A Tale of Three Location Trackers: AirTag, SmartTag, and Tile

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***Abstract*—This paper studies the performance of the three most popular location tags (Apple's AirTag, Samsung's SmartTag, and Tile) through *controlled* experiments – with a known large distribution of location-reporting devices – as well as *in-the-wild* experiments – with no control on the number and kind of reporting devices encountered, thus emulating real-life use-cases. We build upon prior research by conducting an expanded and comprehensive analysis of these devices, incorporating new methodologies and broader geographical contexts. Specifically, we leverage improved data collection techniques and deploy 22 volunteers across 29 countries, examining the tags' performance under various conditions, including user mobility, population density, and mobile market share.**

Our findings highlight crucial updates in device behavior, with AirTag showing marked improvements in location report frequency, likely due to firmware updates. Companion device density emerged as the primary determinant of tag performance, overshadowing technological differences between products. Additionally, we find that post-COVID-19 mobility trends could have contributed to enhanced performance for AirTag and SmartTag. Tile, despite its cross-platform compatibility, exhibited notably lower accuracy, particularly in Asia and Africa, due to limited global adoption. Spaital error for all tags are well-modeled by log-normal distributions, demonstrating the need for improved location estimation methods to reduce occasional significant inaccuracies.

I. Introduction

LOCATION tracking technologies have become increasingly prevalent in recent years, with products like Apple's AirTag, Samsung's SmartTag, and Tile offering consumers the ability to monitor the location of personal belongings. These devices continuously broadcast Bluetooth Low Energy (BLE) packets and rely on a network of compatible devices to relay their position, raising questions about their accuracy, effectiveness, and potential for misuse (e.g., stalking). While previous research has explored the performance of some of these tags, our study aims to provide a more comprehensive and up-to-date analysis of the location tracking ecosystem.

This paper specifically serves as an extension to [1], which compared the performance of Apple AirTag [2] and Samsung SmartTag [3] in both *controlled* and *in-the-wild* experiments. The original study utilized custom-developed crawlers for each tag's companion apps (FindMy and SmartThings) to collect detailed location histories reported by devices. Controlled experiments provided insights into tag behavior, e.g., how frequently their location is reported. The tags were deployed in a secluded area alongside Apple and Samsung devices at increasing distances and in a busy campus cafeteria where WiFi connectivity provided an estimate of the surrounding device population. Complementary in-the-wild experiments explored opportunistic location reporting under varying conditions, e.g., user mobility, population densities, times of day, and days of the week. These experiments involved four volunteers traveling across six countries, each carrying both tags attached to a smartphone equipped with a custom app that logged contextual data such as GPS location and connectivity, etc.

This extension addresses limitations of [1] and presents expanded investigation into the performance of BLE tags across a broader range of devices and geographical contexts. Our study includes three most popular products in the market: AirTag, SmartTag, and Tile [4], the latter of which supports both iOS and Android platforms via Life360 [5] and Tile application. This selection allows us to compare *device-dependent* tags (AirTag and SmartTag) with *app-dependent* alternatives (Tile), offering insights into how different approaches to building a location-reporting ecosystem affect performance.

Our methodology advances the original study by implementing a more rigorous data collection process. First, we improve the crawlers, enabling more precise, minute-by-minute location monitoring. Next, we significantly expand the scope of in-the-wild experiments with 22 volunteers traveling across 29 countries, providing a more global perspective of tags' performance. By comparing our findings with those of the original study, we evaluate how shifts in real-world conditions have influenced tag effectiveness. Furthermore, the larger dataset enabled statistical modeling of the tags' distance from ground-truth locations, providing an in-depth evaluation of the methods used by manufacturers to estimate a tag's location. Our key findings are the following:

Update in Device Behavior. Controlled experiments revealed significant changes in AirTag behavior, likely due to firmware updates. AirTags now broadcast Bluetooth signals with strength comparable to SmartTags and Tile devices, leading to a marked increase in location report frequency. This improvement was particularly evident in the campus cafeteria experiment, where the prevalence of iOS devices boosted AirTag performance.

Importance of Companion Device Density. Contrary to earlier findings in [1], our experiment in the wild reveals that the efficacy of location tags is primarily determined by the prevalence of compatible location-reporting devices rather than the specific technology employed. We observe a general correlation between tag performance and the estimated likelihood of encountering companion devices, derived from population density and the country-level mobile market-share.

Poor Tile Performance. Tile's accuracy is notably lower than that of AirTag and SmartTag, despite its compatibility with both iOS and Android. Performance varies by region, with the highest accuracy observed in the Americas and Europe, while accuracy is significantly lower in Asia and Africa. This disparity appears to result from infrequent location updates, likely due to the limited global adoption of Life360/Tile.

Impact of COVID-19. Following the relaxation of COVID-19 social-distancing measures (2020–2022), public mobility and activity levels gradually returned to pre-pandemic norms, increasing the number of active companion devices available in the environment. This rise in mobility likely contributed to improved location-reporting performance. Compared to the findings in [1], AirTags and SmartTags demonstrate enhanced accuracy, reflecting the greater availability of nearby companion devices as public activity resumed.

Statistical Modeling for Enhanced Tracking. We apply statistical models to analyze spatial (positional) errors relative to the GPS ground truth. Spatial errors for all tags follow a log-normal distribution, with heavy tails indicating occasional significant deviations. We also find that SmartTag significantly underestimates its margin of error compared to its competitors, raising concerns about the reliability of its location updates in accurately representing true positional uncertainty.

II. Background and Related Work

Location tags such as AirTag, SmartTag, and Tile use the BLE protocol [6] to transmit unique identifiers with a range of up to 100 meters. Additionally, SmartTag+ and AirTag support Ultra Wideband [7] which further extends the range while allowing more precise device localization. Ultra Wideband is only supported by iPhone 11 or later for AirTags, and Samsung Galaxy S21 or later for SmartTag.

Remote tracking is enabled by location-reporting devices, such as iOS devices for AirTags, Samsung devices for SmartTags, or any mobile device with Life360/Tile application installed and location tracking enabled for Tile. These updates use the reporting device's GPS coordinates as an approximation, allowing tag owners to track their tags via companion applications. This process is designed to preserve privacy, revealing neither the tag owner's identity nor that of the reporting device.

