Interface Illusions: Uncovering the Rise of Visual Scams in Cryptocurrency Wallets

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ABSTRACT

Cryptocurrencies, while revolutionary, have become a magnet for malicious actors. With numerous reports underscoring cyberattacks and scams in this domain, our paper takes the lead in characterizing visual scams associated with cryptocurrency wallets—a fundamental component of Web3. Specifically, scammers capitalize on the omission of vital wallet interface details, such as token symbols, wallet addresses, and smart contract function names, to mislead users, potentially resulting in unintended financial losses. Analyzing Ethereum blockchain transactions from July 2022 to June 2023, we uncovered a total of 24,901,115 visual scam incidents, which include 3,585,493 counterfeit token attacks, 21,281,749 zero-transfer attacks, and 33,873 function name attacks, orchestrated by 6,768 distinct attackers. Shockingly, over 28,414 victims fell prey to these scams, with losses surpassing 27 million USD. This alarming data underscores the pressing need for robust protective measures. By profiling the typical victims and attackers, we are able to propose mitigation strategies informed by our findings.

CCS CONCEPTS

• **Security and privacy → Web application security**; **Phishing**;
• **Applied computing → Digital cash**.

KEYWORDS

cybercrime, scam, cryptocurrency wallet, phishing, visual scam

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1 INTRODUCTION

The blockchain market is a vast field that encompasses various applications, such as digital currencies, smart contracts, and decentralized platforms. According to Fortune business insights [28], the global market size reached $11.14 billion in 2022 with a projected market size of $469.49 billion by 2030. However, as the market expands, the risks of cryptocurrency scams are increasingly evident.

Meanwhile, cryptocurrencies have attracted extensive attention from attackers. CipherTrace reports that total losses exceeded $681 million due to major hacks, thefts, and frauds up to July 2021 [13]. In February 2022, cryptocurrency exchange platform Wormhole lost $320 million after a cyberattack [42]. Recently, emerging scams are also profiting from cryptocurrencies such as the BitConnect Ponzi scheme that resulted in billion-dollar losses [4, 12] and Squid coin scam where fraudsters solicited investments by using the name of "Squid Game", netting $3 million in profits [43].

Traditional cryptocurrency scams have been studied deeply [25, 44, 54, 56]. However, a burgeoning category remains underexplored: the visual scams associated with cryptocurrency wallets, a cornerstone of Web3 [18]. This scam exploits the absence of crucial wallet interface details—token symbols, wallet addresses, and smart contract function names—to mislead victims into purchasing counterfeit tokens, initiate transactions to attackers, and trigger unintended smart contract function calls (Section 2).

This paper takes the first step to characterize the visual scams of cryptocurrency wallets. We expose three types of visual scams: Counterfeit Token Scam, Zero-Transfer Scam, and Function Name Scam (Section 3). By analyzing 2,542,283 blocks, encompassing 439,890,433 ERC-20 transactions between July 2022 and June 2023, we identify 24,901,115 visual scam incidents orchestrated by 6,768 distinct attackers. Our analysis identifies that over 28,414 victims were defrauded, resulting in losses exceeding 27 million USD.

To further illuminate the ecosystem of these emerging visual scams in cryptocurrency wallets, we conducted a comprehensive study (Section 4). Our objectives were to understand the scam strategies and determine which user demographics are most susceptible.

Based on our quantitative measurement results, we have reported the scammer and toolkit addresses to Etherscan [19] and received their acknowledgment. Besides, we propose mitigation approaches for cryptocurrency wallets, such as educating new-coming wallet users, balancing the security-critical information and UI design, and integrating effective real-time detection methods (Section 5).

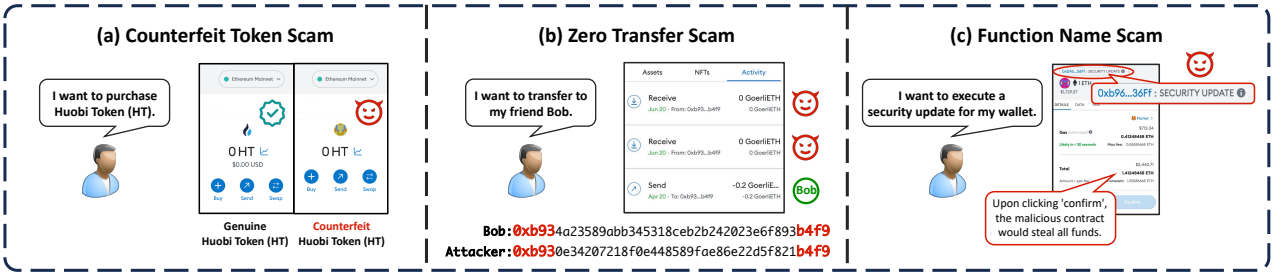


Figure 1: Motivating Example of Visual Scams

We believe this work will raise awareness among the security community regarding visual scams, and encourage the development of more secure wallets to promote long-term growth of the industry. We summarize the contributions as follows:

• We introduce the first large-scale longitudinal measurement study for visual scams in cryptocurrency wallets, identifying 24M scam incidents executed by 6,768 attackers.

• We discover the unique ecosystem of visual scams in cryptocurrency wallets, revealing the profile of scam tokens, victims and attackers, and evaluating their profit gains of such scams.

• We propose possible mitigation approaches for cryptocurrency wallets, such as educating new-coming wallet users, balancing the security-critical information and UI design, and integrating effective real-time detection methods, based on our quantitative findings.

2 BACKGROUND

2.1 Motivating Example

Cryptocurrency wallets like MetaMask [39], Coinbase [14], and Trust Wallet [53] are pivotal interfaces for users to manage their on-chain assets. They allow transactions, such as buying, storing, and transferring, with just a few simple clicks. With the rise of mobile computing, wallets have expanded to mobile apps and browser extensions. However, in aiming for user-friendly designs, some wallets omit "unnecessary" but security-sensitive details, giving scammers a chance to conduct visual scams.

As shown in Figure 1-a, Alice intends to buy Huobi Token, whose symbol is HT. When presented with a counterfeit token, the wallet still only displays the "HT". The only discernible visual difference between the genuine and counterfeit tokens is their logos, which can easily deceive Alice due to their resemblance.

In Figure 1-b, when Alice wishes to transfer tokens, the wallet shows a list of recent contact addresses. Alice might choose an address based on matching prefixes and suffixes, assuming it's the right one. However, the wallet's interface omits full address details, making it possible for Alice to inadvertently pick a scammer's address with a similar prefix and suffix, leading to potential losses.

