Safeguarding Blockchain Ecosystem: Understanding and Detecting Attack Transactions on Cross-chain Bridges

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Abstract

Cross-chain bridges are essential decentralized applications (DApps) to facilitate interoperability between different blockchain networks. Unlike regular DApps, the functionality of cross-chain bridges relies on the collaboration of information both on and off the chain, which exposes them to a wider risk of attacks. According to our statistics, attacks on cross-chain bridges have resulted in losses of nearly $4.3 billion since 2021. Therefore, it is particularly necessary to understand and detect attacks on cross-chain bridges. In this paper, we collect the largest number of cross-chain bridge attack incidents to date, including 49 attacks that occurred between June 2021 and September 2024, of which 22 were attacks on cross-chain bridge business logic. Our analysis reveal that attacks against cross-chain business logic cause significantly more damage than those that do not. These cross-chain attacks exhibit different patterns compared to normal transactions in terms of call structure, which effectively indicates potential attack behaviors. Given the significant losses in these cases and the scarcity of related research, this paper aims to detect attacks against cross-chain business logic, and propose the BridgeGuard tool. Specifically, BridgeGuard models cross-chain transactions from a graph perspective, and employs a two-stage detection framework comprising global and local graph mining to identify attack patterns in cross-chain transactions. We conduct multiple experiments on the datasets with 203 attack transactions and 40,000 normal cross-chain transactions. The results show that BridgeGuard's reported recall score is 36.32% higher than that of state-of-the-art tools and can detect unknown attack transactions.

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CCS Concepts

• **Security and privacy** → **Web application security**; • **Applied computing** → **Electronic funds transfer**.

Keywords

Blockchain, Cross-chain, Transaction analysis, Graph mining

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1 Introduction

In blockchain technology, each blockchain network constitutes a relatively independent ecosystem with its own rules, protocols, and characteristics. This isolation leads to the mutual isolation between blockchains, where even the same cryptocurrency can only be used on specific blockchain networks. For example, Ether is the native cryptocurrency on the Ethereum network [35]. If someone needs to use Ether on other blockchains, they typically have to undergo a series of complex exchange transactions, which inconvenience users and impose limitations. Therefore, with the rapid development of current blockchain technology and the formation of a multi-chain ecosystem, cross-chain bridges, as decentralized applications (DApps), have emerged to bridge this gap, providing users with solutions to achieve interoperability of assets between different blockchain networks.

Cross-chain bridges, through smart contracts and other technical means, enables users to swiftly transfer assets between different blockchain networks, thus achieving cross-chain liquidity of assets. According to DappRadar[1], there are currently over 440 cross-chain

[1]https://dappradar.com/rankings/defi/18?category=defi_cross-chain

bridge DApps implemented based on various cross-chain mechanisms, making them an indispensable part of the blockchain ecosystem. However, as bridges between different blockchain networks, cross-chain bridges often carry a substantial amount of asset value, and their hidden vulnerabilities make them targets for hackers. In recent years, many security incidents of cross-chain bridges have emerged. The top three security incidents with the highest losses in the Rekt attack database[2] are all related to cross-chain bridges, with Ronin Network losing $624 million, Poly Network losing $611 million, and BNB Bridge losing $586 million, respectively. Particularly, Thorchain suffered three attacks within just two months (on June 29, July 16, and July 23, 2021). The frequency of these security incidents indicates that the security issues of cross-chain bridges have become a significant challenge in the current blockchain field.

Despite growing attention to cross-chain bridge safety, few studies and solutions have been developed. While some research, such as Xscope [38], analyzes security incidents and proposes rule-based detection, and SoK papers [14, 15, 20] discuss attack surfaces and defense methods, there is still a lack of comprehensive analysis and scalable solutions due to the ongoing development of cross-chain mechanisms and the variety of attacks.

Scope and Contributions. In order to provide valuable insights for enhancing cross-chain bridge security, this paper focuses on a comprehensive empirical study of cross-chain bridge security incidents. Specifically, we obtain cross-chain bridge security reports covering 49 cross-chain bridge security incidents from June 2021 to September 2024 from well-known security organizations such as SlowMist [30], Rekt [8] and Certik [5]. Subsequently, we construct a dataset containing 203 attack transactions and 40,000 normal attack by heuristic methods and propose a cross-chain attack detection method based on cross-chain transaction execution graphs (xTEGs). In experiments, we first evaluate the effectiveness and efficiency of BridgeGuard, then compare it with existing state-of-the-art tools. Our work contributes primarily in three aspects:

- **Comprehensive analysis:** To the best of our knowledge, this paper is the *first* to conduct an in-depth analysis on the issue of cross-chain bridge attacks from the perspective of on-chain transactions, and collect the most comprehensive dataset of cross-chain attacks. Specifically, 49 cross-chain bridge attacks that occurred between June 2021 and September 2024 are investigated.
- **Tool design:** Based on our empirical findings, we develop a tool named BridgeGuard[3] for detecting cross-chain attack transactions. BridgeGuard integrates graph representation and network motif techniques to extract the global and local features of transactions as the basic of detection.
- **Experimental evaluation:** BridgeGuard's recall is 36.32% higher than that of state-of-the-art tools, and its final transactions per second (TPS) reached 65 transactions. In addition, BridgeGuard can detect attack transactions that are not disclosed in security reports.

[2]https://rekt.news/zh/leaderboard/
[3]https://anonymous.4open.science/r/BridgeGuard-220E/

2 Understanding Bridge Attacks in Real-World

2.1 Cross-chain Bridge Business Logic

Cross-chain bridges are decentralized applications that serve as channels connecting different blockchain networks, enabling the transfer and exchange of assets and data across different chains [22]. Implementation of cross-chain bridges can be achieved through methods such as atomic swaps [12], relay chains [16], sidechains [29], etc. Typically, a normal and complete cross-chain bridge business workflow will have three phases: source chain, off-chain, and target chain. As shown in Fig. 1, the complete cross-chain flow is demonstrated.

- **On source Chain:** (1) The user initiates a **deposit transaction** request on the source chain to the router smart contract of the cross-chain bridge. (2) The router contract forwards the request to the corresponding token contract. (3) The token contract lock the asset in the vault and generate a lock event. (4) The Router contract verifies the authenticity of the locking event, and then generates the deposit event.
- **Off chain:** (5) The source chain message is passed down the chain. (6) The off-chain verifies that the source chain information is reliable and then passes the information to the target chain. The off chain verification methods include native verification, local verification and external verification.
- **On target chain:** (7) The router contract forwards the verified request to the token contract. (8) The token contract initiates a **withdrawal transaction**, which transfers or mints funds from the vault to the user and generates an unlock event. (9) The router contract receives the unlock event and generates the corresponding withdrawal event.