Despite privacy safeguards, measures to deter malicious tracking remain insufficient, as discussed in [8]. Vendors only alert users if an unpaired tag from the same manufacturer is detected nearby for an extended period, leaving users vulnerable to cross-vendor misuse (e.g., AirTags used to stalk Samsung users). To address this, Apple released "Tracker Detect" [9], an Android app for manually scanning for AirTags, while Heinrich et al. [10] proposed a system that automatically alerts users after encountering the same AirTag in three separate locations within 24 hours. Briggs et al. [11] extended this design to support generic tags, not just AirTags. However, these methods are limited by MAC address randomization [12], which causes tags to appear as new devices to third-party apps over time.

Prior work on the global performance of location tags in real-world scenarios has been limited. Instead, Givehchian et al. [13] explored the privacy implications of BLE protocol devices, such as location tags, demonstrating that physical-layer identification is possible but often unreliable. Hernández et al. [14] studied the efficiency of finding AirTags and Tile tags on a university campus through real and simulated experiments, where they model the probability of locating a tag based on the flow rate of individuals carrying compatible smartphones within the tag's detection range. They showed that AirTags had a range of 10–30 meters (consistent with [1]) and that in populated areas, both tags relayed their location within one hour 98% of the time.

[1] examined the performance of two popular Bluetooth Low Energy (BLE) location tags—Apple's AirTag and Samsung's SmartTag—through controlled experiments and real-world scenarios. The study compared the tags' accuracy and responsiveness in reporting locations, considering factors such as population density, user mobility, and the number of nearby reporting devices. It found that both tags perform similarly, typically locating within 100 meters in about 10 minutes. Despite Samsung's more aggressive update strategy, the paper claimed that real-time use of either tag for stalking is impractical, though half of a victim's movements could be backtracked with a one-hour delay. This paper servers as an extension to [1] by addressing the following limitations:

1) The scope of [1] was limited to AirTag and SmartTag, both of which lack cross-platform compatibility, limiting insights into tags that work across multiple operating systems. *This extension includes Tile due to its longstanding presence since 2012 and its recent expansion through integration with Life360's user base in 2021.*
2) The crawling methodology relied on Optical Character Recognition (OCR) [15] to extract tag locations from their respective companion applications. This approach introduced potential errors of up to one minute in the reported location timestamps. *We enhance this methodology to achieve second-level granularity in location updates without using OCR.*
3) The "in-the-wild" data collection was conducted in 6 countries during the COVID-19 pandemic (March to August 2022), when social distancing measures likely reduced the density of nearby companion devices, impacting the representativeness of the results. *We conduct a more expansive real-world measurement campaign across 29 countries after such regulations were lifted.*

III. Methodology

Our study focuses on three prominent BLE trackers currently available in the market: Apple's AirTag, Samsung's SmartTag, and Tile (Mate). Figure 1 provides a visual overview of our platform for analyzing the tags of interest. Our approach centers on two key components: data collection servers and mobile vantage points. The former runs on MacOS and Linux, hosting custom crawlers that continuously query and record location data from the tags' companion apps (FindMy, SmartThings, and Tile). The mobile vantage points are Android smartphones equipped with a custom case housing all three tag types, which we deployed to volunteers across numerous countries.

Fig. 1. On the left, two data collection servers (MacOS and Ubuntu) run the FindMy, SmartThings, and pytile crawlers. On the right, a sample 3D mockup of our vantage point, a Galaxy A34 equipped with three tags.

Fig. 2. 3D-printed cases for the Redmi Go (left), Galaxy A34 (center), and Galaxy S21+ (right), used as vantage points.

A. Tag Crawlers

The real-time location data of different tags are provided in each of their companion app: FindMy for AirTag (iOS and MacOS exclusive), SmartThings for SmartTag (Samsung Android exclusive), and Tile/Life360 app (available on both iOS and Android) for Tile. Since there is no official APIs published by the manufacturers, we designed custom "crawlers" that automate location monitoring for each type of tags deployed during the data collection stage. Previous crawlers for AirTags and SmartTags, as used in [1], relied on automated interactions to "pin" their locations to Apple Maps and Google Maps, respectively. Next, Optical Character Recognition (OCR) was used to read coordinates and timestamps from the maps, calculating the reporting time based on the crawling epoch and the "last seen" time (e.g., "X minutes ago") displayed in their companion apps. This approach introduced potential errors of up to one minute for 47% of location reports. To address this limitation, we developed a more reliable and precise method for collecting location data, capturing both coordinates and exact reporting timestamps with second-level granularity.

1) AirTag Crawler: Our AirTag crawler leverages an open-source bash script [16] designed to run on macOS with an authenticated Apple account. During each execution, the script opens the FindMy Application and parses its cache file[1], which stores the most recent location information of devices owned by the Apple account. To continuously monitor deployed AirTags, we set up two macOS servers to execute the script at one-minute intervals.

2) SmartTag Crawler: For accessing SmartTag data, we leverage the cache file[2] utilized by the SmartThings app, which contains detailed metadata for the currently selected device. Our custom automation script, executed via the Android Debugging Bridge (ADB), iterates through each registered SmartTag. At each iteration, the script prompts the app to refresh the cache file for the selected tag, then extracts the precise location coordinates and timestamps directly from the app's internal data structure. To ensure minute-level location probing for each SmartTag, we run the SmartTag crawlers across 4 rooted Samsung devices (A34 5G) simultaneously.

3) Tile Crawler: We developed a Python script leveraging the pytile library [17], which interfaces with a custom API for Tile devices. This script, automated to run at one-minute intervals, authenticates with the Tile service and retrieves location information for all associated trackers.

B. Vantage Point

Our vantage points consist of three rooted Android smartphones. [1] employed Xiaomi Redmi Go devices to compare the performance between AirTags and SmartTags. For this extension study, we also introduce the Samsung Galaxy A34 and S21+ to incorporate Tile and address the battery limitations of the Redmi Go, which, with its 3,000mAh capacity, often depleted too quickly. Each tag was securely mounted on a custom-designed, 3D-printed cover attached to the back of the mobile device, as shown in Figure 2. The devices were further configured to avoid reporting the location of any of the attached tags; for Samsung devices, we disabled "Offline finding" option in the Find My Mobile settings to exclude the device from SmartThings network. Additionally, we verified that neither the Life360 nor Tile applications were installed. Note that Android devices cannot be involved in Apple's FindMy network, thus precluding any inadvertent location reporting of AirTags.

