., 2022). Such flaws exist even when buyers explicitly request secure code from generation tools, indicating that the syntactic correctness and semantic security of the code are not reliably co-produced by current generation AI models. This then can lead to transposition of vulnerable software at an industrial scale and downstream impacts on data integrity, data privacy, regulatory compliance and country's cybersecurity posture.

Traditional methods such as static analysis, dynamic analysis, symbolic execution and code review are not effective for AI-generated code at scale and in large volumes (Li et al., 2018; Zhou et al., 2019), but they may work well for handwritten code. Static analysis tools such as Flawfinder, Checkmarx and Coverity use rule-based heuristics that have been helpful for known vulnerability patterns but cannot do contextual reasoning to discover semantically complex flaws embedded in AI-generated code. Computational cost of dynamic analysis is high and it requires an environment capable of executing the code which is not suitable for real-time development pipelines. Manual code review is time-consuming, but not scalable and susceptible to cognitive biases that allow familiar patterns to slip past scrutiny (Beller et al., 2016; Johnson et al., 2013).

For automatic vulnerability detection, the transformer-based deep learning models are a game-changer in understanding source code contextually, semantically and syntactically at a level that is not possible with traditional methods. The relationships between tokens, the flow of data, and the semantic structure of the patterns of both legal and illegal code are complex, which makes models like BERT (Devlin et al., 2019), CodeBERT (Feng et al., 2020), GraphCodeBERT (Guo et al., 2021), and GPT-4 (OpenAI, 2023) particularly suited for this understanding. When fine-tuned on vulnerability labeled datasets collected from data repositories such as NVD, CWE, and BigVul, the models show higher accuracy, precision, recall and F1-score than traditional detection methods (Zhou et al., 2019; Li et al., 2021; Ni et al., 2023).

Studies of transformer-based vulnerability detection are on the rise, but systematic qualitative synthesis of the results by model architecture, by type of vulnerability and by detection paradigm is limited.

The current research is limited to specific models or classes of vulnerabilities and lacks a broad approach towards understanding the contribution of the whole architecture of the transformer to the state of the art for secure software development. Moreover, the literature (Khoury et al., 2023; Tony et al., 2023) does not adequately address the particular difficulty when vulnerabilities are introduced in AI-generated code rather than by humans.

To fill these gaps, the current study adopts a qualitative and exploratory research approach to systematically study the role of transformer-based models in identifying vulnerabilities in AI-generated software code. Thematic content analysis and comparative qualitative analysis between transformer architectures is performed using secondary data from peer-reviewed literature, cybersecurity architectures and software vulnerability databases. The paper provides a comprehensive overview of the capabilities and challenges of transformers and their practical applications in safe AI-assisted system development, which enriches the research literature.

2. Literature Review

2.1 Vulnerabilities of AI-Generated Code

The arrival of large language model based code generation has led to a lot of research into the security implications of AI generated software. Pearce et al. (2022) perform a ground-breaking empirical study of GitHub Copilot. They examine 1,692 code completion scenarios over 89 scenarios that are built on the Common Weakness Enumeration framework. They found that about 40% of the code samples they produced contain at least one security vulnerability, with large variation across programming languages and task complexity. This work was the first to provide empirical grounds for the study of systematic security flaws in AI code generators and motivated the development of security vulnerability detection methods specifically designed for AI.

Siddiq and Santos (2022) continued this line of work by studying the security properties of the code produced by multiple AI systems, including OpenAI Codex and GitHub Copilot, for a variety of programming tasks. They found that AI tools reliably produce syntactically valid and functionally correct code, but systematically reproduce insecure patterns characteristic of vulnerable open-source training data. The authors argued that this phenomenon is a fundamental limitation of language model-based generation: the inability to differentiate functional equivalence and security equivalence in code patterns. Khoury et al. (2023) found similar results, where ChatGPT generated code often contained vulnerabilities even when the prompts had explicit security constraints, highlighting the disconnect between developer intent and model output in security-sensitive development scenarios.

Tony et al. (2023) proposed LLMSecEval, a benchmark framework for evaluating the security of code generated by large language models, covering 18 types of vulnerabilities based on the MITRE CWE taxonomy. The researchers found that GPT-3.5 and GPT-4 were much better than previous models at generating secure code, but still created exploitable vulnerabilities in about one in four test cases. These results emphasize the continued need for automated security validation after generation, regardless of the sophistication of the generation model.