As depicted in Figure 1-c, Alice is misled into upgrading the wallet's security and approves a smart contract labeled `securityUpdate`. The wallet only shows the attacker-configured smart contract function name, concealing that the underlying transaction will transfer Alice's balance to the scammer.

2.2 Threat Model

The visual scams in cryptocurrency wallets neither require access to user devices or exploiting the devices with vulnerability, *i.e.*, privilege escalation, nor do they require users to install compromised wallets or malicious apps. The root cause of such scams is mainly the omission of vital details, such as the truncation of Ethereum addresses and the simplistic display of token symbols and function names. The scams revealed in our paper—Counterfeit Token Scam, Zero-Transfer Scam and Function Name Scam, are designed to mislead users to purchase the wrong token, make transactions to the incorrect address, or invoke evil functions. These scams highlight the dilemma of balancing user-friendliness and a security-centric design within the constraints of limited GUI space.

3 DETECTION APPROACH

In this section, we begin by illustrating the mechanisms behind Counterfeit Token Scam, Zero-Transfer Scam, and Function Name Scam. Following that, we present the detection methodologies and their corresponding implementations based on their scam logic.

3.1 Counterfeit Token Scam

Scam logic. In Counterfeit Token Scam, a victim, referred to as Alice, intends to purchase or exchange Huobi Token. However, an attacker sends a counterfeit Huobi Token address to her. Despite being counterfeit, the wallet displays the token symbol, HT, which matches the genuine token's symbol, thereby deceiving Alice.

The root cause of this issue lies in the two fundamental attributes specified in the ERC-20 standard: *token name* and *token symbol* [51]. The symbol usually serves as a shorter version of the name. Despite these attributes act as the primary features for rendering on wallets and identifying tokens, they can be freely defined by the token's creator during contract deployment. This flexibility allows attackers to deploy counterfeit tokens with attributes identical to the genuine ones. Meanwhile, for the sake of user-friendliness, cryptocurrency wallets only display these two attributes on the UI, omitting the token address, which differentiates genuine and counterfeit tokens. As a result, the visual similarities between genuine and counterfeit tokens can lead to significant risks of deception.

Detection methodology. To detect counterfeit tokens, we first summarize the most popular forgery methods employed by counterfeit tokens; then we traverse the full ERC-20 token list to discover the counterfeit tokens which satisfy these forgery methods. Specifically, to summarize the forgery methods, we look at scam

Table 1: Forgery Methods of Counterfeit Tokens

Forgery Method	Token Name	Token Symbol	Source
Benign	Tether USD	USDT	
Identical	Tether USD	USDT	[22, 25]
Cross	USDT	Tether USD	[23, 24]
Combo	TetherToken	USDT	[33, 49]
Homograph	Tether USD	ᑌSDT	[45, 49]

reports [3, 22], and academic researches [25, 33, 45]. Finally, we summarized the following four methods and examples in Table 1.

• **Identical forgery**, where the counterfeit token's name and symbol are identical to the genuine one. For example, a counterfeit token (address `0x6d9952`[1]) has identical symbol and name to the genuine USDT token (address `0xdAC17F`[2]). The identical forgery has the most convincing deceptive effects. Due to some cryptocurrency wallets and blockchain explorers tagging identical forgery tokens with warning labels, we witness the attackers also employ the following evasion forgery methods.

• **Cross forgery** involves swapping the name and symbol fields of the genuine token when assigning them to the counterfeit token, *i.e.*, a counterfeit token (address `0x89E894`[3]) has a swap symbol and name to the genuine USDT token. We've noticed a variation of cross forgery where the counterfeit's name and symbol are either both USDT or both Tether USD, like `0x4a401c`[4].

• **Combo forgery** entails adding or removing keywords—`["s","coin","token","usd","defi","protocol"]`, to the fields of the genuine token, ensuring that the semantic meaning of the counterfeit token's attributes remains unchanged, *i.e.*, a counterfeit token (address `0x966657`[5]) uses TetherToken as its name, instead of the exact match Tether USD.

• **Homograph forgery** involves replacing standard letters with visually similar special characters, *i.e.*, a counterfeit token (address `0xA9ffFc`[6]) using the Ethiopic letter "ᑌ" in place of "U", aiming to make the counterfeit token's attributes visually consistent with the genuine USDT token.

Implementation. To begin our comprehensive detection, we sourced the ERC-20 token dataset from the Blockchair [6] database, which served as our primary candidate dataset. As of September 26, 2023, we have fetched 799,519 tokens. Drawing inspiration from previous phishing detection research [38], our study focuses on cryptocurrencies with the highest market capitalization. To this end, we retrieved a list of the top 200 cryptocurrencies from CoinGecko [16]. For each targeted token, we applied the aforementioned forgery methods to compile the list of potential counterfeits. Subsequently, we excluded genuine tokens verified by CoinGecko and defined by cryptocurrency exchanges [19], and examined whether any ERC-20 token matched entries from this list.

Specifically, for identical forgery and cross forgery, we sanitize the name and symbol fields of the tokens, retaining only numbers and letters converted to lowercase for respective matching. For combo forgery, we test all the scenarios of adding or removing keywords and then proceed with the corresponding match. For homograph forgery, we assess whether the token fields are visually similar to the genuine tokens by substituting with special characters. Given the absence of a complete homograph table, we constructed one base on Unicode Database [50], and previous related works [47, 57]. The full list of homographs used in our study can be found in Table 5 in Appendix E. Finally, we detect 9,442 ERC-20 counterfeit tokens targeting at the top 200 cryptocurrencies.

3.2 Zero-Transfer Scam

Scam logic. We have identified two distinct types of Zero-Transfer Scam. One is crafting victims' recent transaction records by impersonating recipients, and the other is crafting victims' recent transaction records by impersonating senders. Both types of impersonation attacks capitalize on the previous transactions between two parties, commonly referred to as `Alice` and `Bob`, which can be observed on the blockchain.

• **Impersonating recipient attack** is launched in the following manner: ❶ The attacker generates numerous account addresses and selects an address that has the same prefix and suffix to `Bob`, denoted as `B0b`, to act as the impersonating recipient. ❷ The attacker uses the `transferFrom` function to send a zero-amount from `Alice` to `B0b`. Notably, within the ERC-20 specification, if the transfer amount is zero, there's no need for authorization from the `approve` function [51], which allows the attacker to make a transfer from `Alice` without needing `Alice`'s private key. ❸ Above step results in a transfer record from `Alice` to `B0b` appearing in `Alice`'s transaction records, which has a similar appearance to the previous genuine records. When `Alice` plans another transfer to `Bob`, she might mistakenly copy `B0b`'s address from her recent transaction records. This error is due to the truncated display of account addresses, where both `Bob` and `B0b` appear identically as "`B...b`".