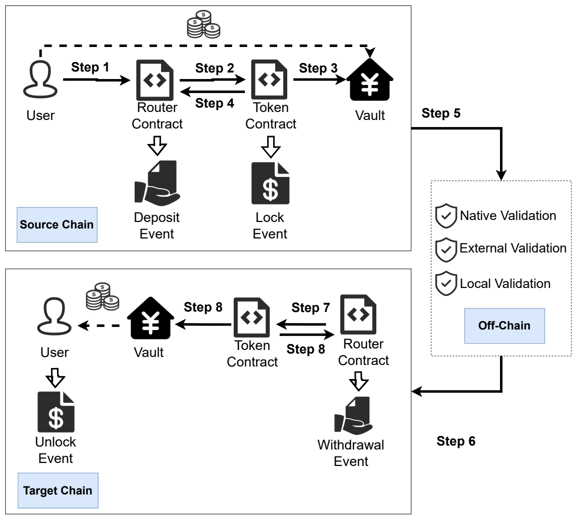


Figure 1: Typical cross-chain bridge procedures.

The cross-chain transaction process of cross-chain bridges typically involves communication and asset transfer between multiple blockchains, offering users the convenience of cross-chain asset exchange. However, this process also introduces complex security challenges, making cross-chain bridges a target for attackers.

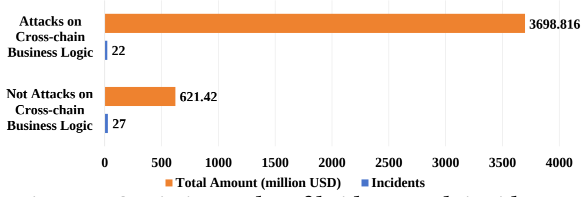


Figure 2: Statistic results of bridge attack incidents.

2.2 Analyzing Bridge Attacks

2.2.1 Data Collection and Statistic. To summarize the attacks on cross-chain bridges, we first collect real cross-chain bridge attack incidents with two main sources:

Academic Sok papers on cross-chain bridge attacks. Zhang *et al.* [39] counted 31 cross-chain bridge attack cases that occurred from July 2021 to July 2023. In addition, Notland *et al.* [21] counted 34 cross-chain bridge attacks that occurred from 2021 to 2023. However, these two papers do not cover or summarize the new attack incidents and patterns that occurred after 2023.

Attack incident summarized by security companies.

- Slowmist[4] provides a chronological list of blockchain attack incidents, with a total of 1,497 cases recorded so far, including 42 incidents related to cross-chain bridges.
- Rekt News[5] ranks attack cases by the amount of loss incurred. Currently, it has recorded 92 cases.
- ChainSec[6] archives attacks related to decentralized finance (DeFi), categorized by different blockchains and years, containing 148 DeFi attack incidents.

Finally, we collected 49 cross-chain bridge attack incidents from June 2021 to September 2024, the largest academic dataset to date. The detailed list, including attack details, is in Appendix A.1. Based on the cross-chain business logic, we categorize the incidents into those targeting business logic and those not. The non-business logic incidents include private key leaks, flash loans, and rug pulls, detailed in Appendix A.2. Of the 49 incidents, 22 targeted cross-chain business logic, causing financial losses nearly six times greater than non-business logic attacks, as shown in Fig. 2.

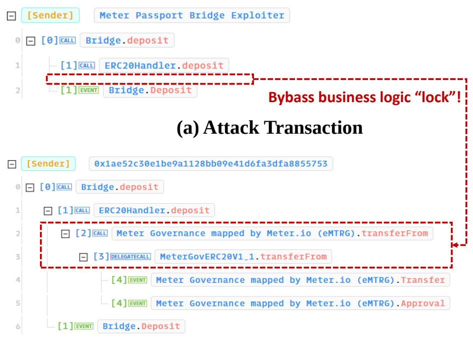
2.3 Attack on Cross-chain Bridge Business Logic

Attacks against cross-chain business logic cause significantly more damage than those that do not. Thus, we focus our analysis of attacks against cross-chain bridging business logic.

2.3.1 Attack on Source Chain (denoted as $\mathcal{A}_{src}$). This attack happens in the source chain where the deposit transaction occurs.

Attacks on Token Contracts. Token contracts on the source chain, whose main function is to lock tokens and generate token-locking proofs. In this type of attack, the hacker first locks a small number of tokens or none at all. Then, by triggering a cross-chain business vulnerability in the token contract, the hacker generates proof of locking beyond the amount locked in the first step, in order to spoof subsequent cross-chain business validation. Here we provide an example of an attack incident that occurred on the

[4]https://hacked.slowmist.io/en/
[5]https://rekt.news/zh/leaderboard/
[6]https://chainsec.io/defi-hacks/


```
[Sender]  Meter Passport Bridge Exploiter
0  [0]CALL  Bridge.deposit
1      [1]CALL  ERC20Handler.deposit
2      [1]EVENT  Bridge.Deposit
```

(a) Attack Transaction

```
[Sender]  0x1ae52c30e1be9a1128bb09e41d6fa3dfa8855753
0  [0]CALL  Bridge.deposit
1      [1]CALL  ERC20Handler.deposit
2          [2]CALL  Meter Governance mapped by Meter.io (eMTRG).transferFrom
3              [3]DELEGATECALL  MeterGovERC20V1_1.transferFrom
4                  [4]EVENT  Meter Governance mapped by Meter.io (eMTRG).Transfer
5                  [4]EVENT  Meter Governance mapped by Meter.io (eMTRG).Approval
6      [1]EVENT  Bridge.Deposit
```

(b) Normal Transaction

Figure 3: Traces of the attack and normal transactions of Meter.io Bridge

Meter.io bridge on February 5, 2022, resulting in an estimated loss of $4.2 million. The Meter.io bridge offers two deposit methods, `deposit()` and `depositETH()`. However, the `deposit()` function failed to prevent the deposit of ERC20 tokens and did not correctly execute the burning or locking logic for cross-chain deposits. As shown in Fig. 3, this allowed the hacker to simulate a deposit action on the source chain by using the `deposit()` function.