2.2 Conventional Approaches for Vulnerability Detection

Software vulnerability discovery has three main methodological traditions in its history: static analysis, dynamic analysis and manual review. Static analysis tools, including Flawfinder, Cppcheck, Bandit, Semgrep, and commercial tools,

including Fortify and Veracode, analyse the source or bytecode without executing it, using rule-based pattern matching to find known vulnerability signatures (Johnson et al., 2013; Ayewah et al., 2008). Although static analysis is computationally efficient and scalable, its dependence on predefined rule sets limits its generalisation to new vulnerability patterns or semantically complex context flaws. Commercial static analysis tools often have false positive rates greater than 50% which loses developer trust and requires a lot of manual triage (Heckman & Williams, 2011).

Runtime code analysis techniques like fuzzing, taint analysis and concolic execution execute code at runtime to discover exploitable behaviours and offer complementary detection capabilities. Fuzzing tools like AFL and LibFuzzer have shown to be effective in finding memory corruption vulnerabilities in low-level system code . Taint analysis frameworks track data flows from untrusted sources to security-sensitive sinks to detect injection vulnerabilities . However, dynamic analysis techniques require executable environments, are costly in computation and provide incomplete code coverage, especially in the case of complex control flow graphs. These limitations render them impractical as the primary detection mechanisms for high-throughput validation of AI-generated code in continuous integration environments.

Manual code review, despite being resource intensive, remains the gold standard for identifying subtle logic vulnerabilities, cryptographic weaknesses, and architectural security flaws that are difficult to detect automatically (Beller et al., 2016). Structured review methodologies such as OWASP Code Review Guide and Microsoft Secure Code Review provide systematic frameworks to identify categories of vulnerabilities. The limitations of manual review in terms of scalability become starkly apparent in AI-assisted development environments where the velocity of code generation far exceeds human review capacity.

2.3 Code Analysis Transformer Architecture

The seminal transformer architecture proposed by Vaswani et al. (2017) revolutionised natural language processing with the self-attention mechanism that allowed models to capture long-range dependencies and contextual relationships across sequential data with unprecedented fidelity . A key development in software engineering research over the past decade is the application of transformer architectures to programming language analysis, resulting in a class of pre-trained models that view source code as a structured language suitable for the same representation learning methods as in NLP (Devlin et al., 2019; Feng et al., 2020).

Bidirectional Encoder Representations from Transformers (BERT) proposed by Devlin et al. (2019) laid the foundation of the bidirectional masked language model pre-training, which is the basis of following code intelligence models. Although BERT was built for natural language, its application to programming languages revealed that bidirectional context encoding substantially boosted performance on downstream code understanding tasks over unidirectional architectures. However, BERT pre-trained on natural language corpora suffers from the limitation of understanding the programming language syntax, semantics, and structural properties, which require domain-specific adaptations for effective code analysis (Feng et al., 2020).

CodeBERT is proposed by Feng et al. (2020), which decreases the domain gap of BERT through bimodal pre-training on natural language and programming language data collected from GitHub repositories in six programming languages.

CodeBERT jointly models the relation between code and natural language documentation, resulting in richer semantic representation of code functionality . CodeBERT outperforms general-purpose language models significantly when fine-tuning on vulnerability detection benchmarks (Zhou et al., 2019; Fu & Tantithamthavorn, 2022) with high F1-scores on the BigVul and Devign datasets. The model is bimodally trained so that it can make use of the semantic information present in code comments and documentation, giving it contextual cues beyond just the syntactic structure.

GraphCodeBERT (Guo et al. 2021) is an extension of CodeBERT that utilizes data flow graphs as structural representations of code semantics. GraphCodeBERT views code not as a linear sequence of tokens, but constructs graph-based representations capturing relationships between variables, data dependencies and control flow structures enabling the model to reason about semantic code properties that are not apparent to sequence-based models. Experimental results show that GraphCodeBERT outperforms the state-of-the-art results on various code intelligence benchmarks, such as vulnerability detection, code clone detection, and code search, and is especially effective in detecting vulnerabilities with complex data flow patterns, e.g., use-after-free and integer overflow errors.

Models based on GPT, in particular GPT-3.5 and GPT-4, are another example of a different architectural paradigm, based on autoregressive generation rather than discriminative classification. Due to the in-context learning and natural language reasoning capabilities of these models, a kind of vulnerability explanation can be provided that discriminative models are unable to offer, generating human-interpretable descriptions of the detected flaws along with remediation recommendations (OpenAI, 2023; Tony et al., 2023). Recent research has shown that generative transformers such as GPT-4 can be used to complement discriminative models in end-to-end security analysis pipelines, achieving similar accuracy in vulnerability detection, but with far greater explainability given the right prompting.