• **Impersonating sender attack** is the other subcategory of Zero-Transfer Scam. The attack process unfolds as follows: ❶ The attacker generates numerous Ethereum addresses and selects an address similar to `Alice`, denoted as `Al1ce`, to act as the impersonating sender. ❷ The attacker then uses `Al1ce` to initiate a zero-amount transfer to `Bob`. This creates and inserts a transfer record from `Al1ce` to `Bob` in `Bob`'s transaction history. ❸ Later, when `Bob` wishes to transact with `Alice`, he may mistakenly choose `Al1ce` as the recipient. This error is facilitated by the omitted display of account addresses on cryptocurrency wallets, where both `Alice` and `Al1ce` appear indistinguishably as "`Al...ce`".

Detection methodology. The detection methodology for Zero-Transfer Scam can be divided into the following steps. First, we analyze the display patterns of the popular cryptocurrency wallets and reveal to which degree the impersonating address will have an identical appearance to the genuine one. Then, if `Alice` received a zero-transaction from `B0b`, or if `Bob` received a zero-amount transfer from `Al1ce`, we take these transfers as zero-transfer attacks. What worse, if `Alice` makes a non-zero-amount transfer to the impersonating recipient `B0b`, or if `Bob` initiates a non-zero-amount

[1] `0x6d995217db76437ea053770dDaB27aA90a298bCa`
[2] `0xdAC17F958D2ee523a2206206994597C13D831ec7`
[3] `0x89E89442Cc2B6e24D43759a7BF5EE1a0029D7BB1`
[4] `0x4a401c912755b2b1e6e486655a74A01c4d455B66`
[5] `0x966657c10A2529Cf7A08B310A13ae0b338B209A6`
[6] `0xA9ffFc9764Ad80362460cb3fb52E53A752053f5d`

Table 2: Address Display Patterns of Transfer Records in Mainstream Cryptocurrency Wallets

Wallet Client	Display Pattern	Total Users [11]
MetaMask Extension	`0xaaa...bbbb`	22M
MetaMask Mobile	`0xaaaa...bbbb`	10M
Coinbase Wallet Mobile	`0xaaaa...bbbb`	10M
imToken Mobile	`0xaaaa...bbbb`	1M
Trust Wallet Extension	`0xaaa...bbbbb`	1M
Trust Wallet Mobile	`0xaaaaa...bbbbbbb`	10M

transfer back to the impersonating sender `Al1ce`, we define this transaction as a successful zero-transfer attack.

Specifically, to thoroughly identify impersonating addresses, we examined mainstream wallets spanning both mobile platforms and browser extensions. These include MetaMask [39], Coinbase [14], imToken [26], and Trust Wallet [53]. Subsequently, we manually assessed how many digits of the address in the transaction history were obscured by each wallet.

Implementation. After examining six mainstream wallet clients, as shown in Table 2, we find that showing the first three and the last four hex digits of the account addresses represents the majority of wallets' abbreviation patterns. Besides, we have considered the collision risk of legitimate addresses. The collision probability is $1/16^{3+4} = 1/268,435,456$, while there have been 439,890,433 ERC-20 transactions in the past year. Ideally, there would be two coincidences, which is negligible to numerous attacks.

After the timestamp of a normal transfer from `Alice` to `Bob`, if `Alice` make a zero-amount transfer to the impersonating recipient `B0b`, or if `Bob` receive a zero-amount transfer from the impersonating sender `Al1ce`, we define these zero-amount transfers as zero-transfer attacks. Following the attack, if `Al1ce` or `B0b` receive transfers from the victim, the attack is considered to be successful.

We retrieve the list of genuine tokens from CoinGecko [16]. To boost our traversal performance, we deployed an Ethereum full node with Erigon [35]. We traverse through all ERC-20 transfers to obtain all genuine token transfers with a zero-amount, while building hash tables for quicker retrieval. For every zero-amount transfer, we determine the presence of zero-transfer attacks and successful attacks based on the method defined above.

3.3 Function Name Scam

Scam logic. Smart contracts are increasingly utilized in various sectors, including finance, gaming and other legal industries, to conduct business autonomously without human intervention. Like the traditional computer programs, each function in a contract is defined by its name and body. When users engage with these contracts, most cryptocurrency wallets only present the function's human-readable name, instead of the function code.

However, a concerning trend has emerged where attackers assign deceptive function names, such as `securityUpdate` or `claimRewards`, that don't align with the function's code behavior. Instead of executing the expected actions, these malicious functions merely seek users' authorization to steal their cryptocurrencies. By pairing these misleading function names with phishing webpages or messages, attackers can trick users into signing transactions or granting permissions that, concealed from them, drain their funds.

Detection methodology. The key to detecting function name scams lies in determining whether the direction of funds flow aligns with the function name semantics. For instance, `securityUpdate` implies funds hold, `claimRewards` indicates funds inflow, while `transfer` suggests funds outflow. Specifically, we focus on transactions where funds are outgoing, even though the function names do not inherently suggest such outflow semantics.

To retrieve function names with misleading semantics, we employ the snowball algorithm. Initially, we gathered deceptive function names from anecdotal reports. We then iteratively assess function names based on the nearest semantic embedding distance and manually label those with misleading semantics. In the final step, we investigate whether such functions launch outgoing transactions.

Implementation. By examining all Ethereum transactions over a year, we pinpointed 25,982 function names that were actually used. Our initial dive into scam reports [20, 21] highlighted two potentially deceptive function names: `securityUpdate` and `claimRewards`. Inspired by them, we concentrate on two specific types and manually inspect 1,000 function names to expand the seed set. The first type is those misleading users with "free rewards"—`["upgradeReward","benefitFunds","claimBounty","claimGift','claimFreeTokens","bonusReward"]`. The second type is those misleading users with "system routine"—`["updateProtections","login","safeUpgrade","updateSystem"]`. With these 12 names as seeds, we employed a method inspired by feature propagation [29] to sift through all the function names.