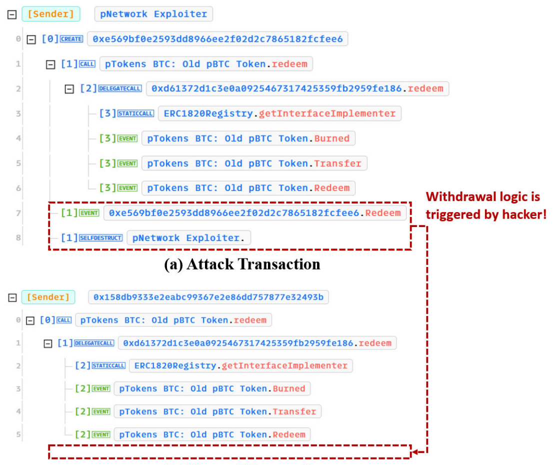
Attacks on Router Contracts. Attacks against router contracts are built on the basis that there is an existing token lock, but the business logic of the router contract is faulty, thus generating a fake deposit event. Take ThorChain #1 as an example. In the ThorChain #1 incident[7], the attacker performed a token lock, but the token's ERC20 token symbol is "ETH". However, there is a logic error in the router contract that recognizes the tokens that are topped up as genuine Ether.

Finding 1: In attacks against the source chain, attack transactions often exhibit abnormal function call chains and unexpected triggering of specific contract events.

2.3.2 Attack Off Chain. Most off-chain attacks against cross-chain Bridges are aimed at external authentication. This may be because the bridges will choose an external verification mechanism to achieve fast multi-chain adaptation [3]. While external validation enables fast multi-chain adaptation, it introduces new trust assumptions. Therefore, the external verification approach is one of the more fragile of all cross-chain mechanisms.

In Section 2.1, we mention that once a valid deposit event is generated, an off-chain repeater monitors and acquires the event. The repeater then passes this information to the target chain. However, if the off-chain repeater is in the hands of an attacker, then the attacker can pass the information directly to the target chain without having to make a deposit on the source chain. Using the Levyathan incident[8] as an example, we explain how this type of event is generated. The Levyathan project's tokens have a `mint()` function that allows its owner contract, `MasterChef`, to mint new tokens. While TimeLock is the owner of `MasterChef`, the `Timelock` itself should have only been operated by a multi-signature contract; however, the hacker took ownership of the `Timelock`.

[7]https://hacked.slowmist.io/zh/?c=Bridge
[8]https://rekt.news/levyathan-rekt/



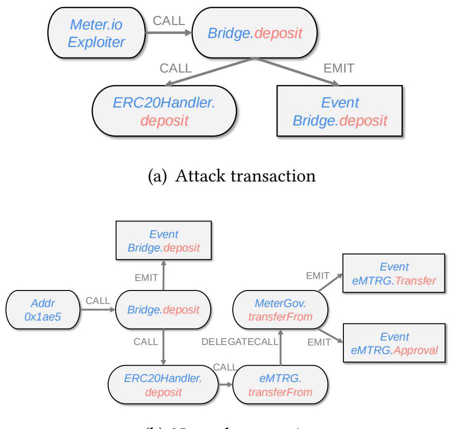
```
[Sender]   pNetwork Exploiter
[0]CREATE 0xe569bf0e2593dd8966ee2f02d2c7865182fcfee6
  [1]CALL pTokens BTC: Old pBTC Token.redeem
    [2]DELEGATECALL 0xd61372d1c3e0a0925467317425359fb2959fe186.redeem
      [3]STATICCALL ERC1820Registry.getInterfaceImplementer
      [3]EVENT pTokens BTC: Old pBTC Token.Burned
      [3]EVENT pTokens BTC: Old pBTC Token.Transfer
      [3]EVENT pTokens BTC: Old pBTC Token.Redeem
  [1]EVENT 0xe569bf0e2593dd8966ee2f02d2c7865182fcfee6.Redeem
  [1]SELFDESTRUCT pNetwork Exploiter.
```

(a) Attack Transaction

```
[Sender]   0x158db9333e2eabc99367e2e86dd757877e32493b
[0]CALL pTokens BTC: Old pBTC Token.redeem
  [1]DELEGATECALL 0xd61372d1c3e0a0925467317425359fb2959fe186.redeem
    [2]STATICCALL ERC1820Registry.getInterfaceImplementer
    [2]EVENT pTokens BTC: Old pBTC Token.Burned
    [2]EVENT pTokens BTC: Old pBTC Token.Transfer
    [2]EVENT pTokens BTC: Old pBTC Token.Redeem
```

(b) Normal Transaction

Figure 4: Traces of the attack and normal transactions in the pNetwork Bridge incident.



(a) Attack transaction

(b) Normal transaction

Figure 5: The call chain obtained from the traces of transactions of Meter.io Bridge

> **Finding 2:** Most off-chain attacks target cross-chain bridges that use external authentication mechanisms and do not construct malicious cross-chain transactions on chain.

2.3.3 Attack on Target Chain (denoted as $\mathcal{A}_{tgt}$). This attack happens on the target chain where the withdrawal transaction occurs.

Attacks on the target chain mainly target router contracts, since the withdrawal operation usually has to be initiated by a router contract. Once the cross-chain business logic of the router contract is faulty, it can result in the hacking of funds. We use ChainSwap[9] as an example to explain how such events arise. In the router contract on the target chain, there is a receive function for verifying the existence of a lock event on the source chain. However, the receive function does not check the legitimacy of the incoming signer. As a result, an attacker can fool the ChainSwap's router contract on the target chain by simply generating a random address and generating a corresponding signature. In the attack against the target chain, we find some characteristic patterns of the attack transactions, such as the attacker creating an attack contract and then self-destructing, which directly triggers the router contract mint of the target chain.

> **Finding 3:** In attacks against the target chain, attack transactions often exhibit similar characteristic patterns as those attacks against the source chain.

2.4 Discussion of Attack Transactions

We present a comparison of normal transactions and attack transactions on cross-chain bridges from two perspectives: trace and call chain. This provides a more intuitive understanding of their differences and offers insights for the subsequent design of a cross-chain transaction detection tool.

Transaction patterns of $\mathcal{A}_{src}$. We take the Meter.io Bridge incident as an example of $\mathcal{A}_{src}$. Fig. 3 shows the trace comparison of the attack transaction *0x2d39* and a normal transaction *0x0ad55* on Meter.io Bridge. It is illustrated that the cross-chain business logic is not executed correctly, allowing the hacker to bypass the deposit logic. To further observe the execution process, we visualize the call chain from the trace data in Fig. 3, focusing on each `CALL` or `DELEGATECALL`, with the caller as the starting point and the callee as the endpoint. The call chains for the attack and normal transactions are presented in Fig. 5. It is evident that the hacker's call chain of the attack transaction is shorter, i.e., lacks the transfer of ERC20 tokens, indicating successful bypassing of the deposit business logic on source chain.