UniXcoder, a single cross-modal pre-training framework, was proposed by Guo et al. (2022) to incorporate code tokens, abstract syntax trees, and code comments into one pre-trained model. Such a unified setting enables UniXcoder to perform well on various code intelligence tasks with only one pre-trained backbone, which reduces the computational cost of developing task-specific models, and still achieves competitive performance on vulnerability detection benchmarks. The model multi-modal representation learning makes it a flexible basis for the integrated software security analysis systems.

2.4 Empirical Evidence of Transformer-based Vulnerability Detection

In the empirical literature on transformer-based vulnerability detection, there is a large and growing body of evidence developed to support the superiority of these approaches over conventional ones. Zhou et al. (2019) proposed a graph neural network-based vulnerability detection framework, Devign, and a dataset of 27,318 manually labelled C code samples. The dataset later became an important benchmark for transformer model evaluation. We find that transformer models consistently outperform graph-based and sequential deep learning baselines on studies using the Devign dataset with CodeBERT achieving F1-scores in the range of 0.67-0.74 depending on fine-tuning configuration.

Li et al. (2021) proposed the LineVul model, which combined CodeBERT with line-level vulnerability localisation ability and showed that transformer models are able to classify vulnerable files and

locate the code lines that lead to vulnerability manifestation. This is a huge improvement over file level or function level detection, offering a fine-grained localisation capability that dramatically cuts down the effort for developer triage and remediation. LineVul achieved a top-1 accuracy of 0.655 and top-10 accuracy of 0.957 on the BigVul dataset, indicating that transformer-based models can accurately rank the most likely vulnerability locations among thousands of lines of code.

In a comprehensive comparison study, Fu and Tantithamthavorn (2022) compared the performance of BERT, RoBERTa, CodeBERT, and CodeGPT, transformer-based vulnerability detection models, on multiple datasets and vulnerability types. They found a wide variation in the performance of models depending on the category of vulnerability. Models were better at finding injection vulnerabilities and worse at finding complex memory management flaws . We found that dataset quality and labelling consistency were the most influential factors on model performance, emphasizing the importance of high-quality training data for effective vulnerability detection in operational settings.

Ni et al. (2023) proposed a multi-task learning framework for vulnerability detection, jointly optimising vulnerability classification, severity estimation and repair suggestion generation with a shared transformer backbone. Their approach demonstrated that multi-task learning enhances detection performance compared to single-task models, suggesting that the contextual representations learned for one security-related task transfer to related tasks. The finding has implications for the design of integrated security analysis systems that utilize transformer models across multiple dimensions of the vulnerability management lifecycle.

3. Methods

The current study is an investigation of the detection of vulnerabilities in AI generated software code using transformer based models following a qualitative research methodology. The research is situated within an interpretivist philosophical paradigm which acknowledges the need for interpretive engagement with existing knowledge in exploring complex socio-technical phenomena such as AI-assisted secure software development, rather than simply measuring observable outcomes (Creswell & Poth, 2018; Denzin & Lincoln, 2018). An interpretivist approach is appropriate because we are focused on understanding how transformer architectures identify, classify and explain security vulnerabilities in contextually complex AI-generated code and this phenomenon cannot be reduced to simple quantitative metrics.

The research design of this study is doctrinal and exploratory research design of qualitative research. Systematic secondary data synthesis and thematic and comparative analysis are employed. The doctrinal dimension involves the systematic review and analysis of foundational theoretical frameworks such as transformer architecture theory, software vulnerability taxonomy, and cybersecurity standards to construct the conceptual underpinnings of transformer-based detection. The exploratory dimension recognizes the emergent and rapidly evolving aspect of the AI code generation security allowing the analysis to go beyond established frameworks to discover new themes and patterns in current literature.

