

Your Code is 0000: An Analysis of the Disposable Phone Numbers Ecosystem

José Miguel Moreno

Universidad Carlos III de Madrid IMDEA Software Institute

Madrid, Spain

josemore@pa.uc3m.es

Srdjan Matic

IMDEA Networks Institute

Madrid, Spain

srdjan.matic@imdea.org

Narseo Vallina-Rodriguez

IMDEA Networks Institute

Leganés, Spain

narseo.vallina@imdea.org

Juan Tapiador

Universidad Carlos III de Madrid

Madrid, Spain

jestevez@inf.uc3m.es

Abstract—Short Message Service (SMS) is a popular channel for online service providers to verify accounts and authenticate users registered to a particular service. Specialized applications, called Public SMS Gateways (PSGs), offer free Disposable Phone Numbers (DPNs) that can be used to receive SMS messages. DPNs allow users to protect their privacy when creating online accounts. However, they can also be abused for fraudulent activities and to bypass security mechanisms like Two-Factor Authentication (2FA). In this paper, we perform a large-scale and longitudinal study of the DPN ecosystem by monitoring 17,141 unique DPNs in 29 PSGs over the course of 12 months. Using a dataset of over 70M messages, we provide an overview of the ecosystem and study the different services that offer DPNs and their relationships. Next, we build a framework that (i) identifies and classifies the purpose of an SMS; and (ii) accurately attributes every message to more than 200 popular Internet services that require SMS for creating registered accounts. Our results suggest that the DPN ecosystem is globally abused for fraudulent account creation and access, affecting all major Internet platforms and online services.

I. INTRODUCTION

Originating in the late 1990s, Short Message Service (SMS) have experienced a resurgence among online service providers (e.g., Alphabet, Meta) to deliver notifications, enable Two-Factor Authentication (2FA) and enhancing the security of online accounts [15], [23], [33]. Online services using SMS-based 2FA technologies assume that phone numbers are uniquely linked to an individual. However, this assumption does not hold with Disposable Phone Numbers (DPNs). DPNs are shared phone numbers that any individual can use to receive SMS messages on a public website, so their metadata and content is published for anyone to see. Users can take advantage of DPNs to register at online services without giving their true personal phone number, either for privacy reasons or to conduct fraudulent actions.

Despite its potential for abuse, the DPN ecosystem remains relatively unexplored. The most recent prior systematic study of DPNs and their usage dates back to 2018 [37], a time before the expansion in popularity of SMS-based 2FA for web and mobile services. According to Duo Labs, 2FA usage has increased from 28% in 2017 to 78% in 2021, becoming the preferred user authentication method [8]. As a result, the key findings of [37] have become obsolete.

These reasons, and their potential impact on web services, motivate us to systematically measure and investigate the

current DPN ecosystem and the evolution of the purposes it supports in the context of 2FA. Specifically, we seek answers to the following research questions: (i) How widely used are DPNs? (ii) What services are sending messages to DPNs? And (iii) What is their potential for abuse? To answer these questions, we develop a methodology to automatically gather and process a large-scale and longitudinal dataset containing 70.95M messages received by 17,141 unique DPNs, collected over a time span close to 12 months. Using this dataset, we make the following contributions:

- (i) *Study on the usage of DPNs.* We measure the volume of messages received by DPNs over time. We find that these numbers receive collectively more than 1.4M messages per week. A language analysis of message contents suggest a wide international user base.
- (ii) *Service attribution.* We develop a framework to accurately attribute an SMS message to more than 200 popular global Internet services that require a registered account. We observe in our dataset messages sent by online service providers of all sectors, sizes, and geographical scope, including global companies (e.g., Uber, Facebook, Amazon, WhatsApp), security-sensitive industries (e.g., banking), and services developed by smaller and more geographically localized organizations (e.g., Paytm in India).
- (iii) *Measuring the potential for abuse.* We develop a framework to infer and classify the purpose of an SMS as a proxy to measure their potential for abuse. We observe that nearly 80% of messages contain a One-Time Password (OTP), a single-use link, or both. This figure presents a significant increase with respect to the trend reported in the 2018 measurement [37], where this metric was at 67.6%. As these messages are closely related to 2FA processes, we hypothesize that DPN usage is closely related to anonymity or account fraud.

Our findings suggest that the DPN ecosystem is an expanding and thriving field, and that the global SMS-based 2FA industry is oblivious to—or chooses to ignore—potential account abuses arising from it.

Ethics issues and dataset release. The dataset gathered and analyzed in this study might contain sensitive data since it involves phone numbers that, due to number rotation, might have belonged in the past or might belong in the future to a

real user, and also SMS messages that can potentially contain personal data or access credentials. We obtained approval from our IRB to conduct this study provided that (i) we make no efforts to deanonymize the data in a way that could facilitate linking messages to actual users; (ii) we inform affected parties in case that any security or privacy concerns are identified during the study; (iii) we do not use the collected data for any secondary purposes other than the scope of this study; and (iv) we share the dataset on demand with other researchers provided that they agree on using it for research purposes and under conditions similar to those described above. CSV files with the list of analyzed gateways and the services found in the messages are available at <https://github.com/josemmo/your-code-is-0000>.

II. BACKGROUND

Disposable Phone Numbers (DPNs) are publicly available phone numbers offered by *Public SMS Gateways* (PSGs), or simply *gateways*. DPNs allow receiving messages from a wide catalog of international phone numbers without the need for a SIM card. PSGs are usually free services that do not require registering an account, so multiple users can simultaneously use the same DPN at any time. However, there are gateways offering “premium” DPN services that require a single-use payment to read the most recent messages.

The SMS messages received by a DPN are compiled in an *inbox*. Depending on the gateway offering the service, some inboxes have a smaller capacity than others. For example, some only list the latest 30 messages while others index all messages received over the last months. SMS messages published in an inbox typically have four attributes:

- *Receiver*. The international number of the message recipient.
- *Sender*. The party that, allegedly, sent the message. Typically, the sender is an online service (e.g., Amazon or WhatsApp) that sends automatically-generated messages. This data can be displayed as an international phone number, a short code [47] or a sender ID [9]. We note that PSGs providing the sender data in the form of short code or string sender ID may be incorrect due to their dependency on poorly implemented or maintained Caller ID Lookups [2].
- *Reception timestamp*. The date and time when the message was received. It is displayed as a date string using the timezone of the gateway’s server (e.g., “1st Jan 2022, 12:34 pm”) or as a relative timestamp (e.g., “12 hours ago”). The latter format allows accurately determining the date when an SMS message was received but not its time.
- *Content*. The actual payload of the SMS, often containing OTP codes and Single-use Links. OTPs are short numeric codes that are sent to the user of an online service to verify its identity or confirm an action by inputting the code in an application. Typically, these codes are 4 to 6 digits long with dashes or spaces to make them more readable. Single-use links are the equivalent to OTPs in the form of URLs, but instead of inputting a code, the user is expected to click and visit the link. Some gateways redact their text content to remove numeric codes.