Transaction patterns of $\mathcal{A}_{tgt}$. We take the pNetwork Bridge incident as an example of $\mathcal{A}_{tgt}$. In the withdrawal process on the target chain, pNetwork failed to correctly interpret the withdrawal event, resulting in the initiator of the withdrawal event being the hacker's address rather than the cross-chain bridge address. Fig. 4 displays the trace data of both the attack transaction *0x0eb55* and a normal transaction *0xeda1* on the pNetwork. Fig. 6 illustrates the call chain. It can be observed that the attacker first created the attack contract, and the lack of validation by the cross-chain bridge on the legitimacy of the initiator resulted in the attacker successfully initiating the withdrawal event using the attack contract. Subsequently, upon completion of the attack, the attacker invoked the `selfdestruct()` function to destroy the contract.

The existing attack detection method, XScope, requires a security pattern check of transaction pairs in the complete cross-chain process. However, we found that in many cross-chain bridge attacks, attackers may exploit off-chain verification vulnerabilities or manipulate verification mechanisms, resulting in transactions of $\mathcal{A}_{src}$ or $\mathcal{A}_{tgt}$ that lack corresponding deposit or withdrawal transactions on the target or source chain, respectively. In the dataset we collected, 65.7% of attack transactions can not find corresponding deposit or withdrawal transactions on the target or source chain. This limitation affects the detection capability of XScope.

Even when a transaction on the source chain is identified as an attack transaction, it is often difficult to establish a clear link with the withdrawal transaction on the target chain. The complexity of cross-chain business logic makes the superficial information of attack transactions on the source chain appear completely normal

[9]https://rekt.news/chainswap-rekt/

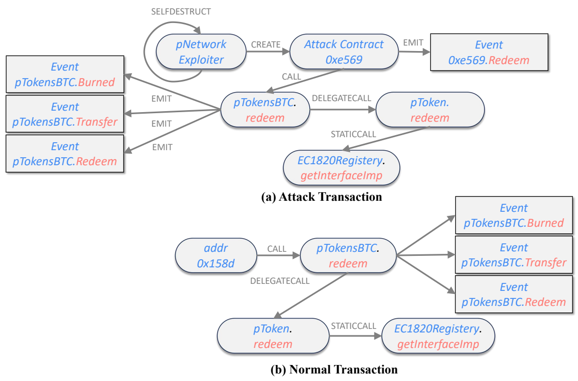


Figure 6: The call chain obtained from the traces of transactions of pNetwork Bridge

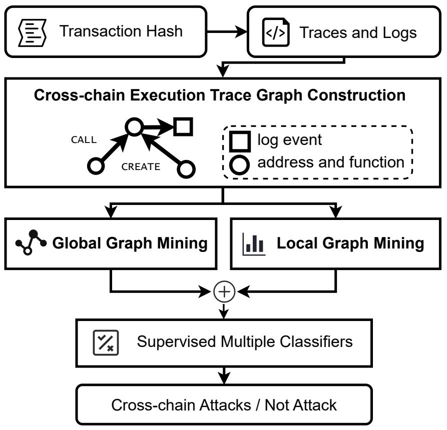

Transaction Hash
Traces and Logs
Cross-chain Execution Trace Graph Construction
CALL
CREATE
log event
address and function
Global Graph Mining
Local Graph Mining
Supervised Multiple Classifiers
Cross-chain Attacks / Not Attack

Figure 7: The workflow of BridgeGuard.

compared to legitimate operations on the target chain. For these attacks, where it is challenging to find links to deposit or withdrawal transactions, analyzing the execution flow of individual transactions provides an effective solution.

Finding 4: Single attack transactions on the cross-chain bridge, both on the source and target chain (i.e., $\mathcal{A}_{src}$ and $\mathcal{A}_{tgt}$), exhibit different transaction patterns in their transaction structures compared to normal transactions.

3 BridgeGuard: Detecting Cross-chain Attack Transactions

3.1 Challenges and Solutions

Due to the complexity and significance of cross-chain bridges, efficiently detecting cross-chain attack transactions is not a trivial task. Although significant efforts have been made in the field of DeFi smart contracts [6, 18], such as reentrancy attacks [17, 27], honeypot attacks [33], and flash loan attacks [26], the rules designed in these works do not take into account the potential defects of cross-chain bridge DApps. According to the analysis and findings in Section 2, we summarize the challenges (C) faced by our attacks transactions detection tool for cross-chain bridges, BridgeGuard, and give our proposed solutions.

C1: Expressing the execution process of cross-chain bridge transactions in a generic manner. The operation of cross-chain bridges involves complex interactions between multiple on-chain and off-chain components. Therefore, we need a universal and precise method to represent the execution process of these transactions. Additionally, the execution of cross-chain transactions involves various associated relationships, including asset transfers, cross-chain verifications, event triggering, etc., which are difficult to be effectively represented in existing works (such as XScope [38]). Since cross-chain transactions may involve calls and interactions between multiple contracts, a more flexible and comprehensive approach is needed to capture and represent these complex associated patterns. This approach not only needs to consider the internal logical relationships of transactions, but also needs to span across different chains to fully understand the execution process of cross-chain transactions.

C2: Identifying the differences in patterns between cross-chain attacks and normal transactions. Based on our empirical research analysis, cross-chain bridge attack transactions may occur on either the source chain or the target chain (i.e., $\mathcal{A}_{src}$, $\mathcal{A}_{tgt}$). According to Findings 1 and 3, cross-chain attack transactions have characteristic patterns, such as abnormal function call chains and unexpected triggers of specific contract events. Therefore, we need a method to accurately identify these pattern differences to distinguish between normal transactions and potential attack behaviors. To achieve this goal, we characterize the features of the Cross-chain Transaction Execution Graph (xTEG) at both coarse and fine levels to comprehensively express transaction patterns.

To address C1, we propose the modeling method of *Cross-chain Transaction Execution Graph (xTEG)* (see Section 3.2.1). Through this method, the relationships between each invocation and the called contracts and functions in the transactions can be clearly expressed. To address this C2, we perform global graph mining on xTEGs by mapping high-dimensional data to low-dimensional vectors, and perform local graph mining focuses on identifying recurring substructures in xTEGs, which represent specific contract execution patterns.

3.2 BridgeGuard Overview

As shown in Fig. 7, BridgeGuard detects cross-chain business logic attacks that occur on both the source and target chains. BridgeGuard starts from the cross-chain bridge attack event and obtains the log information and execution information of the attack transaction. BridgeGuard uses the tool BlockchainSpider [36] to obtain transaction-related data, including logs, traces, token transfers, and other information. Then, this information into a cross-chain transaction execution graph. After that, BridgeGuard conducts global graph mining and local graph mining of xTEG. Finally, BridgeGuard conducts attack detection based on supervised multiple classifiers. The pseudocode of BridgeGuard is illustrated in Algorithm 1.