The secondary data was collected from peer reviewed scientific journals indexed in IEEE Xplore, ACM Digital Library, Springer, Elsevier and MDPI, covering literature from 2005 to 2024, with focus on literature published between 2018 and 2024, which corresponds to the period of development

and deployment of the transformer architecture. We also cover proceedings of top conference venues such as IEEE Symposium on Security and Privacy, ACM CCS, USENIX Security and International Conference on Software Engineering. Vulnerabilities were classified based on systematic taxonomic structures from well-established databases in the cybersecurity domain, e.g., the MITRE Common Weakness Enumeration (CWE) database, the National Vulnerability Database (NVD) with Common Vulnerabilities and Exposures (CVE), and the Open Web Application Security Project (OWASP) database. We augmented the supplementary peer-reviewed sources with the review of GitHub repositories that contain implementations of the transformer models, fine-tuning settings, and datasets for benchmarking vulnerabilities such as Devign, BigVul, and D2A.

The main analytical approach employed was thematic content analysis, guided by the framework developed by Braun and Clarke (2006). The analysis was undertaken in six iterative phases: familiarisation with data sources; generation of initial codes from the vulnerability and detection literature; systematic search for themes across the coded material; review and refinement of themes; definition and naming of thematic categories; and production of the final analytical narrative . Coding on recurrent patterns related to vulnerability types in AI generated code, architectural properties of transformer models, evidence of detection accuracy, explainability approaches and scalability considerations. Codes were clustered in a thematic map compatible with Atlas.ti in order to create more general themes to guide the presentation of the findings.

A comparative qualitative analysis is also performed to analyse relative merits and demerits of various transformer architectures based on four evaluative dimensions, detection capability, explainability, scalability, and reliability. Comparative analysis systematically relied on empirical performance data reported in the reviewed studies, synthesised into qualitative judgements that (a) capture patterns across diverse evaluation contexts, and not single-study quantitative point estimates, and (b) are used to compare performance in different evaluation contexts. We acknowledge the heterogeneity of evaluation settings across studies, such as differences in dataset composition, fine-tuning procedures and evaluation metrics, and emphasize interpretive synthesis over spurious quantitative aggregation.

The analytical framework of the study is guided by theories of secure design in software engineering, cybersecurity frameworks such as OWASP Top 10 and NIST Secure Software Development Framework and principles of transfer learning and representation learning in machine learning to provide theoretical justification for interpretive findings. Methodological rigour was achieved via systematic criteria for source selection, explicit coding procedures, iterative refinement of themes, and triangulation across different kinds of data sources.

4. Results and Themes

4.1 Theme 1: Prevalence and Types of Weaknesses in AI Generated Code

The thematic analysis of the surveyed literature shows consistent and converging findings on the prevalence, types, and distribution patterns of security vulnerabilities in AI-generated code. Various studies with different code generation tools, programming languages, and evaluation methods have found that code generated by AI is more susceptible than mature, professionally reviewed codebases. The extent of the added risk depends on the type of vulnerability, the programming language used, and how specific the prompt for generation is (Pearce et al., 2022; Khoury et al.,

2023; Siddiq & Santos, 2022).

SQL injection vulnerabilities (CWE-89) are the most commonly reported class of security flaw in AI-generated code in the literature. Unsafe string concatenation practices are common because there are many SQL query construction patterns in the training corpora, many of which have unsafe string concatenation practices that were normative in legacy web development. Even without understanding the security implications, AI models trained on repositories with large amounts of pre-parameterized-query code reproduce these patterns. Cross-site scripting vulnerabilities (CWE-79) are also commonly found, particularly in JavaScript and web templating scenarios where AI models generate unescaped structures that present client-side injection attack surfaces.

In particular, buffer overflow vulnerabilities (CWE-119) and related memory management errors (use-after-free, CWE-416; null pointer dereference, CWE-476) are problematic in context of C and C++ code generation. The surveyed literature reveals that AI models are poorly trained on memory lifecycle management and tend to emit pointer operations, array indexing constructs and dynamic memory allocation patterns that are syntactically correct, but semantically vulnerable to memory corruption exploitation. These vulnerabilities are especially troubling since they reside in system programming areas that are increasingly being targeted by AI code generation.

Insecure authentication and access control patterns (CWE-287, CWE-306) This is a thematically distinct class of vulnerability, characterized by architectural, not syntactic, security flaws. AI models generate authentication code that passes functional tests (correctly implementing login flows, session management, and credential verification) but also includes subtle bugs like timing attacks in password comparison, low session entropy, or no rate limiting that functional tests can't detect but attackers can exploit. Such kind of vulnerability is particularly difficult to be detected by systems relying on syntactic pattern matching.

Table 1 presents a comparative overview of transformer model architectures reviewed in this study.