III. RELATED WORK

Reaves *et al.* conducted in 2016 the first large-scale study of the DPN ecosystem [36]. Their work analyzed 400 DPNs in 28 countries and showed how PSGs contribute to online account fraud. The authors conducted a follow up study in 2018 that doubled the size of its dataset but they did not observe any discernible change in the ecosystem [37]. Thomas *et al.* conducted a longitudinal analysis of Phone-Verified Accounts (PVAs) underground sellers and their infrastructure, proposing multiple strategies that service operator can leverage to combat fake accounts [40]. In 2019, Hu *et al.* measured Disposable Email Services (DEA) [21], which share commonalities with DPN as both services can be abused for verifying and managing online accounts. Dmitrienko *et al.* carried a study on multiple Two-Factor Authentication (2FA) schemes and weaknesses in their implementation, showing how malware can intercept messages with single-use codes [11]. Following the same research line, Lei *et al.* investigated how to exploit Android APIs to steal OTP codes sent through SMS [27].

IV. METHODOLOGY

This section describes our methodology to identify and crawl the PSGs, and the post-processing techniques used to parse and analyze the messages. Figure 1 provides an overview of our pipeline.

A. PSGs Identification

To compile a recent and global list of widely used PSGs, we leverage two complementary methods:

- (i) *PSGs extraction from the Tranco list*. Using the Tranco top-3M list¹ [26], we perform an initial automated token-based search to find possible PSGs using the Python library WordSegment [24] and keeping the entries matching a set of predetermined keywords.² This method identifies 17 sites offering DPN services, 15 of which are still indexed by Tranco as of Dec. 2022.
- (ii) *PSGs extraction from search engines*. Some gateways are accessed exclusively through mobile apps instead of websites, so they are likely missed by Tranco. We leverage Google’s search engine to increase our coverage using the same set of keywords. This step reveals 12 more gateways, 3 of which are offered by apps published on Google Play.

We manually review each candidate to discard unrelated, parked or expired domains. Additionally, we also remove PSGs which (i) are stale and had not received a single message in months; (ii) are copies of another gateway belonging to the same provider; or (iii) are aggregators that harvest and publish messages from other gateways. We note that aggregators are easy to identify because they contain duplicate DPNs that appear in other PSGs, and they publish messages at a slower rate compared to the original source.

¹Generated on the 14th of June, 2021. Available at <https://tranco-list.eu/list/NK2W>.

²*sms, msg, number, numbers, phone, free, get, receive, online, temp, otp, inbox, virtual, verify, verification and code.*

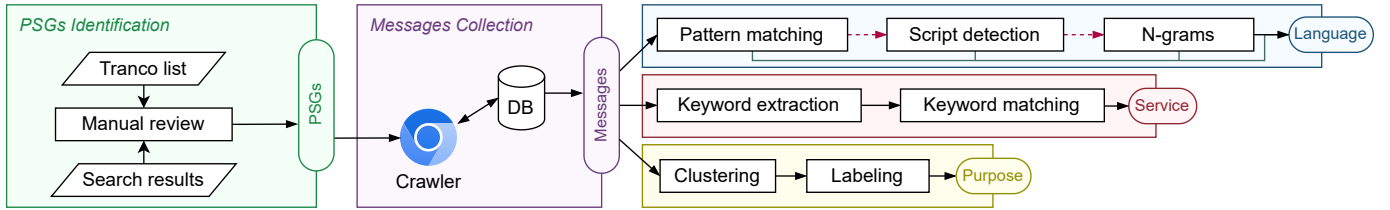


Fig. 1. Our pipeline for identifying PSGs, crawling messages and post-processing of data. For language detection, arrows with full lines (green) indicate passed check, while dashed lines in (red) denote a check that failed.

B. Messages Collection

We use a purpose-built Chromium-based crawler instrumented with Playwright [13] to fetch the DPNs and their messages for each gateway identified in the previous step. We use an actual web browser instead of a simpler and easier-to-maintain script because some PSGs need to run JavaScript code on the client-side to properly render webpages. For those cases, sending crafted HTTP requests and parsing their responses is not enough. The PSGs accessible exclusively through Android mobile apps are implemented as WebViews, and we observe their traffic to find the HTTP requests that fetch the DPNs from the remote server. Then, we crawl these gateways with our purpose-built crawler, sending HTTP requests using the `fetch` Web API [30]. This approach allows us not having to maintain two separate codebases.

As mentioned in Section II, some PSGs keep a copy of all received message for a long time, while others only show the latest n messages. To minimize the number of messages that might get lost, we crawl PSGs at different sampling periods. We fine-tune the crawler using the reception timestamp of the oldest message in an inbox and the popularity of the gateway. We periodically adapt the crawling rate to guarantee that we do not miss too many messages in case a PSG starts receiving more traffic. Due to the lack of unique message IDs, we assign our own identifier to messages. The identifier we use is a composite key formed by the receiver (*i.e.*, DPN), the sender, the reception timestamp and the text content. Thanks to this identifier, we can track DPNs and messages across different PSGs to detect and remove duplicates.

C. Language and Service Identification

A DPN can receive messages from online services with a global user base, and also from other regional ones. For this reason, we first need to detect the message language.

Language Detection. Guessing the language of short messages is an open research problem [5]. We first normalize the message to remove punctuation, duplicate spaces and other defects (*e.g.*, corrupted Unicode characters), and then automatically assign the language to those messages that contain highly distinctive substrings (*e.g.*, “verification code”) or use Unicode characters [44] unique to world languages (*e.g.*, the Modi script in Hindi). If this process fails, we use the JavaScript `franc` library [48] to determine the language.

Sending Service. Gateways often include the service name as the “sender” from a given message, but this information might be inaccurate due the presence of services with outdated Caller ID Lookups. We choose to use our own list of keywords to map a message to the associated service. To extract the keywords, we (*i*) normalize the message text and remove diacritics using the Normal Form Decomposition (NFD) [45], (*ii*) tokenize the content separating by whitespace and add the unigrams as keywords, and (*iii*) use the unigrams to generate bigrams and add them as keywords as well. Then, two of the authors manually analyzed the list of the top-10k most frequent keywords and flagged those that were service names or strictly related (*e.g.*, branded domain names, *mottos*). After this process, we end up with a list of 1.7k meaningful keywords and 212 unique services. We note our keyword-based approach might incorrectly attribute a message to a service if its text contains the service name but it was not sent from the particular service. To limit the number of wrongly attributed services, we iterate over the keyword-flagging process to create more specific keyword-matching rules for the services with most mislabels. We measure the accuracy of our service classifier by manually labeling a sample of 4k randomly selected messages, offering an accuracy of 99.10%. Most mislabels are attributed to false negatives (*i.e.*, messages from a known service but tagged as “unknown”) in 0.78% of cases.