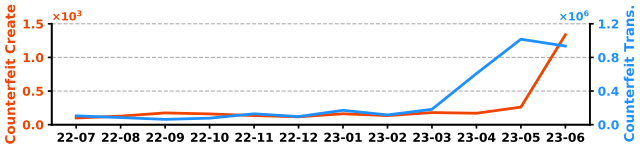
Utilizing Google's pre-trained Bert model [17], we extracted feature vectors from function names. For each seed, we identified the three closest function names by Euclidean distance, incorporating them for the next iteration. This cycle repeated two times, culminating in the identification of 156 function names. We manually reviewed these function names and excluded 16 whose semantics suggested fund outflows, leaving 140 potentially misleading function names. During the traversal process of Ethereum transactions, if we identified a transaction that results in fund outflows and its input data aligned with any of the misleading function names, we determined that this transaction is an instance of Function Name Scam. Finally, we identified 17 distinct scam functions originating from seven deceptive function names, which are fully presented in Table 4 in Appendix D.

4 MEASUREMENT

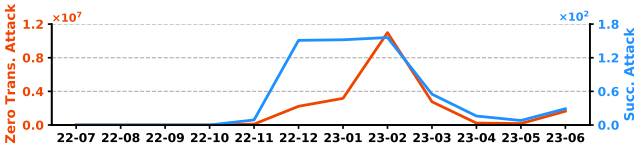
In this section, we conduct a comprehensive study to determine: when visual scams occur, and which tokens are targeted by scammers. Interestingly, we also examine the types of victims they primarily target and the toolkits employed by the scammers, and estimate the revenue garnered from such scams.

4.1 Landscape

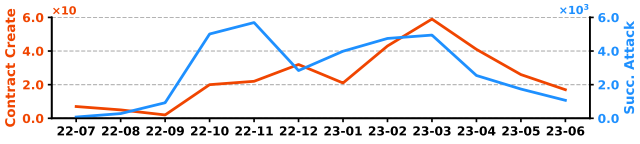
Scale. Our study was conducted on the Ethereum blockchain from July 1, 2022 to June 30, 2023. Within this period, we examined 2,542,283 blocks, encompassing 439,890,433 ERC-20 transactions. Leveraging the detection approach detailed in Section 3, we successfully identified a total of 24,901,115 visual scam attacks, comprised



(a) Timeline of Counterfeit Token Scam



(b) Timeline of Zero-Transfer Scam



(c) Timeline of Function Name Scam

Figure 2: Timeline of Visual Scams

Table 3: Distribution of Visual Scams

Scam Type	Analysis Dimension	Category (Top 5)	# (%)
Counterfeit Token	Token Types (# of Tokens)	USDT	2,115 (22.4%)
		ETH	1,449 (15.3%)
		USDC	984 (10.4%)
		HT	653 (6.9%)
		BTC	401 (4.2%)
	Forgery Methods (# of Tokens)	Identical	3681 (39.0%)
		Cross	3309 (35.0%)
		Combo	1713 (18.1%)
		Homograph	739 (7.8%)
Zero-Transfer	Token Types (# of Succ. Attacks)	USDT	307 (53.3%)
		USDC	194 (33.7%)
		BUSD	18 (3.1%)
		DAI	13 (2.3%)
		QNT	12 (2.1%)
Function Name	Function Names (# of Succ. Attacks)	securityUpdate	25,442 (75.1%)
		claimRewards	4,979 (14.7%)
		claimReward	2,911 (8.6%)
		claimQuestRewards	528 (1.6%)
		upgradeStrength	11 (0.03%)

of 3,585,493 counterfeit token attacks, 21,281,749 zero-transfer attacks and 33,873 function name attacks.

According to the results, we determined 5,307 counterfeit token scammers who issued 9,442 counterfeit tokens, 1,193 zero-transfer scammers who utilized 1,057 malicious contracts, and 268 function name scammers who deployed 309 malicious contracts based on 17 deceptive functions. In total, these scams resulted in financial losses of 27,359,760 USD for 28,414 victims (see Section 4.4).

Timeline. The digital realm has witnessed dynamic shifts in terms of security threats over recent years. Moreover, the timeline pattern of the three visual scams varies a lot, as shown in Figure 2.

Historically, the creation and transfer volumes of counterfeit tokens have remained at a relatively low level. However, there was a sudden surge in 2023 Q2. In June 2023, counterfeit creations and corresponding transfers were 7.43 times (1,337 vs 180) and 5.12 times (935,086 vs 182,668) more than in March 2023 respectively.

Zero-Transfer Scam was first identified on TRON network [27]. It didn't take long before Ethereum became a major target, with attacks amplifying in scale from December 2022. Over the next two months, the scale of zero-transfer attacks expanded dramatically, peaking at 5,254,205 attacks in February 2023, with the number of successful attacks reaching its peak of 153 monthly cases. Subsequently, the trend started to decline, but there was a sign of a potential rebound in June 2023.

For Function Name Scam, there were only 75 successful function name attacks in July 2022, but this number soared to 5,693 in November. Throughout the year, two peak periods of Function Name Scam emerged: the first around November 2022 and the second around March 2023, which was larger in scale and duration.

Distribution. Table 3 depicts the distribution of the three scams according to their token types, forge methods and function names. Among the top 200 cryptocurrencies, we witness that 181 have been subject to counterfeiting. Out of the 9,442 counterfeit ERC-20 tokens we detected, 6,353 are designed to imitate legitimate ERC-20 tokens (*e.g.*, USDT and USDC), while 3,089 are modeled after non-ERC-20 tokens (*e.g.*, BTC and ETH). USDT tops the list as the most frequently forged token, with a total of 2,115 counterfeits. It's followed by ETH and USDC, which have 1,449 and 984 counterfeits respectively. This highlights a notable issue: many victims seem to lack a basic understanding of blockchain, given that ETH and Bitcoin are not ERC-20 tokens, which can not be bought through Ethereum token transaction.

Finding I: *Many victims of visual scams have a limited understanding of cryptocurrency, as evidenced by their attempts to purchase Bitcoin on the Ethereum blockchain.*

Regarding forgery methods, only 39.0% of counterfeit tokens precisely replicate genuine tokens. This observation underscores a key difference between counterfeit cryptocurrencies and traditional counterfeit currencies in the real world, which often aims for a precise imitation. However, 61.0% of ERC-20 counterfeit tokens deliberately diverge from their genuine versions, which indicate that they tend to utilize such difference to bypass possible mitigation applied by cryptocurrency wallets.