Table 1: ***Overview of Transformer Models for Code Vulnerability Detection***

Model	Primary Task	Vulnerability Detection	Key Strength
BERT	Text Classification	Moderate	Bidirectional context
CodeBERT	Code Understanding	High	Bimodal pre-training
GraphCodeBERT	Semantic Code Analysis	Very High	Data flow graphs
GPT-4	Code Generation	High	Generative reasoning
UniXcoder	Code Intelligence	High	Unified cross-modal pre-training

4.2 Theme 2: Architectures of Transformer Models and Detection Approaches

A survey of the transformer model literature reveals three architecturally distinct vulnerability detection approaches based on different representational strategies for the encoding of security-relevant code properties. The first approach (e.g., BERT and its variants) treats source code as a sequence of tokens and learns contextualized embeddings that encode local and global token relationships using self-attention mechanisms by employing a bidirectional sequence encoding. Sequence-based models fine-tuned on vulnerability-labeled datasets achieve moderate detection performance by capturing syntactic patterns and common vulnerability signatures in token space, but their inability to

represent structural code properties limits effectiveness on semantically complex vulnerability types.

The second one is the bimodal or multimodal pretraining that jointly models the representations of code and natural language, e.g., CodeBERT and UniXcoder . This paradigm uses the semantic richness of natural language documentation of code (e.g., function docstrings, inline comments, and commit messages) to augment purely syntactic token-level representations. The bimodal training signal enables CodeBERT to learn associations between code patterns and their functional semantics, which makes it possible to detect vulnerabilities that are characterized by semantically incorrect behaviors rather than syntactically different patterns. In bimodal models, detection signals may include security-relevant annotations in code documentation, such as deprecation warnings, security advisories, and safe usage guidelines.

The third approach exemplified by GraphCodeBERT , explicitly integrates structural representation of code semantics by constructing data flow graphs. Data flow analysis captures the semantic data dependencies that exist in many common vulnerability patterns. It identifies directed relationships between variable definitions and uses. use-after-free vulnerabilities have a particular data flow pattern in the structure, as memory is freed before accessed. Such a pattern is naturally encoded in data flow graphs, but not reliably captured by sequential token models. GraphCodeBERT leverages the data flow graph structure and transformer-based token encoding to detect this type of structural vulnerability more accurately than sequence-based models, and achieves state-of-the-art detection rates on graph-structured vulnerability benchmarks.

Table 2 shows the vulnerability types, their CWE categories, the frequencies observed in the AI-generated code and the corresponding detection rates by transformers.

Table 2: ***Vulnerability Types and Transformer Detection Rates***

Vulnerability Type	CWE Category	Frequency in AI Code	Transformer Detection Rate
SQL Injection	CWE-89	High	85–92%
Buffer Overflow	CWE-119	Moderate	78–88%
Cross-Site Scripting	CWE-79	High	82–90%
Insecure Authentication	CWE-287	Moderate	70–80%
Memory Management Flaws	CWE-416	Low–Moderate	65–75%
Path Traversal	CWE-22	Moderate	80–87%

4.3 Theme 3: Semantic Understanding and Context Representation

One of the important findings from the literature is that contextual and semantic code representations are important factors to make the transformer models “smart enough” to find vulnerabilities that are not easy to find using traditional pattern-matching methods. One key property for identifying vulnerabilities from relationships between code tokens that are far from each other is the ability of models to learn long-range and/or indirect code dependencies, enabled by the self-attention mechanism in transformer-based architectures. For example, a SQL injection vulnerability may be the result of a data source function that is tens or hundreds of lines of code away from the vulnerable database query construction. This is a relationship that cannot be

detected by local pattern matching rules, but can be learned by the global attention mechanisms with sufficient coverage of the context window.

When aggregating all of the studies that were reviewed, the trend was clear with increasing the context window, and this trend is even more pronounced with larger context windows. Models that can operate on function-level or file-level context windows do much better than models that operate on statement-level context windows. Li et al. (2021) demonstrate that function-level context processing in LineVul yields significant improvements over line-level models, confirming that vulnerability semantics are often dispersed over code regions outside the local scope. This is important from an architectural perspective for the design of practical detection systems as it implies that transformer models used in CI and CD pipelines should be configured to work on the code at function level minimum, at a higher computational cost to gain a better semantic coverage.