D. Purpose Identification

We use a hierarchical divisive clustering to group message into patterns that correspond to activities on an account for a given service. In the first phase, we group messages depending on the associated service and we normalize the message content. To generate the normalized version of the message, we remove multiple whitespaces and punctuation characters, perform stemming, and filter any stopword or token with less than two characters. Next, we replace all IBANs, URLs, email addresses, IP addresses, numeric codes and timestamps by *identifiers* often appear in notification messages informing of user activity, and can be easily detected using regular expressions due to their structured format.

We replace each identifier with a pattern that captures the identifier type and length. For example, an URL with 36 characters is replaced with “URL{36}”, and a sequence of 4 digits becomes “NUMERIC{4}”. Once this process is completed, we use the identifiers to group messages into

clusters. Since a message might contain multiple identifiers, our clustering algorithm prioritizes longer identifiers (e.g., a message with “URL{36}” and “URL{20}”, will be assigned to the cluster “URL{36}”) and those that better capture the *purpose of the message* (e.g., an IP address is usually more representative than a generic numeric code). For the priorities, we follow the same order we use to introduce the identifiers.

We tokenize the normalized messages on the whitespaces and then calculate a fingerprint of the message using SimHash [29]. We leverage the Hamming distance to compare hashes given a similarity threshold [28], which determines the number of bits that can differ among two near-duplicates to be considered similar. We empirically chose a threshold of 10 with 64-bit hashes after experimenting with different values and validating the results against a ground truth of 10k randomly-selected normalized messages.

Lifecycle of an Account. Once a user has provided a phone number to a service, the provider can send messages to notify the user about events associated to their personal account during their lifecycle. We label messages with a tag that captures the type of account activity or *purpose* following the NIST SP 800-63B standard. This specification provides technical guidelines to agencies for the implementation of digital authentication [19]. Each one of the resulting purposes are tied to a particular stage in the lifecycle of an account: (i) creation (a new account is created on the service), (ii) verification (the service requests the user to verify his identity), (iii) activity (the service notifies of user-performed actions or important events), (iv) update (the user’s personal data on the service is modified), and (v) recovery (the service detected an attempt to recover access to an existing account).

Automated Message Labeling. After defining the categories of purposes to monitor, we randomly select 6,429 message clusters and manually assign one category to each. To identify the best label for the cluster, we leverage the normalized version of the messages with the highest number of occurrences. By manually inspecting each message, we label the cluster using one of the five purposes defined above. We also use the message content to generate patterns that can identify other messages serving a similar purpose. In the final step, we apply the obtained patterns to automatically infer the purpose of all messages (and clusters) in our dataset. To evaluate the accuracy of our automated labeling technique, we randomly select 1k clusters and pick the content of the normalized message with the highest number of occurrences to confirm whether the assigned label is correct. We observe that our approach selects the right label in 91.3% of the cases being the most common sources for mislabeling tokens such as “activity” (7.8% of the cases) or “verification” (0.32%).

V. ECOSYSTEM CHARACTERIZATION

We collect 70,951,728 messages from 17,141 unique DPNs offered by 29 different PSGs over a period close to 12 months. We note that the number of gateways decreased over time as some went offline or stopped publishing new messages. For

TABLE I
LIST OF CRAWLED PSGs.

Gateway	Crawl start	Days	DPNs	Prefixes
99dark.com	2021-05-07	336	1,151	9
bfkdim.com	2021-04-29	7	64	8
bulk-pva.com	2021-04-30	240	3	2
cloakmobile.com	2021-04-29	13	19	3
freebulksmsonline.com	2021-04-28	345	501	4
freephonenum.com	2021-04-22	351	10	2
getfreesmsnumber.com	2021-04-27	337	907	20
onlinesim.io	2021-04-22	351	769	28
receive-sms-online.com	2021-04-29	66	7	3
receive-sms-online.info	2021-04-21	352	369	20
receive-sms.com	2021-04-28	345	58	2
receive-smss.com	2021-04-20	353	420	37
receivefreesms.net	2021-04-22	351	28	3
receivesms.cc	2021-04-20	353	56	12
receivesms.co	2021-04-23	350	41	11
receivesms.org	2021-04-22	351	16	5
sms-online.co	2021-04-21	295	5	5
sms-recv.com	2021-07-02	95	5	1
sms-recv.net	2021-04-23	350	247	17
sms-verification.online	2021-05-06	337	22	4
sms.sellait.com	2021-04-26	347	12	1
sms.visatk.com	2021-05-05	335	294	5
smsfinders.com	2021-04-29	344	6	5
smsfree.cc	2021-04-28	345	4,733	47
temp-sms.org	2021-05-06	247	25	2
temp99.com	2021-05-07	336	8,852	13
tempsms.net	2021-05-10	326	12	2
virtnumber.com	2021-04-30	343	66	13
www.spoofofb.com	2021-05-10	333	8	8

reference, the previous measurement from 2018 collected a dataset of 900k messages across 28 months [37]. Figure 2 shows the number of SMS messages, active DPNs, and online PSGs observed daily. While the weekly count of received messages is roughly stable, there are two major events on August and October 2021 where the daily count is considerably lower than on any other date, and a minor event on December. These events are unrelated to the DPN ecosystem and were caused by network downtimes and infrastructure upgrades on our side.

A. Gateways

Table I lists the PSGs that we crawled during our research, along with their crawling period (in days), number of DPNs (i.e., inboxes) and number of different calling prefixes. The number of DPNs offered by PSGs offer on average 645 DPNs that span across 5 different calling prefixes. However, we find a high dispersion within these numbers, with “bulk-pva.com” having merely 3 DPNs as opposed to the more than 8k numbers offered by “temp99.com”. Both gateways remained active for hundreds of days. Over the course of our work, the number of PSGs slowly decreased as some stopped working properly (i.e., receiving new messages), went offline or added protective measures like CAPTCHAs or JS Challenges to prevent their sites from being crawled. In this last case, we did not attempt to circumvent such measures for ethical reasons.