Zero-Transfer Scam primarily focuses on high-circulation ERC-20 tokens. Among the most affected are Ethereum's popular stablecoins, with USDT and USDC accounting for 87.0% of the zero-transfer scams. Stablecoins, due to their 1:1 peg with fiat currencies, possess substantial liquidity and volume in the cryptocurrency market, often serving as trading intermediaries. Their widespread use positions them as prime attractions for attackers.

We observed that the toolkits of Function Name Scam show a long-tail distribution. 75.1% of successful attacks were attributed to the function name `securityUpdate`. Following this, three function names related to "reward"—`claimRewards`, `claimReward` and `claimQuestReward`—together accounted for 24.9% of successful attacks. The remaining function names represented a minor fraction with only 13 successful attacks.

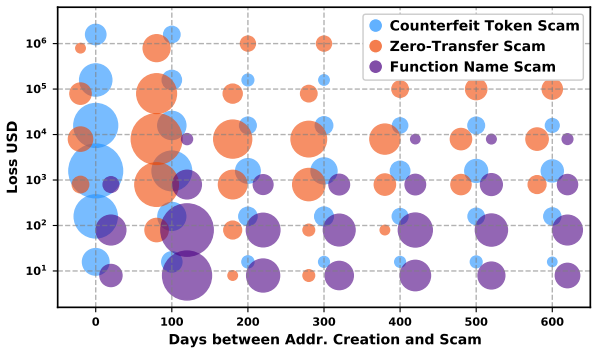


Figure 3: Temporal and Monetary Analysis of Victim Profile

4.2 Victim Profile

Figure 3 provides an insightful victim profile of visual scams based on two metrics: the horizontal axis representing the time elapsed between the account address creation and the scam event, and the vertical axis indicating the victim's cryptocurrency losses (converted to USD). The size of each circle denotes the number of victims. Notably, for Counterfeit Token Scam, we can not directly understand how much financial losses have been made during the victims receiving such counterfeit tokens. To conduct a conservative estimation, we refer to the method used in a previous work—using the value of the corresponding genuine tokens instead [25].

Temporal analysis. As depicted in Figure 3, different types of scams target victims based on their address creation time. Counterfeit Token Scam (blue circle) is situated closest to the left of the graph. Remarkably, 39.1% of account addresses received counterfeit token transfers on the first day of their creation. This suggests a significant portion of the victims had no prior experience with blockchain and Ethereum before falling prey to this scam. Furthermore, 59,1% of the addresses that received counterfeit token transfers were newly created wallets within four months, indicating that attackers predominantly target newcomers.

Finding II: *Newly created accounts, particularly those within the first four months, are favored targets for attackers, enduring approximately 60 percent of the counterfeit token scams.*

Zero-Transfer Scam (orange circle) predominantly targets addresses created within roughly 200 days of their inception. Notably, 37.5% of its victims are deceived within their first four months, suggesting that newer cryptocurrency wallet users are more vulnerable to this visual scam compared to seasoned counterparts.

Function Name Scam (purple circle) shows a broader spread across the timeline, suggesting that more "experienced" users might fall victim to this scam. The victim with the highest loss, `0x0E7A6b`[7], an Ethereum user for six years, was scammed by the deceptive function name `claimRewards`, losing the entire balance of 495 ETH, equals to 956,510 USD.

We uncovered a total of 33,873 successful function name attacks, affecting 27,854 victims. Alarmingly, 10.1% of victims fell for Function Name Scam more than once. The account address `0xD256A2`[8] approved three malicious contracts consecutively 21 times within 98 days, which included calling one `claimRewards` function 18 times, one `securityUpdate` function twice, and another `securityUpdate` function once. This behavior indicates that even after multiple deceptions, the user of this address remained oblivious to the significant risk these contracts posed to their assets.

Finding III: *10.1% of victims were repeatedly scammed by malicious contracts, with someone falling 21 times serially.*

Monetary impact. As shown in Figure 3, Zero-Transfer Scam is the most skewed towards the top of the graph, which means the victims suffer the highest loss among the three scams, with an average loss of $30,126 per victim. Specifically, among the 560 victims of this scam, 42 victims suffered losses greater than 100,000 USD. We discovered that these victims share common characteristics: they had recently made large transfers, or they had significant balances in their wallet addresses.

Given the transparency of blockchain's distributed ledger, we inferred that attackers selectively target valuable addresses by examining on-chain data like transaction histories and account balances. `0x081714D`[9] suffered the most significant loss in this scam, losing 2,030,000 USDC to an impersonating recipient. The victim was deceived only 42 days after the creation of this address and was targeted by 15 distinct attackers simultaneously.

Conversely, Function Name Scam results in the smallest average loss per victim among the three scams, with each victim losing just 377 USD, merely 1% of Zero-Transfer Scam loss. Additionally, 95.9% of victims in Function Name Scam suffered losses below 1,000 USD. Meanwhile, Function Name Scam swindled 27,854 individuals, compared to the 560 victims by Zero-Transfer Scam. This accumulation of small losses sums up, making the total monetary impact of them roughly comparable.

Finding IV: *The profit models of scams vary: some accumulate small amounts, while others rely on a few substantial gains.*

4.3 Attacker Profile

Scamming toolkits. To understand how attackers orchestrate visual scams, we examined the toolkits used in these schemes. Figure 4 illustrates the intricate connections between scam types, cryptocurrencies, attackers and toolkits in this subsection. Furthermore, we conducted a comprehensive campaign analysis in Appendix A.

Interestingly, we found that 6.6% of the counterfeit tokens were established before their genuine counterparts, with an additional 0.4% being created on the exact same day as the genuine ones. This indicates that some attackers might be preemptively targeting newly introduced cryptocurrencies based on pre-launch news.