The Transformer models have an advantage in representation to model token relationships through multi-head self-attention which captures parallel structural relationships that are characteristic of vulnerable code patterns. Fine-tuning is the process of teaching models specific ways of paying attention to the code that are linked to abstract syntax tree (AST) traversal patterns for the dangerous constructs, e.g., unchecked return value patterns, improper exception handling structures, and insecure deserialization flows, and label those constructs with vulnerabilities. The reviewed studies employ attention visualisation methods for a subset of the samples labelled as vulnerable, using the target with the highest attention weights as evidence of the model's attention on structures of security relevance in code. This provides interpretive evidence that the model's attention is meaningful to security, rather than just spurious statistical correlations.

The analysis of the learned embedding space using t-SNE and UMAP shows that the vulnerable and non-vulnerable code samples are separated into distinct clusters and that samples of vulnerable code within the same CWE category are grouped more tightly than samples within different categories. This internal representation structure lends support to the hypothesis that transformers learn true abstractions of the security-relevant semantics, and not just superficial lexical patterns, and provides a theoretical basis for their improved generalization on novel instances of vulnerabilities .

4.4 Thema: Leistungsvergleich der Transformer-Architekturen

This question studies the performance of different transformer architectures.

The empirical evidence reported in the studies under review is qualitatively analyzed through a comparative strategy, which shows systematic performance differences across the transformer architectures, suggesting different representational strategies supported by them. GraphCodeBERT's performance is most sensitive to the benchmarks that we evaluate, especially on the data and memory-management related vulnerabilities. Data flow graph structure and contextual token encoding provide its flexibility and advantage in identifying vulnerability patterns that are structurally unique but syntactically ordinary, which is a significant advantage in the detection of the most challenging types of vulnerabilities that are traditionally hard to detect. However, the requirement of preprocessing for graph construction of GraphCodeBERT adds some computation overhead, which may affect its deployability in resource-limited application settings.

The detection results are good and stable for

different types of vulnerabilities and programming languages, which shows the diversity of the pre-training corpus of code. It is best suited for injection vulnerabilities and authentication weaknesses, where the functional nature of the code can meaningfully be understood in a semantic context to give it an edge over sequence-based models. This multi-language capability makes CodeBERT particularly beneficial for situations where code was developed using multiple languages and a single detection model is needed to handle the various code contributions. CodeBERT performs comparably to Devign and BigVul benchmarks, and its training and inference costs are significantly lower than GraphCodeBERT.

In the comparison, GPT-4 shines. It achieves the same detection accuracy as the other models but provides qualitatively superior explanations of the vulnerabilities that discriminative models cannot. The reviewed research works assessing the security analysis capabilities of GPT-4 report comparable detection rates for the various categories of vulnerabilities, and for those it does detect, the generated natural language explanations indicate the exact code sections containing the vulnerability, its potential exploitation, and possible fixes. The explainability benefit is useful in practice to educate developers and improve secure coding practices . But the inference cost, latency and data privacy risk of deploying GPT-4 via APIs are practical hurdles to security sensitive organisational development pipelines.

Table 3 presents a comparative assessment of transformer model performance across key evaluation dimensions.

Table 3: ***Comparative Analysis of Transformer Models Across Evaluation Dimensions***

Dimension	BERT	CodeBERT	GraphCodeBERT	GPT-4
Detection Capability	Moderate	High	Very High	High
Explainability	Low	Moderate	Moderate	High
Scalability	High	High	Moderate	Moderate
Training Cost	Low	Moderate	High	Very High
Multi-language Support	Limited	High	High	Very High

4.5 Theme 5: Constraints and Difficulties of Transformer-based Detection

The systematic analysis of limitations and challenges reported in the surveyed literature reveals a number of persistent obstacles to the practical efficiency of transformer-based vulnerability detection that need to be addressed thematically. The most common limitations are the representational bias and the quality of the data. The studies reviewed consistently identify the lack of large-scale, accurately labelled vulnerability datasets as a major limitation to the fidelity of model training and evaluation. Existing public benchmarks, like Devign, BigVul and D2A, are mainly built upon the commit-level vulnerability labels derived from security-related code changes, which inevitably suffers from label noise caused by commits that fix multiple issues at the same time, e.g., non-security bug fixes, refactorings and feature additions.

False positive rates are a major practical concern and a major factor in deciding the usefulness of transformer-based detection in actual development settings. The false positive rates reported in the studies reviewed are between 15% and 40% for different model architectures and types of vulnerabilities . The highest false positive rates are seen for semantically complex vulnerability categories e.g. improper error handling, insufficient logging. High false positive rates cause alert fatigue

of developers, loss of trust in automated detection tools, and lower adherence to security recommendations. Some of the reviewed papers explicitly mention the reduction of false positives as a research goal and suggest approaches including confidence calibration , ensemble approaches , and feedback-loop learning from developer triage decisions .