Although we did not perform a longitudinal analysis of the ecosystem, we repeated the PSG identification process

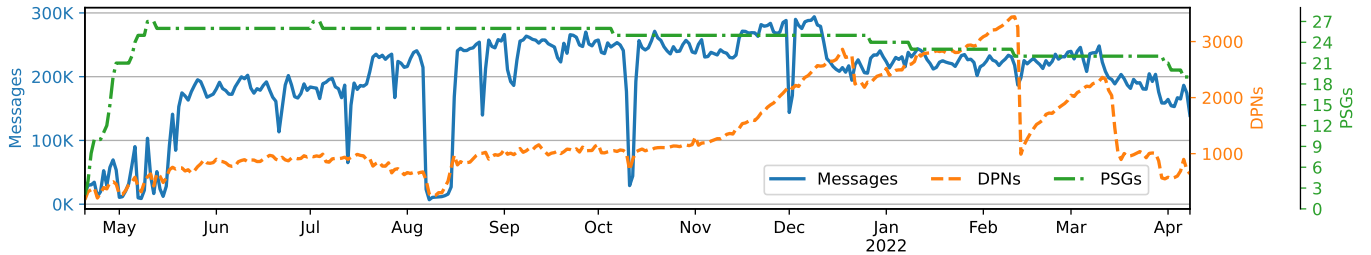


Fig. 2. Daily volume of messages, active DPNs and online PSGs.

described in Section IV-A 18 months after the initial run to find changes in the list of active PSGs.³ As a result, we find 18 new gateways that did not appear before either because they did not exist at the time or were not popular enough. In addition, 14 gateways (half of the entries from Table I) are no longer included in this last outcome. These changes suggest that many PSGs in the DPN ecosystem are relatively volatile, with an approximate 1-year lifespan.

B. DPN Dynamics

In Section II, we hypothesize that a DPN can appear in different gateways. We confirm it by noticing that 9.1% of the DPNs in our dataset appear in more than one PSGs. We attribute this behavior to DPN rotation and infrastructure sharing (*i.e.*, DPN reuse).

DPN rotation. A typical PSG builds its DPN pool by (*i*) acquiring and adding to GSM boxes SIM cards from multiple mobile network operators; or (*ii*) renting VoIP lines from third-party External Short Messaging Entity (ESME) like Bandwidth.com [3] or Twilio [42] to handle the reception of messages. PSGs often distinguishing between so called “*real*” (mobile lines) and “*virtual*” numbers (VoIP lines) in their offerings.⁴ VoIP lines can be rented and canceled at any time, either manually or programmatically. The number can eventually be rented by another provider.

DPN reuse. Some PSGs may share a considerable amount of DPNs that cannot be explained by DPN rotation. We hypothesize that a given operator might reuse the same infrastructure across different gateways under their management or ownership. A clear case of this is the pair formed by 99dark.com and temp99.com, where the former is the API endpoint for an Android app [41] and the latter is a public website. Besides sharing 483 DPNs, other reasons suggest that these two gateways are operated by the same group, such as similar naming and contact information, and same DNS nameservers from Cloudflare. Another not-so-straightforward case is the smsfree.cc gateway, which has hundreds of DPNs in common with other seemingly unrelated PSGs, and is used by (at least) a website [1] and an Android app [14].

³Using the Tranco list generated on the 11th of December, 2022. Available at <https://tranco-list.eu/list/JX5LY>.

⁴The receive-sms-online.info gateway is an example of a website advertising numbers “based on real SIM”. On the other hand, receive-sms.cc announces their DPNs as “virtual phone numbers”.

TABLE II
DPNs LIFETIME. VALUES FOR THE MEAN AND THE QUANTILES (Q) ARE EXPRESSED IN *days* EXCEPT FOR ENTRIES MARKED WITH AN ASTERISK (*), WHERE THE UNIT IS THE *hour*.

	<1d*	1d - 1w	1w - 1m	>1m	Any
Mean	8.04	3.61	18.30	149.77	51.71
Q1	2.89	1.86	11.27	42.36	5.05
Q2	6.17	3.35	18.03	70.37	17.59
Q3	11.56	5.32	26.42	134.16	35.53
DPNs	2,097	2,943	6,943	4,908	16,891
Messages	279k	2.1M	10.7M	57.8M	70.9M
Msgs. w/ service	96k	798k	4.3M	32.1M	37.3M
Services	188	199	211	212	212

The simplest explanation is that smsfree.cc is a white-label API endpoint reused by many platforms (both web and mobile ones) that lends its DPNs to other parties as if it were a mobile carrier. However, given that this PSG also rotates DPNs very frequently (sometimes even daily), it can also be the case that it aggregates phone numbers from other gateways on purpose as soon as they become available to rent.

DPN lifetime. Table II reports the lifetime (in hours or days) during which a DPN is active. To determine the activity window, we calculate the amount of time that passed between the first and the last time when a SMS is sent to a particular DPN. We identify three main patterns: short lived DPNs (12%), phone numbers that are active up to four weeks (58%), and DPNs that receive messages for several months (29%). When inspecting the volume of messages that a phone number receives, we find that it is usually proportional to the DPN lifetime. We observe a similar trend both in the subset of messages sent by a service known by our classifier (“Msgs. w/ service” row in Table II) and in the entire dataset. Long-lasting DPNs tend to receive more messages, being responsible for over 81% of the total messages that we collected. The scenario changes when we check the total number of services for which we observe at least one message. In this case, the breakdown depending on the DPN activity is smoother, and phone numbers that were active for over one month receive messages from only 11% additional services when compared to DPNs which are active for less than one day.

The lifetime distributions that we observe have some implications. First, we notice services being associated with DPNs as soon as the phone number becomes available in a gateway.

This might be a possible indicator of abuse and we explore it further in Section VI-B. Second, DPNs with a long lifetime unnecessarily expose users to higher privacy and security risks. This is the case for services that leak Personally Identifiable Information (PII) such as email addresses or usernames in the SMS they send. While some gateways only display the messages received in the last 24 hours (see Section II), others provide access to historical information. The lifetime of a DPN does not only increase the time window in which scammers can collect sensitive information, but it exposes users to other risks. An attacker that harvests login information by scraping DPN messages can attempt to perform an account takeover if the DPN is still active and is used as a recovery mechanism for accessing an account. Alternatively, the DPN can be abused to discover previously unknown user credentials, in case a service uses SMS messages during the procedure of recovering forgotten usernames and email addresses. Lastly, we notice that if we merge into a single class the two sets of short-lived DPNs (*i.e.*, those that live up to one week), the resulting set of 5,040 numbers received at least one message from all the services that we monitor. This suggests that the 212 services that we monitor are extremely popular and widely used across different countries.