3.2.1 *Cross-chain Transaction Execution Graphs Construction.*

We construct cross-chain transaction execution graphs (xTEGs) to represent deposit or withdrawal operations on cross-chain business processes by taking the execution and log information as inputs. Specifically, the graph is defined as follows.

Algorithm 1 BridgeGuard

```
Input: Transaction hash $tx$
Output: Transaction category $c$
1: $trace \leftarrow$ GETTRACE($tx$)
2: $log \leftarrow$ GETLOG($tx$)
3: $xTEG \leftarrow$ BUILDXTEG($trace$)
4: $global\_feature \leftarrow$ CONCAT(GRAPH2VEC($TEG$), STATISTIC($xTEG$), $log$)
5: $local\_feature \leftarrow$ MOTIF_COUNT($xTEG$)
6: $features \leftarrow$ CONCAT($global\_feature$, $local\_feature$)
7: $c \leftarrow$ CLASSIFIER($features$)
8: return $c$
```

Definition (Cross-chain Transaction Execution Graph, xTEG): *For a given transaction, the execution trace graph (xTEG) can be represented as a directed graph $xTEG = (V, E)$, where V denotes the set of vertices*

$$v \in V = \begin{cases} \text{EOA address,} \\ \text{Contract address and function,} \\ \text{Log event,} \end{cases}$$

and the set of edges E represents various types of operations:

$$e \in E = \begin{cases} \text{CALL, STATICCALL, DELEGATECALL, CALLCODE,} \\ \text{CREATE, CREATE2,} \\ \text{SELFDESTRUCT, EMIT} \end{cases}$$

3.2.2 *Global Graph Mining of xTEG .*

Graph embedding techniques can effectively transform high-dimensional discrete graph data into low-dimensional continuous vector spaces, maximally preserving the structural properties of the graph [37]. Therefore, We employ a graph embedding method Graph2vec [19] to learn global features in xTEG with the following key advantages: unsupervised representation learning that captures structural equivalence, i.e., structurally similar graphs can produce similar embeddings. Graph2vec algorithm extends the concept of word embedding from the Doc2vec algorithm [13] in natural language processing to graph embedding. It treats the entire graph as a document and considers each vertex's rooted subgraph (i.e., neighborhood) as the words in the document. The basic idea of using Graph2vec for xTEG graph mining is as follows: for each vertex in the xTEG, it first generates rooted subgraphs using the Weisfeiler-Lehman kernel (WL kernel) [28] and assigns unique labels to these subgraphs. Then, it treats the collection of all rooted subgraphs around each vertex as its vocabulary. Finally, it employs the Skip-gram optimization model [10] from Doc2vec to learn 16 dimensional vector representations for each xTEG in the dataset.

In addition, besides structural features, basic statistical features of the graph also differ between attack transactions and normal transactions. Therefore, BridgeGuard additionally computes four global graph metrics: the number of nodes $|V|$, the number of edges $|E|$, the number of logs, and network density $D = \frac{2|E|}{|V|(|V|-1)}$. In addition, we mark each transaction as a deposit or withdrawal by identifying functions in the log. To this end, BridgeGuard obtains the global feature $F_{glo} \in R^{21}$ of xTEG.

3.2.3 *Local Graph Mining of xTEG .*

In BridgeGuard's task, it is insufficient to merely characterize the contract execution process globally, as this may only distinguish between attacking and non-attacking transactions. BridgeGuard needs to further distinguish which type of defect causes attacking transactions, therefore, subsequently conducts local graph mining on xTEGs to achieve a more detailed characterization of contract execution patterns.

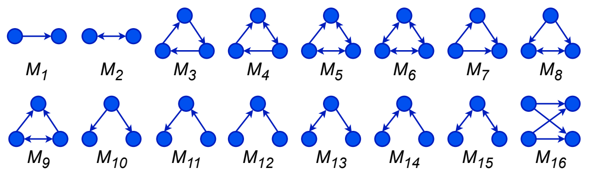


Figure 8: Network motifs.

Network motifs are recurring subgraphs in a network, whose occurrences in complex networks are significantly higher than in random networks [2]. They serve as the fundamental building blocks of networks and are effective tools for revealing higher-order network structures. Inspired by Benson *et al.* [4], we consider motifs to be a pattern of edges on a small number of nodes, as shown in Fig. 8. For each transaction's xTEG, BridgeGuard calculates the frequency of occurrence of these 16 motifs. Specifically, BridgeGuard calculates the directed motif M_1-M_{16} by subgraph matrix computation [4, 36]. Then, BridgeGuard outputs a 16-dimensional localized feature vector, where the frequency of occurrence of the i-th motif is used as the ith-dimensional feature. To this end, BridgeGuard obtains the global feature $F_{loc} \in R^{16}$ of xTEG.

We observe that cross-chain transactions exhibit distinct features in global and local levels. Those two feature vectors are combined by concatenation, i.e., $F = F_{glo}||F_{loc}$, to get a more precise and general characterization, $F \in R^{37}$.

3.3 Experimental Setup

In this part, we perform experiments to demonstrate the effectiveness of the proposed tool, BridgeGuard, in protesting cross-chain bridges against attacks. In particular, we aim to answer the following research questions (RQs):

- RQ1: How effective and efficient is BridgeGurad in detecting the attack transactions of cross-chain bridge incidents?
- RQ2: How do existing attack transaction detection tools for blockchain perform in cross-chain bridges?
- RQ3: Can BridgeGurad find new cross-chain attack transactions?

Dataset. Based on the data collection method introduced in Section 2.2, we collect 22 attacks against cross chain business logic from June 2021 and September 2024. Given that the number of normal transactions on the chain far exceeds the number of attack transactions, in order to make the distribution of the evaluation dataset as close as possible to the actual situation, we mix 203 attack transactions into 40,000 normal transactions at a rate of 0.5%. In the supervised tasks, we divide the dataset into a training set and a test set with a ratio of 7:3. Besides, we conduct ten repeated experiments to obtain averaged results.

Evaluation Metrics. We use precision, recall, F1 score, and support to demonstrate performance. We first obtain true positives (TP), false positives (FN) and false negatives (FN).

Table 1: Results of BridgeGuard under different classifiers.