To precisely document the ground truth location of vantage points over time, we extend the custom Android application used in [1]. Manually installed in our devices, this app utilizes [18] to record GPS location at one-second intervals, providing a much finer granularity of location data compared to the previous study . The app employs a buffering system which stores the location data for up to five minutes before transmitting it to our server via a POST request when internet connection is available. If connectivity is unavailable, the data remains buffered until a connection can be established, ensuring no loss of information. We compare this ground truth against the locations reported by our crawlers to assess tags' performance.

C. Dataset Description

Each location update from GPS or BLE tags includes four data points: <timestamp, latitude, longitude, σ>. As shown

[1]/Library/Caches/com.apple.findmy.fmipcore/Items.data

[2]com.samsung.android.oneconnect/shared_prefs/FME_SELECTED_DEVICE.xml

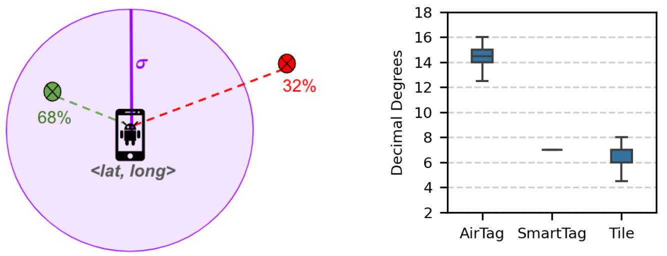

Fig. 3. Illustration of an Android GPS location reported at a specific timestamp, showing latitude, longitude, and σ at 68% confidence interval (left). Precision of reported location coordinates, measured in decimal degrees, collected by our crawlers for different tag types (right).

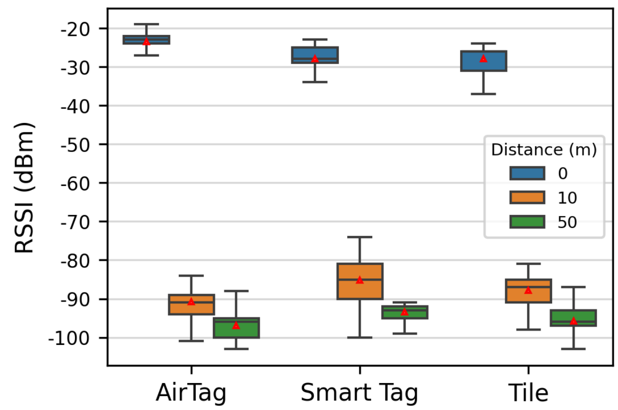

Fig. 4. RSSI strength for each tag type at varying distances. The red triangles mark the statistical average.

in Figure 3 (on the left) , σ represents the radius of a circle centered around the reported coordinates and is guaranteed to contain the true position within a certain probability. In essence, σ serves as an estimate of the location report's margin of error. Android documentation specifies that GPS reports provide σ at the 68th percentile, meaning there is a 68% probability that the actual location lies within this radius. BLE tag manufacturers have not disclosed the confidence interval of σ for their devices. Note that vendorslabel σ differently (e.g., "horizontal accuracy" used by Android and Apple, "horizontal uncertainty" used by Samsung, "accuracy" used by Tile); however, we use σ throughout this paper for clearer referencing.

Coordinate precision—measured by the number of decimal places in location coordinates—is an important indicator of location data quality. As shown in Figure 3 (on the right), location reports from our AirTags crawler demonstrated the highest precision, with over 88% of coordinates having 14 or more decimal degrees. This consistently high precision suggests that Apple's companion devices provide highly detailed location data. In comparison, both SmartTag and Tile reports averaged 7 decimal degrees, offering a margin of error of approximately 1.11 cm at 0.0000001 degrees—still remarkably precise. However, in very rare cases (approximately 0.75%), Tile location reports had fewer than 5 decimal degrees, potentially introducing errors of up to 11.1 meters. While such occurrences were extremely infrequent, they suggest occasional precision limitations. Overall, the location reports collected from our tag crawlers are sufficiently precise to support our analysis of their location tracking capabilities.

D. Ethics

We obtained IRB approval (HRPP-2021-185) and informed participants of our data collection practices through a consent form. While we collect GPS data, we do not gather any identifiable or sensitive personal information.

IV. Controlled Experiment

A. Bluetooth Signal Strength

1) Methodology: We replicated the experiment in [1] in a secluded area, 300 meters away from any building, to isolate the performance of our tags from external interference. This controlled environment contained only our tags and test phones. We positioned three smartphones at varying distances—directly adjacent to, 10 meters, and 50 meters away from each tag type. These devices captured and measured the Received Signal Strength Indicator (RSSI) of BLE beacons emitted by the tags. SmartTags include the device local name ("Smart Tag") within their BLE advertisements. For AirTags, we leveraged the fact that accessories in the FindMy network share the first 6 bytes ("1EFF4C001219") when advertising BLE packets in *separated state* (i.e., when distant from the owner device)[19]. Tile beacons were identified by filtering BLE packets for Tile's 16-bit Service UUID as defined in Bluetooth specifications [20], [21].

2) Results: Figure 4 shows that all three tag types exhibited comparable levels of Received Signal Strength Indicator (RSSI). At most distances, the average pairwise differences between the tags were less than 3 dBm, a variation generally considered insufficient to meaningfully impact Bluetooth connectivity. The notable exception occurred between the AirTag and SmartTag at 10 meters, where the average RSSI difference exceeded 5 dBm. This larger discrepancy suggests that the SmartTag's beacon was received with approximately double the power of the AirTag, potentially influencing device detection range and signal stability at this distance.

Despite the exception at 10 meters, results for the AirTag significantly deviate from those reported in [1]. The previous study found that AirTag beacons were consistently received with an RSSI approximately 10 dBm lower than SmartTag beacons at all distances up to 50 meters, where the AirTag signals were no longer detected. We conjecture that this improvement may be attributed to firmware updates released for AirTags since the earlier study. The AirTags used in [1] were equipped with firmware version 1.0.301, whereas our tags operated on version 2.0.73. Note that these updates occur automatically when an AirTag is within Bluetooth range of its paired iPhone [22], making it challenging to control for specific firmware versions during our experiments.