C. Country and Language Diversity

The international scope of our analysis requires us dealing with DPNs receiving messages in any language. We use the international phone number prefix of a DPN to associate it to a country (*e.g.*, “+44” is the international code for the United Kingdom). This allows us to locate DPNs in 57 different countries. Using the language detection method described in Section IV-C, we identify up to 31 languages in our dataset. The diversity of languages we find suggests an international demand for DPN services. With our approach, we could not conclude the language in merely 4.9% of the messages either due to their short length and the presence of ambiguous words (*e.g.*, “Code: 0000”). Unsurprisingly, English is the most prevalent language in our dataset, accounting for over 75% of the messages, followed by a long tail of other languages such as Indonesian (3.0%), French (2.9%), Portuguese (2.8%), Spanish (2.1%), Arabic (1.7%), Chinese (1.6%), and Russian (1.0%). We do not find a 1-to-1 mapping of languages and countries where this language is spoken. For example, only 30% of German-written messages are sent to DPNs with the German international call prefix. Instead, we see messages being sent globally regardless of their language. This global scope is clearly appreciable for English messages, half of which are sent to non-English speaking countries.

D. OTPs and Single-use Links

In their 2018 study, Reaves et al. [37] found that 67.6% of the messages sent to DPNs contained a code or OTP, thus concluding that receivers were being used for account verification and user authentication [36]. In this paper, we extend this methodology and distinguish between Single-use Codes (*i.e.*, OTPs) and Single-use Links. We find OTPs are

still on the rise, with 77.02% of messages containing them. Single-use Links are less popular, being present in just 2.18% of messages, followed by 0.80% offering both an OTP and a link. Given that only 14M messages in our dataset (20%) have neither of these single-use means, and that sending services use them to verify authenticated actions (*i.e.*, that require user intervention), we conclude that DPNs are predominantly being used to create accounts on online platforms.

E. Malicious URLs

After discarding the aforementioned Single-use Links, we end up with 451,165 messages that contain a URL. These amount to 178k unique URLs after removing duplicates. In an attempt to find malicious or harmful URLs in messages sent to DPNs, we use the Google Safe Browsing API [17] to identify web resources flagged as phishing, malware or spam. To account for shortened links, we expand their URLs before checking them against Safe Browsing’s database. This expansion is performed by sending an HTTP request to the shortened URL and retrieving the final “location” header without effectively loading the contents of the destination website. We use a list of publicly-known shortener services to determine which items need to be expanded.⁵

With this pipeline, we find merely 41 URLs spread across 125 messages that are considered harmful by Google. All of them fail in the “social engineering” category. Most malicious URLs appear to be either Apple-related scams or phishing campaigns targeting banks.

VI. ANALYSIS OF SERVICES

This section presents the analysis of the services found sending SMS to DPNs. Our analysis focuses on answering two questions: (*i*) whether DPNs are actually being used for creating accounts on online services, and (*ii*) measuring their potential for abuse. Given the technical limitations of qualitatively analyzing all 70M messages in our dataset (which includes a long tail of small and lesser known services), we focus on the subset of 46,041,215 entries only containing SMS from the top 212 services. We still consider it a representative subset of the ecosystem as it is an order of magnitude larger than the whole dataset from the previous study [37]. As mentioned in Section IV-C, this list of services is based on the most occurring keywords found in our dataset.

Table III lists the top-10 online sending services with more messages to DPNs. We find lesser-known —yet demanded— services like DENT [10] (which offers free mobile phone lines), regional operators like Disney+ Hotstar [34] (an Indian streaming platform recently acquired by The Walt Disney Company), and well-known companies with a global userbase (*e.g.*, Uber, WhatsApp). Services like Google, Netflix, Telegram and Tinder are not included in Table III because, individually, they account for less than 1.5% of the total number of messages. In fact, there is a long tail of sending services in the DPN ecosystem. We find examples of companies operating

⁵See <https://github.com/boutetnico/url-shorteners>.

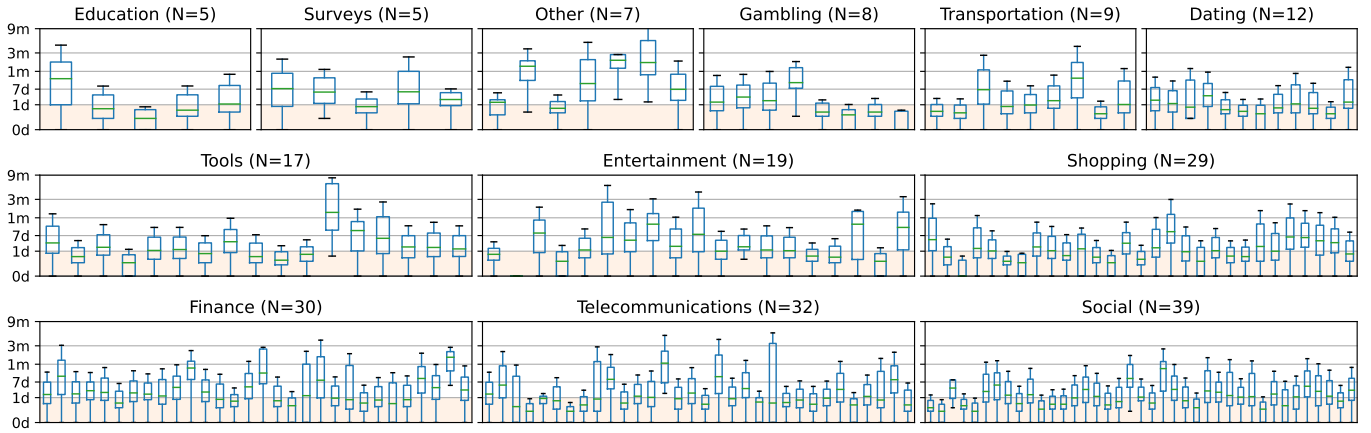


Fig. 3. Time-to-First-Message per service grouped by service category.

TABLE III
TOP SERVICES BY VOLUME OF MESSAGES.

Service	Category	Messages	DPNs
Uber	Transportation	10.2%	58.2%
DENT	Communications	8.4%	4.1%
Facebook	Social	3.7%	77.2%
WhatsApp	Communications	2.8%	69.3%
Instagram	Social	2.8%	68.2%
PayPal	Finance	2.6%	45.0%
Amazon	Shopping	2.6%	69.3%
Shopee	Shopping	2.5%	12.1%
Disney+ Hotstar	Entertainment	2.5%	0.292%
TikTok	Social	1.5%	72.5%
Other	N/A	35.1%	99.8%

in a particular country or world region (*e.g.*, Smood [38] and Careem [7], a mobility app from Uber used in the Middle East) and recognized names in the Finance (*e.g.*, HSBC, Chase, Citibank), Telecommunications (*e.g.*, AT&T, Deutsche Telekom, Overbit) and even Public Administration (*e.g.*, NHS, government agencies from Spain and India) sectors.