Methods	Precision (%)	Recall (%)	F1-score (%)
BridgeGuard$_{DT}$	92.00	81.25	86.63
BridgeGuard$_{XGBoost}$	80.90	80.00	80.45
BridgeGuard$_{MLP}$	71.00	70.00	70.50
BridgeGuard$_{KNN}$	**92.00**	**86.50**	**89.16**

Table 2: Ablation experiments of BridgeGuard.

Features	Precision (%)	Recall (%)	F1-score (%)
BridgeGuard	92.00	86.50	89.16
BridgeGuard (w/o F_{glo})	88.00	81.00	84.35
BridgeGuard (w/o F_{loc})	82.00	85.00	83.47

3.4 RQ1: Effectiveness and Efficiency

To answer RQ1, first, we run BridgeGuard on the dataset with the supervised setting. Specifically, we obtain features F including global and local features of xTEGs for each transaction. Using the 36-dimensional features as input, we utilized various supervised classifiers are utilized as classifiers, including Decision Tree [31], eXtreme Gradient Boosting (XGBoost) [7], Multilayer Perceptron (MLP) [25], and K-Nearest Neighbor (KNN) [24].

Table 1 shows the classification results of attack transactions detection on cross-chain bridges. The attack transactions are treated as the positive sample and the other defects are treated as the negative sample. The experimental results demonstrate that the proposed features achieve an F1 score of over 70% across several classifiers, though there are significant differences in performance between them. Notably, BridgeGuard$_{KNN}$ performs the best with an F1 score of 90.25%, likely due to its adaptability to nonlinear decision boundaries. Therefore, BridgeGuard$_{KNN}$ is selected as the primary classifier in subsequent experiments.

To further validate the contribution of each feature of the proposed BridgeGuard, we conduct an ablation study as follows. We separately remove the global features (i.e. w/o F_{glo}) or remove the local features (i.e., w/o F_{loc}). The results are as shown in Table 2. Overall, recall is higher when using global features, while precision is higher when using local features. This may be due to the fact that global features are more inclined to capture the overall structure and major patterns, while local features are more focused on local details and specific structures. We can see that using only global features and using only local features resulted in a decrease in precision of 10% and 4%, respectively. Thus, the combination of global and local graph mining enables us to better capture the characteristics of transaction attacks, resulting in better results.

To evaluate the efficiency of BridgeGuard in practical detection, we conduct experiments to measure the time taken for its identification process. These experimental results are crucial for determining the usability and scalability of BridgeGuard in real-world environments. We record the detection time for different steps in BridgeGuard and list the results in Table 3.

As shown in Table 3, BridgeGuard's final transactions per second (TPS) reached 65 transactions (i.e., $\frac{1000}{15.212}$), whereas the average TPS of Ethereum is 12.4 [1]. Therefore, by pre-executing transactions in the pending transaction pool, BridgeGuard has the capability to uncover such malicious behavior before the attack transactions are

Table 3: The time consumption of BridgeGuard.

Step	Avg. Time ($second^{-3}$)
xTEG Construction for Transactions	0.253
Global Graph Mining	0.332
Local Graph Mining	14.6
Attack Detection Classifier	0.027
Total	**15.212**

Table 4: Comparison with different tools

Tools	Transactions	Precision (%)	Recall(%)	F1-score(%)
XScope	Attack ($\mathcal{A}_{src}$, $\mathcal{A}_{tgt}$)	100.00	43.68	60.80
	Normal	100.00	100.00	100.00
DeFiScanner	Attack ($\mathcal{A}_{src}$)	0.00	0.00	0.00
	Attack ($\mathcal{A}_{tgt}$)	0.00	0.00	0.00
	Normal	98.00	100.00	99.00
BridgeGuard	Attack ($\mathcal{A}_{src}$)	86.00	**66.00**	**74.68**
	Attack ($\mathcal{A}_{tgt}$)	90.00	**94.00**	**91.96**
	Normal	100.00	100.00	100.00

recorded on the blockchain. This efficient speed not only enhances the detection rate of malicious transactions, but also allows for timely defensive measures to mitigate potential losses. We notice that the most time-consuming part mainly lies in the local graph mining step. This is because calculations need to be performed for each network motif (a total of 16 considered in BridgeGuard), which is equivalent to traversing the entire graph multiple times. This highly computationally intensive process requires a significant amount of computational resources and time.

3.5 RQ2: Comparison with Existing tools

To address RQ2, we compare the performance of the state-of-the-art methods in detecting attack transactions. The methods included in the comparison are:

- XScope [38] proposes security facts and inference rules for cross-chain bridges, and then designs security properties and patterns to detect cross-chain attacks from normal transactions.
- DeFiScanner [34] focuses on detecting smart contract vulnerabilities on Ethereum from a transactional perspective. DeFiScanner employs a neural network that can detect transactions with different categories.

Table 4 presents the performance of different models in detecting cross-chain attack transactions. We observe that XScope performs exceptionally well in detecting normal transactions. However, when it comes to detecting attack transactions, the recall was only 43.68%, suggesting that XScope has a high false negative rate in detecting attack transactions. Similarly, DeFiScanner shows strong performance in detecting normal transactions (F1-score=99%), but in terms of detecting attack transactions, whether for deposit or withdrawal attacks, all metrics were zero, indicating that the tool completely failed to identify any attack transactions. In contrast, BridgeGuard not only effectively identified the majority of attack transactions (with a recall of 80%), but also demonstrated high precision, meaning that most transactions flagged as attacks were indeed genuine attack transactions.

Table 5: Newly detected attack transactions

System	Newly Detected Attack Transactions
Thorchain #1	0x99f95561c60471f1a07a8dec48d8d4f1f26cf82658d2c11645c515ee57c052b6
	0x1522b5a8e1256b605a987e997b295fae073ceab59895eec4b1f9eb3e22a366ca
pNetwork	0x975cbc1c5f9718e1aaf41288664bc99a78952d62593487baac979f3741d81e94
	0x72beef34380fa2cf96f1320f6b3cb921f9ad371970a38fed8cbde0925cef6914

In summary, BridgeGuard outperforms both XScope and DeFiScanner in detecting cross-chain bridge attack transactions, especially in identifying withdrawal attack transactions where BridgeGuard nearly achieves optimal performance. The recall of BridgeGuard is 42.5% higher than the Xscope tool. In contrast, XScope exhibits a high false negative rate in attack detection due to its reliance on predefined security patterns, which limits its ability to adapt to emerging attack patterns, making it easier for attackers to evade detection. DeFiScanner, on the other hand, is almost ineffective in detecting cross-chain bridge attacks, as it is designed for general DApp attack detection and does not account for the specific business logic of cross-chain bridges (as discussed in Section 2). Therefore, BridgeGuard stands out as the most reliable option, maintaining high precision while also delivering superior recall performance.