B. Update Frequency

1) Methodology: We placed three of each tag types for a week in a university cafeteria which serves approximately

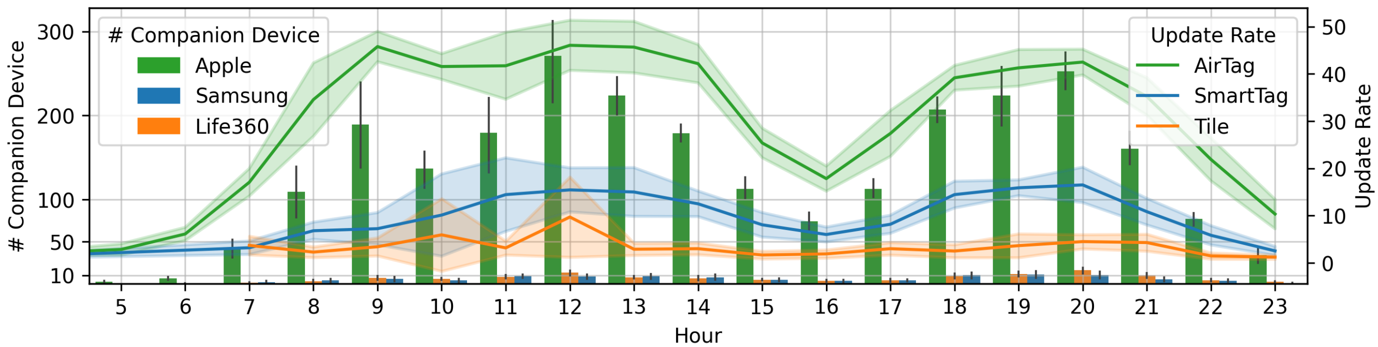

Fig. 5. Update rates of Tags at different times of day in a campus cafeteria.

1,200 people daily from 7am to 11pm. Throughout the experiment, we ran our custom crawlers while collaborating with the university's IT department to monitor the presence of tag-compatible devices nearby the deployed tags. Specifically, we leveraged the department's shared data which identify the manufacturer of mobile endpoints connected to the cafeteria WiFi. This allowed us to obtain an exact count of AirTag-compatible devices (iPhones, iPads) present in the area. Since the FindMy network is activated by default on Apple devices, this count directly represented potential AirTag reporters.

While we could also obtain the total number of Samsung devices, this would overestimate SmartTag-compatible devices since users must opt-in to *Offline finding*. To refine our count, we filtered network traffic with destination containing `chaser-eu02-euwest1.samsungiotcloud.com`, which is the domain URL for geolocation reports of SmartTags generated by non-owner devices (with "eu02-euwest1" representing the region subdomain) [23]. By counting unique devices sending requests to this domain, we achieved a more accurate tally of SmartTag-compatible devices. The percentage of Samsung devices which opted-in for SmartThings ranged from 11% to 26% per hour during our experiment.

For Tile, we counted the unique number of devices sending API requests to URLs containing `life360.com` or `tile-api.com`, as Tile locations can be reported by devices with either the Life360 or Tile app installed (and where users have opted-in to report locations of Tile tags).

The collected data was aggregated into time-segmented counts of each tag-compatible device type, ensuring complete anonymization of individual users. This approach allowed us to estimate the number of active location-reporting devices for each tag type present in the cafeteria at different times. We acknowledge that devices not connected to WiFi were not captured in our data, although the cafeteria's poor cellular coverage likely minimized this issue.

2) Results: Figure 5 illustrates the update rate as a function of surrounding compatible devices for AirTag, SmartTag, and Tile. The graph presents, for each hour, the average tag update rate and device count over the 4-day experiment period. Shaded areas and error bars indicate the standard deviation for each metric. The figure shows significant differences in performance and device prevalence among the three tag types. AirTags demonstrate the highest update rate, peaking at around 50 updates per hour during busy lunch periods. This performance correlates with the consistently high number of Apple devices, which often exceed 100 in working hours. In contrast, both SmartTag and Tile had far fewer companion devices present, generally less than 10 in most hours. Despite this limitation, SmartTags maintain their update rate between 10-20 updates per hour. Tile devices show the lowest performance, with update rates typically below 10 per hour. These findings highlight the critical role of ecosystem size in tag performance, with AirTag's update frequency benefiting from its higher popularity of compatible devcices. The data also suggests that SmartTag's network, while smaller, may be more aggressive in reporting locations compared to Tile's network.

To further analyze these results, we examine the update rate as a function of the number of companion devices present within an hour. Figure 6 compares the update rates for each tag type when there are fewer than 25 companion devices nearby. Note that our controlled experiment yields limited data for SmartTag and Tile at higher companion device counts. In the figure, circular markers represent the average update rate at each measured device count, while shaded regions indicate the standard deviation where data is available. Our observations reveal that SmartTag employs the most aggressive location reporting strategy. Its update rate generally increases with a higher number of companion devices, peaking at 23 updates per hour with 19 devices present. Notably, SmartTag requires 8 companion devices to achieve more than 10 location updates per hour. In contrast, AirTag and Tile converge to similar update rates, consistently remaining below 10 updates per hour when fewer than 21 companion devices are nearby. An interesting exception occurs for Tile at 16 companion devices, where the update rate often "spikes" above 20.

Figure 7 illustrates the relationship between AirTag update rates and larger numbers of companion devices. The bar plots represent the frequency of occurrences for each range of Apple device counts. Our analysis reveals that AirTag's update rate initially plateaus between 10-20 updates per hour when 30-70 Apple devices are present. However, as the number of Apple devices further increases, the update rate continues to rise, averaging over 45 updates per hour with more than 300 companion devices nearby. This finding contrasts with the results reported in [1], which suggested a consistent update rate of 10-15 across all Apple device counts.