Overall, we find the top services by volume account for 65% of all messages received by DPNs and offer an ample range of services, including Social Media, Entertainment, Education, and even sensitive ones such as Telecommunications and Finance. Globally-known services like TikTok, Facebook, WhatsApp and Amazon have their messages spread across more than half of all DPNs. Conversely, highly localized services like the aforementioned Disney+ Hotstar have a higher density of messages that concentrate in just 50 DPNs, 41 of which have an Indian country prefix. DENT is an interesting case, as it is the second service with most messages sent to DPNs yet it only appears in 694 receivers from 45 different countries. If we sort by DPN coverage, we find two online services with more than 10k receivers that do not appear in Table III as they each account for less than 0.50% of messages. These services are Bigo Live [4] and Kwai [25], two social media platforms similar to TikTok functionality-wise. The median number of services that appear in a DPN is 40, with a maximum of 167

services (covering 78.7% of the known services lists). All the DPNs we found in our dataset contain at least one service from the top 212.

A. Evidence of Usage

Given all the online services we labelled require users to create an account, we can safely assume these messages are sent by the service as a consequence of an action performed by the user (*e.g.*, registration, login, transaction confirmation). Therefore, users must be registering accounts on online services using DPNs in order for these messages to appear in our dataset. Besides some exceptions like Google, most services make a 1-to-1 relation between user accounts and phone numbers. In practice, this means that a given phone number can only be tied to a single service account. For this reason, and considering that DPNs are by definition shared between multiple users, there is an incentive to register an account on a popular service as soon as a DPN becomes available on a gateway.

To verify this dynamic, we measure how long it takes for an online service to appear in a DPN, presumably as a direct result of an account registration or recovery (*i.e.*, re-verification) event. Figure 3 provides boxplots for each service grouped by category. These boxplots represent the *Time-to-First-Message* (TTFM) since the DPN was first seen in a gateway until a message from a given service was received. We find a considerable amount of services, especially in the telecommunications category, have a median TTFM shorter than 24 hours (colored area in the chart).

B. Potential for Abuse

We also analyze the rate at which messages from a specific service are being sent to a given DPN. As discussed in Section VI-A, for a service message to appear in a DPN, a user must have previously performed an action that triggered the message. Because service messages involve manual interaction, too many messages in a short period of time might be indicative of some sort of automation. While we cannot conclude that the presence of automation is always

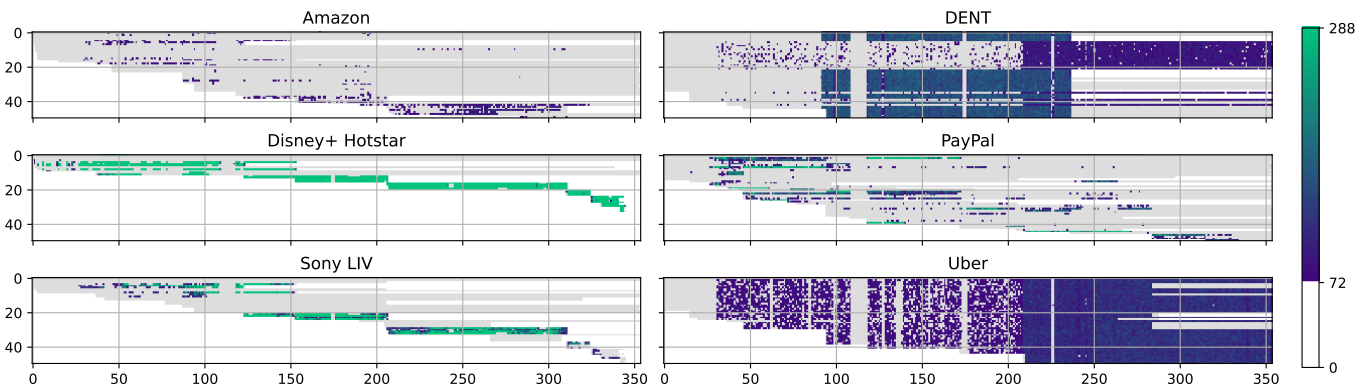


Fig. 4. DPNs with the longest bursts of account-related messages grouped by service. X axis shows days, while every row in the Y axis plots the messages for a given DPN. Gray pixels show the lifespan of a DPN.

related to service abuse (e.g., creation of bot accounts, fake engagement [32]), it is definitely abnormal for a legitimate user to request an OTP verification code or similar multiple times per hour on the same account and for an extended time.

Figure 4 shows the services for which we detect long bursts of account-related messages (i.e., those having any of the purposes mentioned in Section IV-D except “activity”). For each subplot, we pick the top 50 DPNs with the most received messages and only color the days when a phone number received at least 72 messages (roughly equivalent to 3 messages per hour). We also represent as continuous gray lines the DPN lifespan. These services contain DPNs with bursts that extend several days, meaning that some phone numbers kept receiving more than 72 messages per day for more than 100 days straight. In the case of Disney+ Hotstar and Sony LIV, we can attribute this behavior to the two services being only available in India and to the scarcity of DPNs with an Indian calling prefix. For DENT and Uber, we observe this dynamic across a much larger pool of phones.

While there are legitimate uses for DPNs (e.g., registering anonymously on dating sites for privacy reasons), DPNs can also be abused to create fake accounts either manually or using some automation tool as Figure 4 suggests. In fact, many PSGs have banners promoting or advertising services offering PVAs (i.e., phone-verified online accounts available for sale on underground sites, mostly for nefarious purposes like fake social engagement [40]). We posit that a reasonable explanation for that is that the PVA provider and the PSG is the same organization or they are affiliated in some way.

VII. CASE STUDIES

We next present several cases of interest found in our dataset that illustrate the potential for abuse of DPNs.

Free Trials. Oftentimes, popular services offer promotions or *trials* to new users. DPNs allow users to register multiple accounts and obtain access to features that would not be available beyond the trial period. For example, the Indian online e-learning platform BYJU offered a free 1-to-1 class to newly registered users [6]. Our dataset contains around 15k

messages from this platform, 7% of which are associated with activities, when the service notifies of user-performed actions or important events. The remaining 92.5% are either associated with “account creation” or “account verification”, suggesting that users leverage DPNs to test the service or access features that would not be available without paying a subscription.