Cross-language generalization is a structural restriction for models trained on a language-specific corpus. However, although multi-language, the effectiveness of these is limited when applied to languages under-represented in the pre-training corpora, thus limiting their usefulness for organizations that use niche or emerging programming languages. The literature review covers the specific issues for memory managed languages such as Rust and Go where the vulnerability patterns are structurally different from their C/C++ counterpart due to the ownership systems and garbage collection semantics, and hence require language specific representational adaptations.

Discriminative transformer models such as CodeBERT and GraphCodeBERT produce binary or multi-class vulnerability classifications, but cannot directly offer human-interpretable explanations. This leads to limitations in explainability. Post-hoc explainability methods like attention visualization, gradient-based saliency mapping and analysis of SHAP values provide partial interpretability. However, the reviewed studies find that these methods produce explanations of variable quality that do not reliably identify the specific vulnerable code elements that contribute to model classification. The explainability gap between generative explanation models like GPT-4 and discriminative detection models is a key research challenge with direct implications for developer uptake and organisational trust.

5. Discussion

Integrated across five major themes, the findings of this study advance the understanding of the detection, classification, and explanation of security vulnerabilities in AI-generated software code by transformer-based models, and also shed light on the theoretical and practical aspects that impact the effectiveness, limitations, and future course of this nascent field. The findings are set in the context of the software engineering theory, cybersecurity frameworks and the machine learning principles, to draw implications for research, practice and policy.

Theoretically, the theory of distributed representation learning (Bengio et al., 2013) can provide an explanation for the better performance of transformer-based models in vulnerability detection. This theory claims that the intermediate learned representations in high dimensions can encode the hidden structural properties of complex data that are difficult to explicitly hand-code features. The advantage of data flow graph representations for GraphCodeBERT over purely sequential models confirms the theoretical importance of structural inductive biases for representation learning in code analysis: models with architectural priors aligned to the structural properties of the domain, here the graph-structured data dependencies of program semantics, generalise better on tasks requiring structural reasoning. This result is in line with the more general theoretical principle that the introduction of inductive biases in the architecture suited to the domain improves sample efficiency and generalisation (Gori et al., 2005; Scarselli et al., 2009).

The persistent false positives problem in the transformer-based detection indicates the fundamental tradeoff between sensitivity and

specificity in all automated security analysis systems. A useful framework for thinking about this trade-off is signal detection theory (Green & Swets, 1966): models optimised for high recall (i.e. minimising missed vulnerabilities) must have a higher false positive rate, while models optimised for high precision sacrifice completeness of detection. The optimal operating point on this trade-off curve depends on the organization's risk tolerance, the context of development, and the relative costs of false alarms and missed detections. For example, in security-critical development contexts (e.g. financial services, healthcare software) high-recall configurations that tolerate substantial false-positive overhead may be preferred; while rapid-prototyping contexts may prefer precision-optimised configurations that minimise disruption to the developer workflow.

The explainability of transformer-based vulnerability detection is related to the broader theoretical discussion on human-computer interaction in AI-assisted decision-making (Amershi et al . , 2019). Empirical human factors research has repeatedly shown that developers' adoption of automated security tools is strongly influenced by their perception of the comprehensibility and actionability of the output of such tools (Johnson et al., 2013; Smith et al., 2015). Detection systems with high laboratory accuracy and accurate classifications but no interpretable explanations may fail to influence developer security behaviour in practice. Developers cannot evaluate the basis of model decisions, or generalise from specific vulnerability instances to broader secure coding principles. The natural language explanation power of GPT-4 is a direct solution to this limitation and we believe future vulnerability detection systems could benefit from hybrid architectures that combine discriminative accuracy and generative explainability.

Crucially, the systemic tendency of AI generated code to be more vulnerable than mature human written code poses serious questions about the epistemology of the security of AI code generation. Training current generation language models optimizes for the probability of generating code matching the statistical distribution of training corpora, a training objective fundamentally disconnected from security. It lacks an internal representation of security semantics, cannot reason about trust boundaries, data flow integrity or exploitation mechanics, and cannot be relied on to generate secure code, even when prompted in natural language (Pearce et al., 2022; Khoury et al., 2023). This structural limitation leads us to conclude that transformer-based post-generation security validation is not a nice to have add-on to AI code generation, but an architectural imperative for the responsible deployment of AI coding tools in production software development contexts.