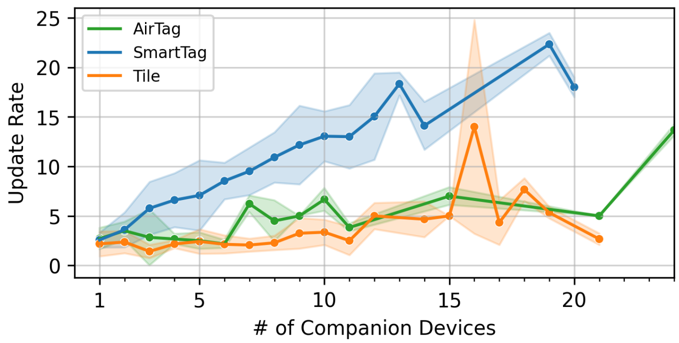

Fig. 6. Update rate of Tags as a function of compatible-devices (<25) per hour

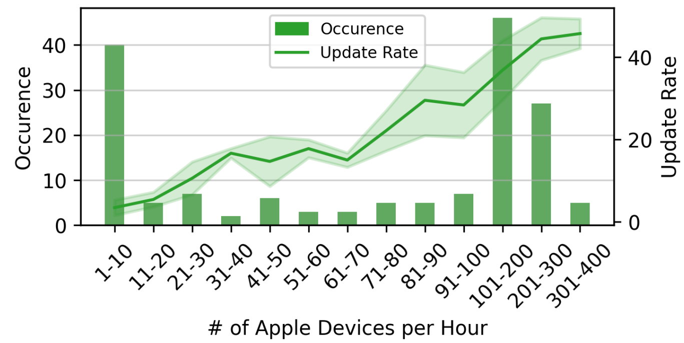

Fig. 7. AirTag update rate over number of nearby Apple devices

Device	Duration	Countries	Cities	# AirTag	# SmartTag	# Tile	Distance (km)
Redmi Go	Mar-Aug 2022	6	20	21,081	3,595	N/A	9,378
Galaxy A34 5G / Note 21+	Dec 2023 - Jan 2024	29	89	70,974	10,5426	8,440	16,305

TABLE I
SUMMARY OF TWO MEASUREMENT CAMPAIGNS. # REFERS TO THE NUMBER OF UNIQUE LOCATION UPDATES FOR EACH TAG.

The observed variation at higher device densities suggests a more complex interaction between AirTag behavior and the surrounding Apple ecosystem than previously understood. This change may be due to recent firmware updates to AirTags since [1], as described in IV-A. Additionally, advancements in the method for identifying companion devices could have played a role. Previously, device identification relied on analyzing traffic logs associated with Apple or Samsung application IDs. In this extension study, however, the IT department utilized advanced device profiling features from wireless LAN controllers [24], which can identify device types with greater accuracy, including specific models (e.g., iPhone 12). This improvement in device identification likely contributed to the differences observed between our findings and those in [1].

V. In-the-Wild Experiment

This section presents our "in-the-wild" deployment of tags, aimed at empirically evaluating their real-world feasibility for location tracking. Our analysis addresses two complementary aspects: (1) a high-level examination of trends in tag performance across geographical regions visited by vantage points, and (2) a more granular investigation, quantifying the expected reliability of individual location updates.

A. Experiment Setup

In [1], Redmi Go devices equipped with AirTags and SmartTags were deployed as vantage points by four volunteers between March and August 2022, covering 9,378 kilometers across six countries and 20 cities. To include Tile as an additional tag and address the Redmi Go's limited battery capacity, we conducted a new measurement campaign from December 2023 to January 2024. In this campaign, updated vantage points—Samsung Galaxy A34 5G or S21+ devices encasing all three tags (see Figure 2)—were distributed to 22 volunteers, who collectively traveled 16,305 kilometers across 29 countries and 89 cities. A detailed comparison of the two campaigns is provided in Table I.

Participants were instructed to carry the vantage points with them as much as possible during their daily activities and travels, limiting interactions to necessary actions such as charging. Additionally, we implemented a filtering process that excluded data recorded within a 300-meter radius of each participant's temporary "home" locations, which include not only permanent residences but also hotels, hostels, or any other accommodation where participants stayed overnight. This was to prevent potential data skew that could occur if a nearby device (such as a neighbor's or family member's phone) consistently reported a tag's location. After applying this filter, we retained 24.7% of the total data collected. We also exclude data from South Korea in our analysis of AirTag, as FindMy support is not expected in the region until Spring 2025 [25].

B. Spatial-Temporal Accuracy

1) Methodology: Spatial error is quantified as the haversine distance [26] between each reported tag location and the actual GPS position of its associated vantage point. Temporal error captures the latency of location updates, measured as the time difference between the vantage point's GPS record and the timestamp of the corresponding tag update. To account for these dimensions jointly, we follow the methodology in [1] to calculate spatial-temporal accuracy for each pair of vantage point and tag type. This is done by grouping reported locations into X-minute intervals for each vantage point, then measuring the distance between the GPS position and each tag's reported position within each interval. If the distance falls within a specified radius, we record a "hit". Spatial-temporal accuracy is then computed as the percentage of hits across all intervals. This provides a direct quantitative insight for real-world tracking: *what is the likelihood that a tag accurately updates its location within X minutes?*

2) Results: We begin our analysis by investigating each tag's accuracy within a given radius. To identify the radii of interest, we analyzed the combined accuracy of the location

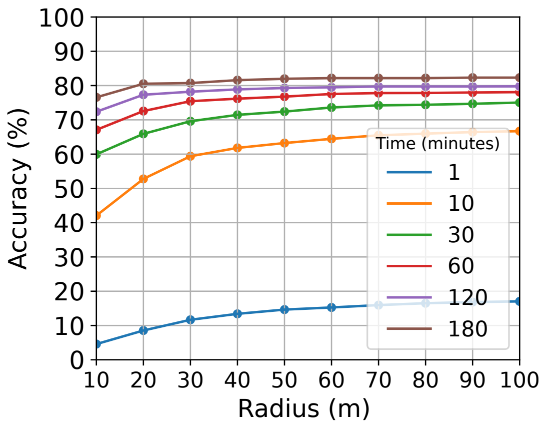

Fig. 8. Combined accuracy of tags vs. radius across different time windows.

tags as we increase the radius of reporting across different time intervals. Figure 8 shows that, in the case of short time intervals (1 and 10 minutes), the accuracy increases as the radius increases, for then plateauing at roughly 100 meters. For longer time intervals, there is no significant improvement in accuracy beyond 50 meters. Accordingly, we will use the following radii in our analysis: 10, 50, and 100 meters.

Figure 9 summarizes tag accuracy across radii of interest; note that "combined" refers to a unified Apple/Samsung ecosystem. Intuitively, Figure 9 (a,b,c) shows that relaxing the responsiveness, i.e., allowing more time to locate a tag within a radius, improves tag accuracy, e.g., the combined tag's accuracy for larger radii (50 and 100 meters) grows from 10% to 80% as the responsiveness grows from one to 120 minutes. Combining tags offers a 15% improvement, on average, over the accuracy of each individual tag.