Phone Chaining. One of the most interesting uses we see for DPNs is the registration of private secondary phone numbers. This is a common practice in the PVA ecosystem and it is usually known as *phone chaining* [40]. Some big actors enabling this are DENT [10] (8% of the dataset are messages from this service), Google Voice [18] and TextNow [39]. In fact, phone chaining is so common in this ecosystem that more than 6K DPNs (36% of the dataset) have been, at some point, registered in one or more of just the previous three services. We also looked for popular mobile phone carriers outside the list of top services and found evidence of new lines being registered online and then their SIM cards being sent by mail. We have obtained evidence of such practices even for carriers located in countries with registration laws mandating Proof of Identity, such as Australia, India and France [20].

Finance. In this category we find cryptocurrency exchanges, FinTech (Financial Technology) apps, and traditional banks. In all cases, we see messages denoting successfully completed account creation and transactions. One of such examples is Empower, a FinTech app that offers microloans. This service has sent messages to at least 131 different DPNs in multiple occasions confirming the deposit of funds, meaning that it can potentially be abused for loan fraud. Outside the top 212 services list, we find users linking DPNs to bank accounts to receive verification codes (e.g., Citibank, HSBC, Barclays) and even opening entirely new accounts, raising concerns for whether this complies with Europe’s PSD2 Strong Customer Authentication (SCA) requirement [12]. We found more than 100 DPNs registered against banks, although this figure is probably a lower bound estimate as we have not thoroughly looked at this matter nor is the focus of this study.

Healthcare. We find evidence of DPNs being used for regis-

tering to medical services such as the British National Health Service (NHS) [31] or CoWIN (India’s COVID-19 Vaccination Program) [22]. In both cases we find sensitive information being sent over SMS after the user has registered to the service. This includes secret single-use codes, COVID-19 test results and appointments including their precise date and location. We also identify cases where the names and surnames of the user are sent alongside the previous information.

Public Administrations. We find various types of SMS messages sent by government agencies. While in most cases these are just innocuous notifications, there are two cases that raise our attention. “CI@ve” [16] is an Identity Provider used to authenticate against the Spanish Public Administration by sending an OTP code to a registered phone number with every login attempt. The presence of this service in the dataset is concerning since it is tied to a citizen or a registered company, and can be used to perform sensitive procedures. We also encounter messages related to “Aadhaar,” India’s ID system and the largest in the world [35], which also sends OTP codes when logging in to banks and other online services [46].

VIII. CONCLUSIONS

Online services have recently doubled down on their efforts to implement account verification and 2FA flows, using SMS as one of the channels to deliver these messages. In this paper, we show that the DPN ecosystem is mostly being (ab)used for circumventing these security mechanisms without needing a personal phone number. We also observe a significant increase in the usage of DPNs for creating fake accounts since the last available measurement from 2018, jumping from thousands of messages received per year to millions. We find that operators of the PSGs offering DPNs seem to be, in some cases, strongly tied to underground markets offering Phone Verified Accounts (PVAs). We also find that online services do not have effective protections against the abuses of this ecosystem: Both global well-recognized services (such as Google and Facebook), banks, governments, and small brands send verification messages to DPNs.

Future Work. Our keyword-based message classification shows a huge long tail of services and purposes yet to be analyzed. Given the scale of the dataset, a more in-depth automated analysis is needed to understand what trends lie in this long tail. One interesting research challenge is the definition of methodologies to identify DPNs and create effective blocklists to mitigate their potential for abuse when accounts are created. A second aspect we plan to explore in our future work is a detailed analysis of the messages with OTP tokens, investigating both message senders and recipients. Across our dataset, we observe nearly 80% of the messages with an OTP code. Fraudsters often abuse these messages to artificially inflate traffic to a range of numbers controlled by a single mobile network operator; in return, the mobile operator shares with the fraudster a portion of the generated revenue [43].

ACKNOWLEDGEMENTS

This research was supported by the AEI grant ODIO (PID2019-111429RB-C21 and PID2019-111429RB-C22) and the Region of Madrid grant CYNAMON-CM (P2018/TCS-4566), co-financed by European Structural Funds ESF and FEDER. José Miguel Moreno was supported by the Spanish Ministry of Science and Innovation with a FPI Predoctoral Grant (PRE2020-094224). Srdjan Matic was partially supported by the Atracción de Talento grant (Ref. 2020-T2/TIC-20184), funded by Madrid regional government, and the PRODIGY Project (TED2021-132464B-I00), funded by MCIN/AEI/10.13039/501100011033/ and the European Union NextGenerationEU. Narseo Vallina-Rodriguez was supported by a Ramon y Cajal Fellowship (RYC2020-030316-I).

The opinions, findings, and conclusions, or recommendations expressed are those of the authors and do not necessarily reflect the views of any of the funding bodies.

REFERENCES

- [1] Receive SMS Online. <https://receive-sms.cc/>, 2022.
- [2] Bandwidth Inc. Caller ID Lookup/Caller Name Lookup. <https://www.bandwidth.com/glossary/caller-id-lookup/>, 2022.
- [3] Bandwidth.com. Bandwidth - The universal platform for global enterprise communications. <https://www.bandwidth.com/>, 2022.
- [4] Bigo Technology Pte. Ltd. Bigo Live – Live Stream, Go Live. <https://play.google.com/store/apps/details?id=sg.bigo.live>, 2022.
- [5] Bishal Bishal and Jerome R. Bellegarda. Language Identification from Very Short Strings. <https://machinelearning.apple.com/research/language-identification-from-very-short-strings>, 2019.
- [6] BYJU’S. BYJU’S – The Learning App. <https://play.google.com/store/apps/details?id=com.byjus.thelearningapp>, 2022.
- [7] Careem Networks FZ-LLC. Careem. <https://www.careem.com/>, 2022.
- [8] Chrysta Cherrie. The 2021 State of the Auth Report: 2FA Climbs, While Password Managers and Biometrics Trend. <https://duo.com/blog/the-2021-state-of-the-auth-report-2fa-climbs-password-managers-biometrics-trend>, 2021.
- [9] Billy Chia. What is an Alphanumeric Sender ID? <https://www.twilio.com/docs/glossary/what-alphanumeric-sender-id>, 2022.
- [10] DENT Wireless Limited. DENT – The world’s first digital & global operator. <https://www.dentwireless.com/>, 2022.
- [11] Alexandra Dmitrienko, Christopher Liebchen, Christian Rossow, and Ahmad-Reza Sadeghi. On the (In)Security of Mobile Two-Factor Authentication. In *International Conference on Financial Cryptography and Data Security*, 2014.
- [12] European Commission. Strong customer authentication requirement of PSD2 comes into force. https://ec.europa.eu/info/publications/190913-safer-payment-services_en, 2019.
- [13] Pavel Feldman and open-source contributors. Playwright. <https://playwright.dev/>, 2022.
- [14] Free Phone Number. Receive SMS. <https://play.google.com/store/apps/details?id=com.receiveSMS.online>, 2021.
- [15] Sergiu Gatlan. Twitter employees required to use security keys after 2020 hack. <https://www.bleepingcomputer.com/news/security/twitter-employees-required-to-use-security-keys-after-2020-hack/>, 2021.
- [16] Gobierno de España. CI@ve – Electronic Identity for the Administration. <https://clave.gob.es/>, 2022.
- [17] Google Developers. Google Safe Browsing. 2022.
- [18] Google LLC. Google Voice. <https://voice.google.com/>, 2022.
- [19] Paul Grassi, James Fenton, Elaine Newton, Ray Perlner, Andrew Regenscheid, William Burr, Justin Richer, Naomi Lefkovitz, Jamie Danker, Yee-Yin Choong, Kristen Greene, and Mary Theofanos. Digital Identity Guidelines: Authentication and Lifecycle Management, 2020.
- [20] GSM Association. Access to Mobile Services and Proof of Identity 2020: The Undisputed Linkages. https://www.gsma.com/mobilefordevelopment/wp-content/uploads/2020/03/Access_to_mobile_services_2020_Singles.pdf, 2020.