3.6 RQ3: Finding New Attack Transaction

To answer whether BridgeGuard can identify new attack transactions that were previously undetected by other tools. By analyzing the false positives generated by the BridgeGuard algorithm, we successfully discover attack transactions that existing tools failed to detect. Table 5 presents the attack transactions that are newly discovered using our new tool.

- **Attack transactions in Thorchain #1 incident**: Two new attack transactions, 0x99f and 0x152 are detected. The sender of these transactions is the same as that of the reported attack transaction *0x92b* Based on the findings of Su et al. [32], transactions initiated by the attacker are highly likely to be attack transactions as well. We also examine the behavior of these transactions, and find that the traces and triggered functions exhibited similar patterns to the known attack transaction.
- **Attack transactions in pNetwork incident**: We also detect two new attack transactions, 0x72b and 0x975. Both of these transactions were initiated by the attacker but are not included in the security report.

The results of this study demonstrate that our approach offers significant advantages in detecting cross-chain bridge attack transactions, particularly for newly identified attacks that were previously undetected by other tools. These newly detected attack transactions provide critical reference points for future security measures and help researchers and developers gain a better understanding of potential security threats and how to mitigate them.

4 Related Work

4.1 Security Analysis of Cross-chain Bridges

Lee *et al.* [15] describe several cross-chain bridging attacks and propose preventive measures for most of them. Notland*et al.* [21] analyzed 34 cross-chain bridge security incidents, identified 8 categories of critical vulnerabilities, and proposed 11 preventive measures. However, these studies are still insufficient in the systematic and comprehensive analysis of attacks, and may not cover all potential attack vectors. Zhang *et al.* [38] discovered three types of vulnerabilities in cross-chain bridges and proposed the Xscope monitoring tool, but its effectiveness and scalability still need to be further studied. Therefore, future research should focus on integrating the existing results and conducting more systematic empirical analysis to improve the security and reliability of cross-chain bridges.

4.2 Detection for DeFi Attacks

Research on DeFi attacks can be divided into two types: detecting from a contract perspective and detecting from a transaction perspective. From the perspective of contracts, Rodler *et al.* [27] mainly used the execution flow analysis method to detect re-entry vulnerabilities in contracts. And Chen *et al.* [6] developed a tool that can detect contract security online and expand to custom vulnerabilities. From the perspective of transactions, Zhou *et al.* [40] conducted a large-scale measurement and analysis of Ethereum transaction logs for the first time and discovered some new types of attacks, such as airdrop hunting. However, Su *et al.* [32] focused on existing attack cases and proposed the tool DEFIER to automatically investigate large-scale attack events.

5 Conclusion and Future Work

In this paper, we studied cross-chain bridge attack incidents and proposed BridgeGuard, a detection tool for attacks targeting cross-chain business processes. By analyzing 49 incidents, including 22 against business processes, we constructed cross-chain transaction execution graphs (xTEGs) and extracted features. Experimental results show that BridgeGuard outperforms state-of-the-art tools, with a recall rate 42.5% higher and the ability to detect newly discovered attack transactions. We believe BridgeGuard provides an effective solution for cross-chain bridge security and a valuable reference for future research.

For future work, we plan to explore several directions. Firstly, we aim to extend BridgeGuard to other types of cross-chain bridges, such as NFT and governance bridges, in order to achieve more comprehensive security monitoring. Secondly, we will focus on optimizing BridgeGuard's performance by improving detection efficiency and reducing resource consumption, thus meeting the requirements of real-world applications. Finally, we intend to investigate the application of large-scale language models (LLM) in cross-chain security to enhance the recognition and defense against complex attack patterns.

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A Appendix

A.1 Cross-chain Bridge Attack Incidents List

The comprehensive list of cross-chain bridge attack incidents is shown in Table 6, which includes details such as the attacked cross-chain bridges, attack date, the amount of losses, information source, attack stage of cross-chain, and reasons.

A.2 Attack that not against cross-chain business logic

As shown in Table 7, these incidents can be concluded as these categories:

- **Private Key Leakage [11].** For an EOA account, the account consists of a public and private key cryptographic pair. Its role is to prove that the transaction was actually signed by the sender and to prevent forgery. For individuals, the private key is the key used to sign transactions, so it is used to safeguard the user's management of the funds associated with the account. If a user compromises their account private key, a hacker will be able to silky-smoothly transfer any asset within their account.
- **Over-Authorisation [23].** A DeFi app obtaining authorisation from users is likely to be at risk of over-authorisation. Authorisation is essentially an on-chain transaction that requires the user to pay gas fee, and in order to avoid repeated authorisations by the user, the developer of a DeFi app will usually set the maximum number of tokens to be authorised to the smart contract by

Table 6: Cross-chain bridge attack incidents and the corresponding taxonomy.