The previous observations also apply to a small radius (10 meters, see Figure 9-a) although with a few important differences. First, one minute is too fast to locate a tag within such a small radius, e.g., an accuracy of 8% versus 17-19% at larger radii. Second, as we relax the responsiveness, the tag's accuracy increases much slower than what is observed for larger radii, e.g., 59% versus 70-71% assuming a responsiveness of 25 minutes. This happens because, as both tags and reporting users might move, it is more challenging to correctly report the right location with such small radius and high responsiveness. Finally, the maximum accuracy caps at 72%, when considering both tags combined, or 6-8% less than what observed for larger radii. Given the slow responsiveness allowed, this reflects errors introduced by approximating a tag's location with the reporting device location, which is unlikely more than 50 meters as per Figure 4.

If we focus on each tag independently, Figure 9-a shows that SmartTag (blue lines) slightly outperforms AirTag (green lines) at a radius of 10 meters. However, at larger radii, this trend does not hold, with both tags performing similarly at radius of 50 and 100 meters. On the other hand, Tile (orange lines) performs significantly worse than other two tags, peaking at just 25-33% on average across radii. These variations are likely influenced by the differing availability of companion devices in the regions visited by the vantage points. To investigate further, we present further analysis based on relevant geographical and social factors.

Popularity of Companion Device. Intuitively, the accuracy of a tag depends on the number of companion devices in their vicinity. While we cannot collect this information in the wild, we approximate using the latest population density dataset from Kontur (November 2023), which provides population density estimates within H3 hexagons at resolution 8, based on satellite imagery of building density [27]. Using this dataset, we initially classified the vantage points' locations into three levels of urbanization: urban ($\geq$1,500 inhabitants per km^2), suburban (300-1,500 inhabitants per km^2) and rural ($<$ 300 inhabitants per km^2), following the widely used classification method established by EuroStat [28]. This revealed that 81.7% of our data points were located in urban areas. Consequently, we excluded data from suburban and rural areas to maintain consistency in our analysis.

We further accounted for the national-level characteristics of vantage points by aggregating the data according to smartphone market-share (MS), obtained from StatCounter Global Stats [29]. Specifically, to evaluate the influence of Apple and Samsung device popularity on the performance of AirTags and SmartTags, we categorized vantage points into countries with high (>40%), medium (20–40%), and low (<20%) market share for these smartphone manufacturers. We summarize the level of urbanization and mobile MS data in Appendix - Table IV.

Figure 10-(a,b) plots the spatial-temporal accuracy of AirTags and SmartTags across regions grouped by the MS of their respective companion devices. The analysis uses a 10-meter radius, which is the maximum distance at which AirTags switch to Ultra Wideband (UWB) to provide precise directional instructions for locating the device[3]. For both tags, accuracy generally improved in countries with higher device popularity. AirTags plateaued at 79.8% spatial-temporal accuracy after 60 minutes in 5 countries with high iPhone MS, compared to 66% in 13 countries with medium MS and 38% in 11 countries with low MS. Similarly, SmartTags reached 70.8% accuracy within 40 minutes in 3 countries with high Samsung smartphone popularity, while achieving 54.8% in 20 countries with medium MS and 48.0% in 6 countries with low MS. These results suggest how tags' reliance on their respective ecosystems could potentially lead to inconsistent performance across regions with varying companion device prevalence.

To further examine this hypothesis, Figure 10-c compares *combined* accuracy—representing a hypothetical unified Apple/Samsung ecosystem—across two groups of countries. The first group ("Strong") includes 5 countries where both Apple and Samsung each have over 30% smartphone MS, shown in red. The second group ("Weak") consists of 6 countries where their combined MS is less than 30%, shown in pink. The plot shows that after 10 minutes, spatial-temporal accuracy in the "Strong" group remains 15.2% higher on average than in the "Weak" group.

[3]For SmartTag+ and SmartTag2, the maximum UWB range is 15 meters. Tile does not support UWB at the time of writing.

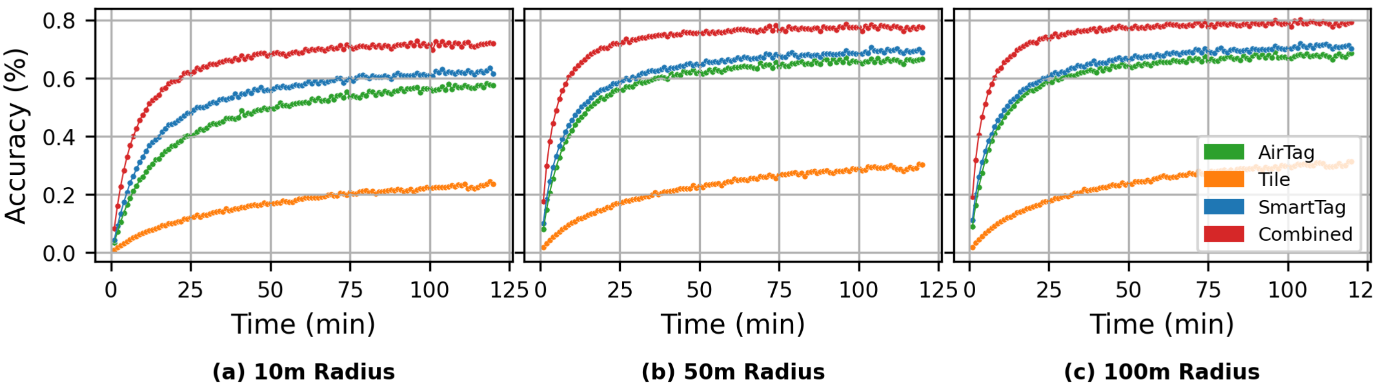

Fig. 9. Spatial-temporal accuracy of tags when considering different radii as "hits".