Finding V: *Counterfeit tokens launched by proactive attackers even appeared before the genuine token ICO.*

In Zero-Transfer Scam, attackers initiated the illusive transaction by invoking `transferFrom` functions in smart contracts. Since this feature allows multiple transfers simultaneously [8], it makes the scam more efficient and cost-effective. 1,193 attackers carried out these 21,281,749 assaults using 1,057 distinct contracts. The

[7] `0x0E7A6b3b5EE4A1228A0334FA8170347A31538c49`
[8] `0xD256A23425B770baB6AF00123a16e387D81D5C00`
[9] `0x081714D70d61d80b078eF0dC88022E08dD53236E`

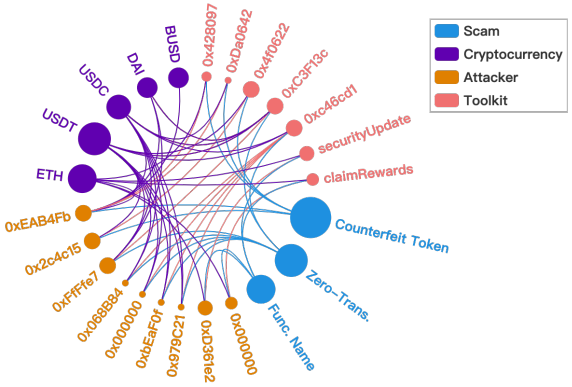
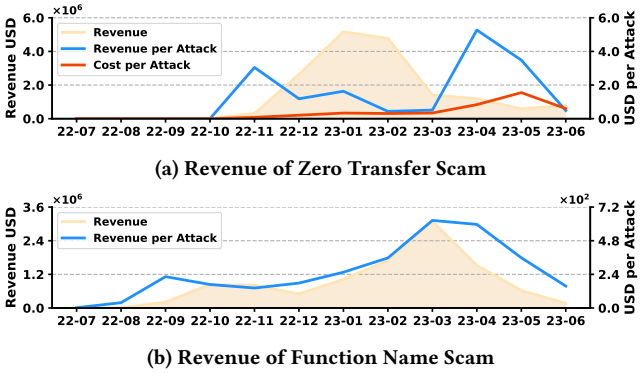


Figure 4: Interconnections within Attacker Profile



(a) Revenue of Zero Transfer Scam

(b) Revenue of Function Name Scam

Figure 5: Revenue of Visual Scams

contract at `0xc46cd1`[10] was harnessed by four different attackers, culminating in 104,137 zero-transfer attacks.

> **Finding VI**: *Alarmingly, certain smart contracts, serving as reusable attack toolkits, have been employed by different attackers.*

In Function Name Scam, only seven distinct function names are associated with 268 attackers. They targeted 17 related functions and deployed 309 unique malicious contracts. A minority of malicious contracts dominate the scale of this scam, with only 9.1% of contracts having more than 100 successful attacks. Among them, five malicious contracts launched over 1,000 successful attacks, collectively accounting for 72.9% of all successful attacks, indicating a significant monopolization in this scam.

Aggressive perpetrators. In Counterfeit Token Scam, the attacker `0xEAB4Fb`[11] stands prominent, having crafted 233 distinct counterfeit tokens, impersonating ETH, DAI, BUSD, USDT and USDC. `0x4f0622`[12] stands out as the most active counterfeit token, whose name and symbol are identical to USDT, which launched an astonishing 580,527 transactions in a mere two days.

Regarding Zero-Transfer Scam, there are some aggressive attackers launching numerous zero-amount transactions to deceive victims. The attacker `0xFfFfe7`[13] emerges as the most active participant, mounting 384,514 attacks through 15,017 contract calls.

In Function Name Scam, `0xD361e2`[14] is notably the most active attacker, who used the deceptive function name `securityUpdate` to execute 15,683 successful attacks, yielding a profit of $1,888,557. On the other hand, `0x000000`[15] emerged as the highest profitable attacker. By employing the `claimRewards` function name, they conducted 1,744 successful attacks, accumulating a remarkable $2,010,241 in profits.

4.4 Revenue Estimation

In this subsection, we shed light on how much the attackers can gain from these visual scams. Notably, for Counterfeit Token Scam, we can not ascertain how much victims spent to purchase counterfeits on phishing websites, since counterfeit tokens hold no value and these websites lure victims by offering abnormally low prices.

Zero-Transfer Scam. The profit per attack for scammers is the difference between the revenue per attack (the blue line) and the cost per attack (the red line) in Figure 5-a. The trend of Zero-Transfer Scam can be divided into two stages, separated by February 2023. In the former stage, the blue line is significantly higher than the red line, with the profit margin reaching as high as 3745%, which attracts a large number of attackers.

In the latter phase, we observed a steep decline in the number of attacks in Figure 2-b. The profit per attack in February 2023 dramatically dropped to 9.8% of the previous month's, indicating the difficulty for scammers to profit from zero-transfer attacks. This decline can be attributed to decreasing revenue and escalating cost—the decreasing average revenue per attack resulted from the rising number of attacks and the disclosure in scam reports, coupled with the continuous rise in Ethereum's gas fees, the main cost for launching zero-amount transfers.

Notably, during April and May 2023, the revenue per attack experienced unexpected spikes. This was attributed to the small base number of zero-transfer attacks at that time and two occasional large losses—`0x44B6A3`[16] and `0x3804d7`[17]. Interestingly, with the reduction of gas fees in June 2023, we can observe a corresponding rebound in the number of attacks in Figure 2-b.

> **Finding VII**: *The correlation between the attacks and the revenue: when the profit is high, attackers flood in; when the operational costs become steep, the attackers tend to sheathe their toolkits.*

Function Name Scam. The only cost for attackers in Function Name Scam is the gas fee to deploy the malicious contracts onto Ethereum, which is negligible compared to the revenues, especially since the gas fee incurred when a user interacts with the malicious contract is paid by the user themselves [8]. `securityUpdate` stands out as the most lucrative deceptive function name, amassing $5,279,297 from 25,442 successful attacks. Close behind are the similarly titled `claimRewards` and `claimReward`, respectively raking in $4,165,771 and $1,030,711 from 4,979 and 2,911 breaches.

[10] `0xc46cd1a4b3D14451F76fda8C33374f8AF749F907`
[11] `0xEAB4Fb43bB45b917bA1Ce0Cb28bdEdC9a4b7d081`
[12] `0x4f06229a42e344b361D8dc9cA58D73e2597a9f1F`
[13] `0xFfFfe71e7e6Bc965712c91b693a75d2bf717FFF0`
[14] `0xD361e29C48841C40506FC6E6211f68a203Ec1Ef1`
[15] `0x00000000001AdC2c0b202D0f72AD9d50F0675296`
[16] `0x44B6A393560f9146E7556F0894b4Ce76875B92f4`
[17] `0x3804d78b3966fC47d77D41AE8ee190A2d90f5da7`

Figure 5-b illustrates the total revenue and revenue per attack. Similar with Figure 2-c, there are two spikes in the revenue trend of this scam, with the latter spike significantly surpassing the former. March 2023 marks the top of revenue, during which attackers collected as much as $3,091,997 in total and $625 per attack.

5 MITIGATION

In this section, based on our invaluable insights, we propose practical and effective mitigation strategies for cryptocurrency wallets.