- [21] Hang Hu, Peng Peng, and Gang Wang. Characterizing Pixel Tracking through the Lens of Disposable Email Services. In *2019 IEEE Symposium on Security and Privacy (SP)*, pages 365–379, 2019.
- [22] India’s Ministry of Health and Family Welfare. CoWIN. <https://www.cowin.gov.in/>, 2022.
- [23] Vasu Jakkal. The passwordless future is here for your Microsoft account. <https://www.microsoft.com/security/blog/2021/09/15/the-passwordless-future-is-here-for-your-microsoft-account/>, 2021.
- [24] Grant Jenks. WordSegment - Python Word Segmentation. <https://grantjenks.com/docs/wordsegment/>, 2018.
- [25] Joyo Technology Pte Ltd. Kwai – Watch cool & funny videos. <https://play.google.com/store/apps/details?id=com.kwai.video>, 2022.
- [26] Victor Le Pochat, Tom Van Goethem, Samaneh Tajalizadehkhoob, Maciej Korczyński, and Wouter Joosen. Tranco: A Research-Oriented Top Sites Ranking Hardened Against Manipulation. In *Network and Distributed System Security (NDSS) Symposium*, 2019.
- [27] Zeyu Lei, Yuhong Nan, Yanick Fratantonio, and Antonio Bianchi. On the insecurity of SMS one-time password messages against local attackers in modern mobile devices. In *Network and Distributed System Security (NDSS) Symposium*, 2021.
- [28] Leon. Simhash. <https://github.com/1e0ng/simhash>, 2020.
- [29] Gurmeet Singh Manku, Arvind Jain, and Anish Das Sarma. Detecting Near-Duplicates for Web Crawling. In *Proceedings of the 16th International Conference on World Wide Web, WWW ’07*, page 141–150, New York, NY, USA, 2007. Association for Computing Machinery.
- [30] MDN contributors. Using the Fetch API. https://developer.mozilla.org/en-US/docs/Web/API/Fetch_API/Using_Fetch, 2022.
- [31] National Health Service. NHS App. <https://play.google.com/store/apps/details?id=com.nhs.online.nhsonline>, 2022.
- [32] David Nevado-Catalán, Sergio Pastrana, Narseo Vallina-Rodriguez, and Juan Tapiador. An analysis of fake social media engagement services. *Computers & Security*, 124:103013, 2023.
- [33] Lily Hay Newman. Google Gets Serious About Two-Factor Authentication. Good! <https://www.wired.com/story/google-two-factor-authentication-default/>, 2021.
- [34] Novi Digital Entmt. Disney+ Hotstar. www.hotstar.com/, 2022.
- [35] Privacy Intl. ID systems analysed: Aadhaar. privacyinternational.org/case-study/4698/id-systems-analysed-aadhaar, 2021.
- [36] Bradley Reaves, Nolen Scaife, Dave Tian, Logan Blue, Patrick Traynor, and Kevin RB Butler. Sending out an SMS: Characterizing the Security of the SMS Ecosystem with Public Gateways. In *IEEE Symposium on Security and Privacy (S&P)*, 2016.
- [37] Bradley Reaves, Luis Vargas, Nolen Scaife, Dave Tian, Logan Blue, Patrick Traynor, and Kevin RB Butler. Characterizing the security of the SMS ecosystem with public gateways. *ACM Transactions on Privacy and Security (TOPS)*, 22(1), 2018.
- [38] Smood.ch. Smood – Suisse Food Delivery. <https://play.google.com/store/apps/details?id=com.jamtech.marabel.smood>, 2022.
- [39] TextNow, Inc. Textnow. <https://www.textnow.com/>, 2022.
- [40] Kurt Thomas, Dmytro Iatskiv, Elie Bursztein, Tadek Pietraszek, Chris Grier, and Damon McCoy. Dialing Back Abuse on Phone Verified Accounts. In *Conf. on Comp. and Comms. Security (CCS)*, 2014.
- [41] TSOFT. SMS Receive Phone Numbers. <https://play.google.com/store/apps/details?id=com.tsoft.moshnumbers>, 2020.
- [42] Twilio. Communication APIs for SMS, Voice, Video & Authentication | Twilio. <https://www.twilio.com/>, 2022.
- [43] Twilio. SMS Traffic Pumping Fraud. <https://support.twilio.com/hc/en-us/articles/8360406023067-SMS-Traffic-Pumping-Fraud>, 2022.
- [44] Unicode, Inc. Glossary of Unicode Terms. unicode.org/glossary/, 2021.
- [45] Unicode, Inc. Unicode Normalization Forms. <https://unicode.org/reports/tr15/>, 2021.
- [46] Unique Identification Authority of India. Aadhaar Myth Busters. <https://uidai.gov.in/my-aadhaar/about-your-aadhaar/aadhaar-myth-busters.html>, 2022.
- [47] Donnie Wang. What is a Short Code? <https://www.twilio.com/docs/glossary/what-is-a-short-code>, 2022.
- [48] Titus Wormer. woorm/franc: Natural language detection. <https://github.com/woorm/franc>, 2021.