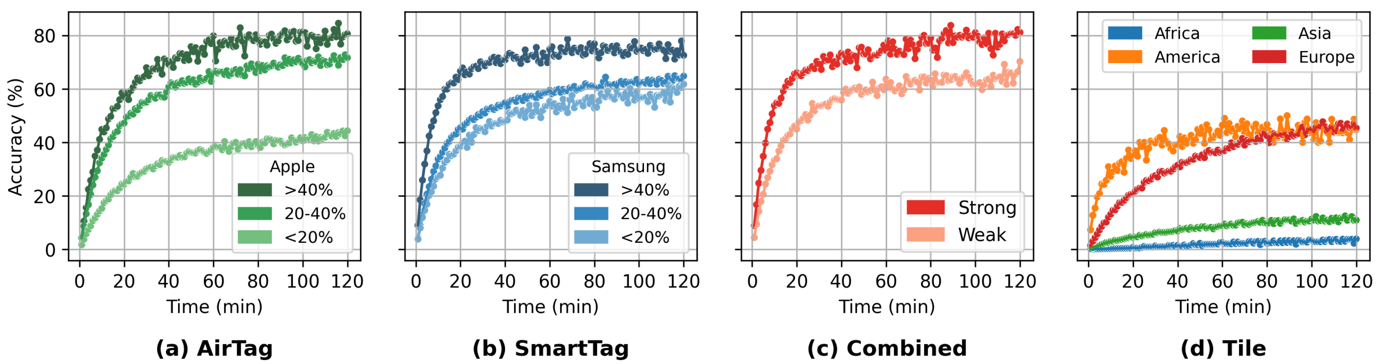

Fig. 10. Spatial-Temporal Accuracy of Tags at a 10-meter radius. (a) AirTag accuracy by Apple's mobile market-share (MS). (b) SmartTag accuracy by Samsung's mobile MS. (c) Combined accuracy in countries with high vs. low Apple/Samsung MS. (d) Tile accuracy across continents.

Finally, Tile's spatial-temporal accuracy was significantly lower than that of AirTag and SmartTag across our vantage points, despite its compatibility with both iOS and Android. However, performance varied across continents, which we plot in Figure 10-d. The highest accuracy was observed in the Americas, plateauing at an average of 44.3% after 50 minutes, followed by Europe, where accuracy steadily increased over time, reaching a similar level after 95 minutes. In contrast, Tile performed poorly in Asia and Africa, with maximum accuracies of 12.5% and 3.9%, respectively. This underperformance is attributed to infrequent location updates, likely stemming from limited global adoption of Life360/Tile.

We further analyzed tag performance in regions where low companion device availability is expected. Figure 11-a shows combined accuracy in these countries under increasingly relaxed geographical precision criteria, where location reports are classified as "hits" if they fall within larger radii from the actual GPS location. At a 100-meter radius, 65.5% of updates were accurate after 20 minutes, a 16.5% improvement over the 10-meter radius accuracy of 49%. This accuracy increased to 72.1% for a 1 km radius, as indicated by the green line. Figure 11-b illustrates the average number of location updates reported by each tag type every 20 minutes, with AirTags, SmartTags, and Tiles providing 2.98, 2.43, and 1.63 updates, respectively, even in regions where Apple and Samsung have low MS. Since manufacturers determine device locations by aggregating data from nearby companion devices collected

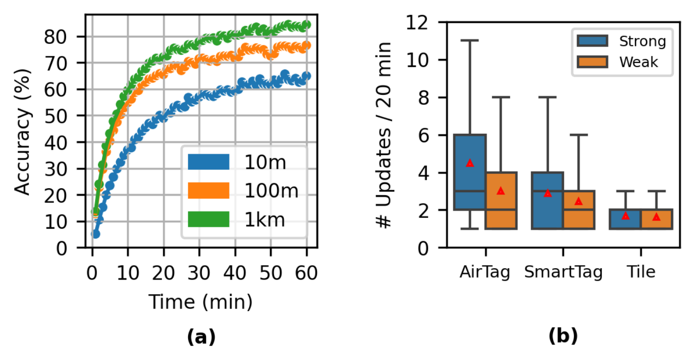

Fig. 11. Combined spatial-temporal Accuracy as a function of radius in countries with low Apple/Samsung popularity (a). Avg. number of location updates per 20 minute window as a function of Apple/Samsung popularity (b).

within specific time windows, these findings suggest that in regions with limited companion devices, tag inaccuracies may result not only from infrequent updates but also from imprecise geolocation calculations.

Mobility and Time of Day We continue our analysis by exploring the effect of different mobility and temporal characteristics on the accuracy of each tag. For this analysis, we assume a responsiveness of 10 minutes and radii of 10, 50, and 100 meters. Figure 12 presents our results across three factors: the vantage point's speed, time of day, and day of the week. To compare with prior findings, we overlay shaded

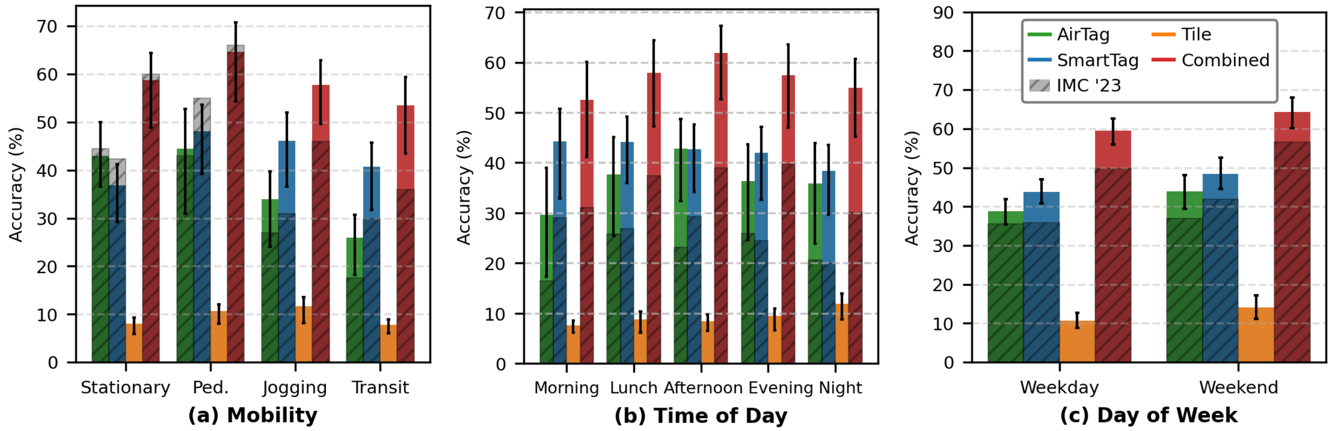

Fig. 12. Evaluation of AirTag, SmartTag, and "combined" accuracy in a 10 minute bucket as a function of mobility (a), time of day (b), and day of the week (c). Shaded regions indicate average results obtained in the previous study.

regions on each bar to represent the average accuracy reported in [1]. Since [1] was conducted during the Covid-19 lockdown, the differences between bar lengths and their corresponding shaded regions may reflect changes in tag performance post-pandemic. Note that Tile (orange bars) lack shaded regions as they were not included in [1].