Educating new-coming wallet users. The naive newcomers to the blockchain are especially susceptible due to visual misdirection from wallets. In Counterfeit Token Scam, 59.1% of victim addresses are newly created within four months. Many victims lack a basic understanding of cryptocurrencies, like attempting to buy Bitcoin on Ethereum blockchain. Moreover, 10.1% of victims remained oblivious even after falling prey to Function Name Scam. As a countermeasure, cryptocurrency wallets should offer comprehensive guidance to newcomers, *i.e.*, educating users about prevalent scam tactics, to avoid potential financial losses.

Balancing security-sensitive information and UI design. Cryptocurrency wallets tend to omit some less "crucial" information on the UI for user-friendliness. In Section 2, we demonstrate the root cause of visual scams stems from the absence of vital details. We suggest the wallet developers balance concise design and detailed information. Specifically, to prevent zero-transfer attacks, we recommend displaying at least 10 hex digits of the transaction address according to our evaluation Appendix C.

Integrating effective real-time detection methods. One effective countermeasure is to notify users when they're about to engage with a scam contract. However, the leading online Ethereum explorer predominantly depends on user reports submitted manually or labels provided by corporate entities [10]. As highlighted in Appendix B, many blockchain anti-scam platforms primarily utilize blocklists. Our findings in Section 4.3 revealed that 7.0% of counterfeit tokens emerged either before or concurrently with their genuine counterparts. Given the rise of such proactive attackers, it's imperative for cryptocurrency wallets to adopt real-time strategies that can accurately identify scam transactions and tokens.

6 RELATED WORK

Blockchain scam. As the ecosystem of cryptocurrencies has expanded, scams aiming to pilfer digital assets have risen. Phillips and Wilder [44] highlighted the proliferation of cryptocurrency scams on visually similar websites. Cryptocurrency exchange scams have been spotlighted by Xia *et al.* [56], whose efforts revealed a loss of over 520k USD. Li *et al.* [36] identified over 10k giveaway scam websites targeting users of popular cryptocurrencies. In the realm of Ethereum smart contracts, Ji *et al.* [31] uncovered the "fake deposit" vulnerability. Wang *et al.* [54] shifted the focus to malicious browser extensions themed around cryptocurrency. Xia *et al.* [55] characterized cryptocurrency scams that capitalize on the COVID-19 pandemic.

Notably, the existing literature seems sparse on scams specifically targeting cryptocurrency wallets, indicating a potential avenue for further exploration. The work most similar to ours is by Gao *et al.* [25], who identified 2,117 ERC-20 counterfeits targeting the top ERC-20 tokens. In contrast, our research reveals that 32.7% of ERC-20 counterfeits target other cryptocurrencies, such as Bitcoin, which are overlooked in their study. Notably, our methods identified 4.5 times more counterfeit tokens (9,442 vs. 2,117). Our analysis of both victim and attacker profiles offers a more comprehensive understanding and mitigation approaches to visual scams.

Web visual phishing. Attackers exploit various visual features, specifically domain names and webpage appearances, to execute fraud. Attacks of homograph domains, which exploit the visual similarities of characters, have been thoroughly measured by Quinkert *et al.* [45]. Kintis *et al.* [33] explored "combosquatting" base on DNS records, revealing a wide spectrum of malicious activities. Moreover, Tian *et al.* [49] highlighted over 90% of detected squatting phishing pages bypassed popular blacklists. In the other way, Lin *et al.* [38] focused on the visual identification of phishing webpages. To the best of our knowledge, none of the mentioned studies delves into the specific threats of visual phishing in cryptocurrency wallet.

PGP fingerprints spoofing. Recent advancements in PGP fingerprint [9] spoofing reveal critical vulnerabilities. Klafter and Swanson [34] highlighted that every 32bit key ID is vulnerable to collisions using modern GPUs. Similarly, Müller *et al.* [40] exposed various weaknesses in OpenPGP standards. In a different approach, Tan *et al.* [48] investigated the effectiveness of various fingerprint representations. These investigations converge on a point shared with Zero-Transfer Scam: the reliance on collision exploitation for spoofing. However, none of these studies focus on the emerging visual scams of cryptocurrency wallets.

7 CONCLUSION

This paper presents the first measurement study on the visual scams of cryptocurrency wallets, providing a novel and comprehensive lens on this emerging cybercrime. Over a span of one year, we identified an alarming 24.9 million scam incidents, shedding light on the strategies and toolkits of 6,768 unique attackers. Our analysis reveals that over 28,414 victims were defrauded, resulting in losses exceeding 27 million USD. By discovering the unique ecosystem of visual scams in cryptocurrency wallets, we reveal the flavor profile of victims and scammers, and evaluate their profit gains from such scams. Our research also provides the recommendation of mitigation strategies informed by our findings.

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A CAMPAIGN ANALYSIS

We define a campaign as a group of scammers launching attacks through the same toolkit. In different scams, the toolkit varies. For Counterfeit Token Scam, the toolkits are smart contracts of counterfeit tokens, which are distributed to various victims; for Zero-Transfer Scam, the toolkits are smart contracts shared by multiple attackers to launch numerous zero-amount transfers; for Function Name Scam, the toolkits are malicious functions with deceptive names.

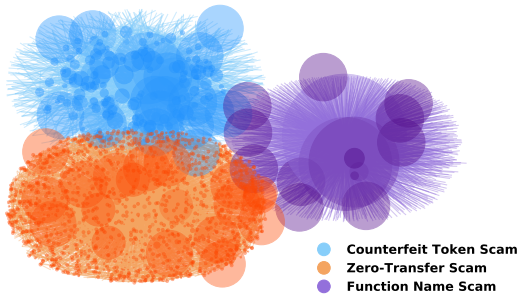

Figure 6: Real-World Campaign of Visual Scams

Figure 6 clusters attack incidents based on different toolkits, providing an intuitive overview of real-world campaigns. Circles represent different scam toolkits, with the size of the circles indicating their attack frequency, and each line represents a real attack incident. In Zero-Transfer Scam, many lines share the same endpoints, represented as darker dots on the figure. This means that some addresses, due to their large balances or recent history of high-value transactions, become attractive targets for multiple attackers. In Counterfeit Token Scam, the significant size differences between the circles indicate the inactivity of many counterfeits. In Function Name Scam, the largest circles indicate that these few campaigns dominate in real-world attacks.