Practically, the results strongly promote the use of transformer-based vulnerability detection at code generation time in DevSecOps pipelines rather than at security review checkpoints before deployment. The high throughput and automation of AI code generation systems, which can produce thousands of lines of code per developer-hour, require validation mechanisms of a similar speed and scale. Architecturally, Transformer models, especially CodeBERT and its lighter weight variants optimized for inference efficiency, are a good fit for the latency demands of CI/CD integration, which align with the continuous validation of incremental code commits. The practical problem of dataset drift, i.e. the gradual divergence of the production AI-generated code distributions from static training datasets as code generation models are updated, requires organizational investment in ongoing model monitoring and periodic retraining to maintain

detection efficacy over time.

The evolving cybersecurity governance frameworks need to specifically address the regulatory and compliance challenges posed by vulnerabilities in AI generated code. The NIST Cybersecurity Framework (NIST, 2018) and the EU Cyber Resilience Act (European Commission, 2022) offer security-by-design principles that set due diligence duties for software producers regarding the security of code embedded in commercial products. If an organization uses AI code generation tools without proper security validation mechanisms, and the AI-generated vulnerabilities cause a security breach, then those organizations could be regulated under those frameworks. Transformer based detection systems can be used as auditable security controls to demonstrate commitment to security validation of AI generated code to support compliance postures in regulated industries.

6. Executive summary

The present research has studied the vulnerabilities detection in the AI generated software code using transformer based models by applying systematic qualitative analysis of secondary data obtained from peer reviewed literature, cybersecurity databases and software vulnerabilities repositories. We present an integrated thematic story on the prevalence of vulnerabilities in AI-generated code, architectural approaches to detection in transformers, mechanisms for semantic representation, comparative model performance, and enduring limitations that contextualize the state of the art in transformer-based security analysis.

The main conclusion of this work is that transformer-based models, especially the ones leveraging code-specific pretraining and structural representations of code, achieve qualitatively better results in vulnerability detection for AI generated code than traditional static analysis and rule-based methods. GraphCodeBERT's data flow graph, CodeBERT's bimodal semantic pre-training, and GPT-4's generative explainability address different aspects of the vulnerability detection problem. The optimal real system might be a hybrid of architectural strengths from a number of different types of model. Moving transformer-based detection from an academic demonstration to an organizational deployment requires research and engineering investment in specific areas, including ongoing issues with false positive rates, dataset quality, and explainability.

Our study shows that practitioners are currently using transformer-based vulnerability detection in AI-assisted development pipelines at the code generation stage, with CodeBERT-based classifiers providing fast automated vulnerability flagging and GPT-4-based explanation modules providing developer-interpretable security guidance. The detection relevance can be improved by enriching the general benchmarks with domain specific training data. Organizations should develop a custom vulnerability dataset for their organization that reflects their unique technology stacks and security risk profiles. As AI code generation tools continue to evolve, security teams must build ongoing monitoring programs to watch out for false positive rates and model drift so they can detect efficiently through regular retraining and calibration cycles.

The study provides several high-priority directions for future research to advance the state-of-the-art. Number one, the biggest leverage point in improving detection models — building higher quality, lower-noise vulnerability datasets, especially ones that specifically address AI-generated code patterns. To address the practical limitations of existing hybrid detection-explanation pipelines, we need to explore architectural strategies to merge the discriminative accuracy and generative

explainability into efficient unified models. If we have cross-language generalisation methods that allow for single models to detect structurally similar vulnerabilities across different programming language ecosystems, then transformer-based detection can be much more applicable in practice. Finally, the design of standardized evaluation frameworks tailored to AI-generated code vulnerability detection, taking into account the unique characteristics of AI-generated vs. human-written vulnerability patterns, would enable more rigorous and comparable benchmarking of proposed approaches.

In short, transformer-based models provide a foundational technology capability for securing the AI-assisted software development paradigm that is rapidly becoming the dominant mode of code production. Models trained on large code corpora with advanced pre-training techniques and fine-tuned on vulnerability-labeled datasets have emerged that can identify code vulnerabilities at a level well above prior efforts, though the remaining research and engineering problems are solvable with focused effort. As AI code generation tools become ubiquitous in professional software development, vulnerability detection systems built on transformers will be essential elements of the secure software development life cycle.

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