Incidents	Attack Date	Incident Loss ($)	Information Source	Attack Stage of Cross-chain	Reason
THORChain #2	2021/07/16	5,000,000	Rekt News	Source Chain	Fake Lock Event
Qubit	2022/01/01	80,000,000	Rekt News	Source Chain	Fake Lock Event
Meterio	2022/02/06	4,200,000	Rekt News	Source Chain	Fake Lock Event
THORChain #1	2021/06/29	350,000	Slowmist	Source Chain	Fake Deposit Event
THORChain #3	2021/07/23	8,000,000	Rekt News	Source Chain	Fake Deposit Event
QAN Platform	2022/10/11	2,000,000	Rekt News	Source Chain	Fake Deposit Event
Anyswap #1	2021/07/10	7,900,000	Rekt News	Off-chain	Verification failure
Levyathan	2021/07/30	1,500,000	Rekt News	Off-chain	Verification failure
Ronin #1	2022/03/29	625,000,000	Rekt News	Off-chain	Verification failure
Rainbow(NEAR) #1	2022/05/02	0	Notland *et al.* [20]	Off-chain	Verification failure
Nomad	2022/08/01	190,000,000	Rekt News	Off-chain	Verification failure
Binance bridge	2022/10/08	566,000,000	Rekt News	Off-chain	Verification failure
Poly Network #2	2023/07/01	10,200,000	Rekt News	Off-chain	Verification failure
Ronin #2	2024/08/06	12,000,000	Rekt News	Off-chain	Verification failure
Poly Network #1	2021/08/11	600,000,000	Rekt News	Off-chain	Verification failure
ChainSwap	2021/07/11	8,000,000	Rekt News	Target Chain	Unverified withdrawal
pNetwork	2021/09/20	13,000,000	Medium	Target Chain	Unverified withdrawal
wormhole	2022/02/03	320,000,000	Rekt News	Target Chain	Unverified withdrawal
Ankr	2022/12/02	24,000,000	Rekt News	Target Chain	Unverified withdrawal
Hypr bridge	2023/12/14	220,000	Rekt News	Target Chain	Unverified withdrawal
X bridge	2024/04/24	1,440,000	Rekt News	Target Chain	Unverified withdrawal
Polygon Plasma	2021/10/21	850,000,000	Medium	Target Chain	Unverified withdrawal
Zapper	2021/06/10	0	Notland *et al.* [20]	Not specific to cross-chain process	Over-Authorisation
Anyswap #2	2022/01/18	3,000,000	Notland *et al.* [20]	Not specific to cross-chain process	Over-Authorisation
Li Finance	2022/03/20	600,000	Medium	Not specific to cross-chain process	Over-Authorisation
Badger	2022/12/02	120,000,000	Rekt News	Not specific to cross-chain process	Over-Authorisation
Rubic	2022/12/25	1,400,000	Slowmist	Not specific to cross-chain process	Over-Authorisation
Hashflow	2023/07/14	600,000	Medium	Not specific to cross-chain process	Over-Authorisation
Socket tech	2024/01/16	3,300,000	Notland *et al.* [20]	Not specific to cross-chain process	Over-Authorisation
ALEX Lab	2024/05/15	4,300,000	Rekt	Not specific to cross-chain process	Private key leakage
Hector Network	2024/01/15	27,000,000	Notland *et al.* [20]	Not specific to cross-chain process	Private key leakage
Orbit chain	2023/12/31	81,500,000	Rekt News	Not specific to cross-chain process	Private key leakage
Heco bridge	2023/11/22	99,100,000	Rekt News	Not specific to cross-chain process	Private key leakage
pGala	2022/11/04	10,800,000	Slowmist	Not specific to cross-chain process	Private key leakage
Harmony	2022/06/23	100,000,000	Rekt News	Not specific to cross-chain process	Private key leakage
Marvin Inu	2022/04/11	350,000	Notland *et al.* [20]	Not specific to cross-chain process	Private key leakage
Allbridge	2023/04/01	57,000,000	Medium	Not specific to cross-chain process	Flash-loan
Zenon	2021/11/21	1,000,000	Rekt	Not specific to cross-chain process	Flash-loan
Multichain	2023/07/06	126,300,000	Rekt News	Not specific to cross-chain process	Rug-pull
Ordizk	2024/03/05	14,000,000	Certik	Not specific to cross-chain process	Rug-pull
Bondly	2021/07/15	5,900,000	Rekt News	Not specific to cross-chain process	Rug-pull
LayerSwap	2024/03/20	100,000	Slowmist	Not specific to cross-chain process	DNS hijacking
Celer Bridge	2022/08/18	20,000	Slowmist	Not specific to cross-chain process	DNS hijacking
EvoDeFi Bridge	2022/03/08	0	Slowmist	Not specific to cross-chain process	DNS hijacking
deBridge	2022/08/06	0	Notland *et al.* [20]	Not specific to cross-chain process	Phishing email
Rainbow(Aurora)	2022/05/02	0	Notland *et al.* [20]	Not specific to cross-chain process	False transaction
Rainbow(NEAR)	2022/08/22	0	Notland *et al.* [20]	Not specific to cross-chain process	Fabricated block
Omni Bridge	2022/09/16	4,200,000	Notland *et al.* [20]	Not specific to cross-chain process	Replay attack
Meson Finance	2024/04/19	0	Slowmist	Not specific to cross-chain process	Hacked twitter

Table 7: A summary of the 27 attacks that were not against Cross-chain Bridge business logic.

Reason	Number	How BridgeGuard Can Be Used
Over-Authorisation	7	Over-authorisation is a vulnerability in cross-chain bridge contracts. If such vulnerable contracts are already deployed, BridgeGuard can assist detection using a pre-execution module.
Private Key Leakage	7	Private key leakage is often due to social engineering attacks. BridgeGuard cannot prevent such leaks, as crypto attack detection studies generally do not address this issue.
Flash-loan	2	By modeling transactions on-chain, BridgeGuard can detect such attacks (similar to the comparative method, DeFiScanner). However, flash-loan attacks are not the primary focus of this study.
Rug-pull	3	Not explicitly discussed in the study.
DNS Hijacking	3	DNS hijacking involves attackers redirecting users to fake domains or IPs and falls under network-layer attacks. These are outside the scope of application-layer attack detection, including BridgeGuard's focus.
Others	5	These issues relate to ecosystem security but focus on social engineering, consensus, or network-layer attacks, not cross-chain logic. (Phishing email: 1, False transaction: 1, Fabricated block: 1, Replay attack: 1, Hacked Twitter: 1)

default. However, such a process also obviously exposes the risk, if the smart contract has a loophole or the contract administrator is evil, then the user's tokens will be at risk of loss, which is the problem of over-authorisation of the Dapp.

- **Others.** Other attacks that are not specific to cross-chain bridges include flash-loan [26], rug pull [41], front-end hacking [9], etc.

B Discussion

Internal Validity. BridgeGuard focuses on attacks caused by on-chain contract defects, while attacks caused by off-chain components are not considered in this paper. Additionally, although BridgeGuard currently supports the detection of four types of on-chain contract defects, its method is based on xTEG, which allows for the detection of additional types of defects. Specifically, in global graph mining, the training parameters of Graph2vec can be adjusted as needed, such as setting a larger embedding dimension to retain more information. In local graph mining, new computing modules can be added based on the substructure features of newly identified defect types. Finally, it is worth noting that BridgeGuard primarily targets cross-chain bridges for fungible asset transfers, and other types of bridges such as Non-Fungible Token (NFT) bridges, governance bridges, ENS bridges, etc., are out of scope. However, our framework can easily be extended to other types of property transfers, as these transactions can also construct xTEGs for detection.

External Validity. In our empirical study, relying on manual labor during the data collection and organization process could introduce human errors. To mitigate this dependence, we ensure that each event was reviewed by at least two paper authors. Additionally, our dataset primarily originates from four public resources (Slowmist, Rekt and ChainSec) and two academic SoK papers (Zhang *et al.* [39] and Notland *et al.* [20]). To the best of our knowledge, theseresources constitute the most extensive accessible database of cross-chain bridge incidents. However, we cannot fully evaluate whether these sources contain biased cases, as we do not know how they collect attack events. This may lead to more attacks being overlooked. Although we cannot confirm the collection pathway for a single data source, we reduce bias in our data by integrating multiple data sources.