B DETECTION EVALUATION

In this section, we rigorously evaluate the detection methodologies for visual scams. To evaluate the recall of our approach for Counterfeit Token and Zero-Transfer Scams, we gathered scam reports from Twitter, given its prominence as the platform for blockchain-related news. Our method successfully detected 16 of 18 counterfeit tokens, reported in the posts [3, 30, 52]. One missing case (`0x75409A`[18]) pertained to the token, ETHM, which falls outside the top 200 in market value. Another undetected token (`0x5F799A`[19]) was designed to forge USDT, with the name "USDT ERC-20" and the symbol "USDT", utilizing a combination of cross forgery and combo forgery. We did not consider the combination of various forgery methods, as it could lead to a significant increase in false positives. As for zero-transfer attacks, our results successfully captured all 550 attacks, reported by [1, 5, 37].

[18] `0x75409AC44f95Ce4106336716E47C03dc817cB56a`
[19] `0x5F799AD15d02B2668d37575B2fB6eBaeee368A05`

We also assessed our tool's recall by comparing it to Scam Sniffer, a reputable anti-scam platform [46]. Scam Sniffer has documented instances of Function Name Scam using a blocklist of malicious contracts. Their records indicate 2,513 successful attacks with a combined loss of 1,833 ETH. When evaluating the recall for this scam, we found that our results entirely cover the data from Scam Sniffer. Impressively, our detection highlighted a total of 33,873 successful attacks, 13 times their count.

As for precision, due to the lack of an off-the-shelf ground truth dataset, we randomly selected 100 scams from each type for manual validation. The results show our method can precisely detect Zero-Transfer and Function Name Scams. Only one false positive was spotted in Counterfeit Token Scam, caused by "counterfeit GALA" (`0x15D4c0`[20]). A deeper dive revealed that owing to a contract upgrade, the token had been migrated [15], signifying that the token in question was the old GALA, not a counterfeit token.

C MITIGATION EVALUATION

In Ethereum, the process of generating similar account addresses involves creating a random private key, and then using ECDSA [32] to compute the public key and account address. This process is repeated continuously until the scammer finds an address to their criteria. Currently, the toolkits used for generating specific addresses mainly include online tools [7] and open-source repositories [2, 41].

To assess the effectiveness of our proposal, we conducted the following experiments. In an Ubuntu server with i9-9900X, 128GB memory and 10 threads running in parallel, generating an Ethereum address with 7 specific hex digits takes 3.63 hours on average (according to 5 repeated experiments). Generating an address with 10 specific hex digits will take 16^3 times longer than one with 7 hex digits, which is 619.52 days. This significantly limits the potential of such scams, as a scammer almost can not afford to generate such an account with specific prefixes and suffixes.

D DETAILS OF FUNCTION NAME SCAM

Table 4: Misleading Function Names in Real-World Scams

Function Name	Function	Func. Selector	Succ. Attack
securityUpdate	SecurityUpdate()	`0x5fba79f5`	25300
	SecurityUpdate(address)	`0x593dae5b`	142
claimRewards	claimRewards(address)	`0xef5cfb8c`	2814
	claimRewards(uint256[])	`0x5eac6239`	1412
	ClaimRewards()	`0x12798972`	486
	claimRewards()	`0x372500ab`	200
	ClaimRewards(address)	`0x0178be5f`	67
claimReward	ClaimReward()	`0x79372f9a`	894
	claimReward()	`0xb88a802f`	881
	claimReward(uint256)	`0xae169a50`	626
	claimReward(uint8)	`0x689f1623`	407
	ClaimReward(address)	`0x63e32091`	102
	ClaimReward(uint256)	`0x92ceb12d`	1
claimQuestRewards	claimQuestRewards(uint256[])	`0xa7b0c81b`	528
upgradeStrength	upgradeStrength(uint256)	`0xd583644b`	11
getBonus	getBonus()	`0x8bdff161`	1
upgradeReward	upgradeReward(uint256)	`0x66bfdc75`	1

[20] `0x15D4c048F83bd7e37d49eA4C83a07267Ec4203dA`

E DETAILS OF ALPHANUMERIC HOMOGRAPH

Table 5: Unicode Homograph Mappings for Alphanumerics

Homo.	Unicode	Target	Homo.	Unicode	Target
Λ	U+039b	A	∪	U+222a	U
А	U+0410	A	Χ	U+03a7	X
𝖠	U+15c5	A	Х	U+0425	X
В	U+0412	B	Ⴤ	U+0423	Y
ß	U+00df	B	¥	U+00a5	Y
Ɓ	U+0181	B	Ζ	U+0396	Z
С	U+0421	C	α	U+03b1	a
ℂ	U+2102	C	а	U+0430	a
Ð	U+0189	D	ь	U+044c	b
Е	U+0395	E	Ь	U+0184	b
Ɛ	U+0190	E	с	U+03f2	c
₣	U+20a3	F	с	U+0441	c
Ƒ	U+0191	F	δ	U+03b4	d
Ғ	U+0492	F	ԁ	U+0501	d
G	U+050c	G	ε	U+03b5	e
Ǥ	U+01e4	G	е	U+04bd	e
Н	U+0397	H	ſ	U+0192	f
Н	U+041d	H	ɡ	U+0261	g
ℍ	U+210d	H	ǥ	U+01e5	g
І	U+0399	I	η	U+03B7	h
І	U+0406	I	ι	U+03b9	i
Ј	U+0408	J	і	U+0456	i
Ĵ	U+0134	J	¡	U+00a1	i
К	U+039a	K	ј	U+0458	j
К	U+041a	K	κ	U+03ba	k
₭	U+20ad	K	к	U+043a	k
М	U+039c	M	ł	U+0142	l
М	U+041c	M	⌊	U+026d	l
𝓜	U+2133	M	о	U+043e	o
N	U+039d	N	τ	U+03c4	t
ŋ	U+014a	N	μ	U+03bc	u
О	U+041e	O	υ	U+03c5	u
Ø	U+00d8	O	ʊ	U+028a	u
O	U+2d54	O	ν	U+03bd	v
O	U+039f	O	∨	U+2228	v
Р	U+03a1	P	ω	U+03c9	w
Р	U+0420	P	χ	U+03c7	x
₱	U+20bd	P	×	U+00d7	x
𝓡	U+211b	R	ɣ	U+03b3	y
§	U+00a7	S	ү	U+04af	y
S	U+0405	S	ζ	U+03b6	z
$	U+0024	S	ʒ	U+0290	z
Т	U+03a4	T	ƶ	U+01b6	z
Т	U+0422	T	|	U+007c	1
₮	U+20ae	T	ƻ	U+01a7	2
U	U+1200	U	Ʒ	U+0417	3
∪	U+222a	U			