Figure 12-a shows average tag's accuracy – 95% confidence intervals reported as error-bars across the different radii considered – as we vary how fast a tag is moving (as per our ground truth). We find that while walking at a pedestrian speed ($<$ 6.0 km/h), the accuracy is maximized for AirTags, SmartTags, and even when combined. The rationale behind this finding is that walking represents a good equilibrium between number of devices the tag may be exposed to, e.g., higher than when being stationary, and the length of the time window for the Bluetooth signal to be picked up by a location-reporting device. As the speed increases, e.g., when jogging (speed comprised between 6.0 and 12.0 km/h) or in transit ($\geq$ 12.0 km/h), the accuracy deteriorates due to the little time allowed for Bluetooh communication.

Figure 12-a also highlights a notable discrepancy in tag accuracy compared to the prior study. In [1], tag accuracy dropped sharply during jogging (46.1%) and transit (36.7%), approximately 20% and 30% lower than accuracy at pedestrian speed. Post-pandemic measurements, however, showed improved accuracy of 57.7% during jogging and 53.5% in transit, representing only a 7% and 11% decrease compared to pedestrian speed. While an overall increase in accuracy was expected with the relaxation of public activity restrictions, this improvement was primarily observed at higher mobility speeds. We conjecture that heightened public activity may increase the likelihood of encountering companion devices moving at similar speeds, such as in crowded public transportation settings. This alignment could help mitigate the spatial errors of location reports typically observed in higher mobility.

Figure 12-b shows average tag's accuracy during different times of the day. Combined accuracy peaks in the afternoon (2 P.M. to 6 P.M.) at an average of 61.8%, followed by the lunch period (10 A.M. to 2 P.M.) and evening hours (6 P.M. to 10 P.M.), both averaging 57%. Lower accuracy is observed during the morning (6 A.M. to 10 A.M.) and night (10 P.M. to 2 A.M.), averaging 52.5% and 54.8%, respectively, likely due to reduced public activity during these periods. We next explore potential impact of weekdays and weekends on the accuracy. Figure 12-c highlights an increase by 4.8% in combined accuracy on weekends compared to weekdays, likely driven by higher outdoor activity levels. Additionally, both plots indicate improved accuracy across various times of the day and days of the week compared to the findings in [1]. This suggests that lockdowns and reduced public interactions during the pandemic had a notable impact on tag performance.

3) Limitation and Discussion: Our dataset is collected from one or two volunteers per country, which may not fully represent the general experience of tag owners in those regions. While volunteers were instructed to roam public areas as extensively as possible while carrying the tags, the dataset could still be significantly influenced by individuals they interacted with frequently—a factor beyond our control. Consequently, we acknowledge the limitations in generalizing these findings to draw conclusive assertions on geographical characteristics of tags' performance. Nonetheless, our results report a consistent trend across countries when grouped by the popularity of companion devices. This underscores the tags' dependence to their respective ecosystems for timely and accurate location updates, reflecting a systemic limitation that extends beyond individual's control.

C. Report Reliability

1) Methodology: Reliability refers to the likelihood that a tag's location report accurately reflects its current ground truth, addressing a key question in real-world use: *to what extent can users trust a freshly updated tag location*? Complementing the broader spatial-temporal accuracy, reliability provides a more immediate measure of confidence in *individual* location updates. Our approach quantifies reliability in three ways:

Confidence Interval of σ. For each tag type, the confidence interval of σ represents the probability that the reported position lies within a specified radius (σ) from the true location.

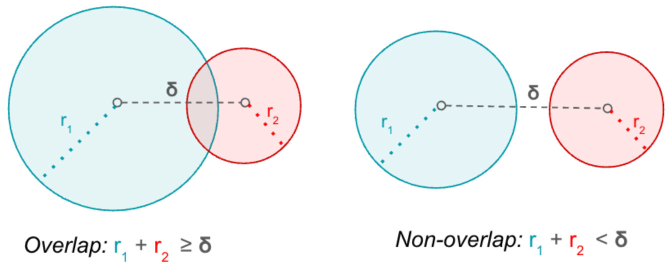

Fig. 13. Examples of overlapping circles (left) and non-overlapping circles (right), based on the sum of their radii relative to the distance between their centers, or δ.

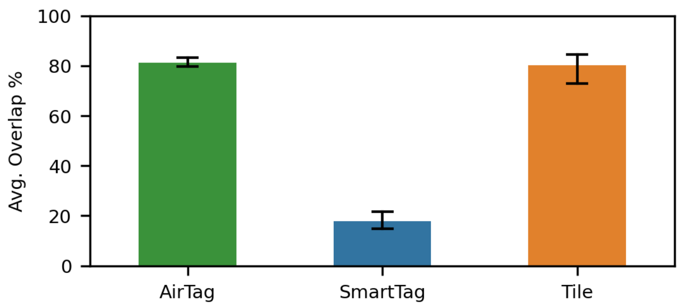

Fig. 14. Median of average overlap probability across tag types. Overlap probability is calculated as the percentage of radii pairs sampled from Rayleigh distributions (parameterized by σ from the tag and corresponding GPS measurement) whose sum exceeds the distance between the tag and GPS measurement.The black error line indicates 95% CI.

This reflects how accurately tags estimate their distance from the ground truth in each of their location updates. In real-world scenarios, where location tracking often relies on a single update (e.g., locating a lost item), this metric quantifies the certainty of the reported information, making it a practical measure of reliability. Since none of the tag manufacturers in our study disclose this metric, we empirically determine the confidence interval for each tag type using our collected data.

To calculate this, we matched each tag's reported location to the most recent GPS measurement recorded within the same one-minute interval. For each valid match, we recorded the following information: the latitude, longitude, and radius (σ_{tag}) reported by the tag; the corresponding GPS latitude, longitude, and radius (σ_{GPS}); and the spatial error (δ), which is the distance between the tag's reported location and the GPS location.

Using these matched data points, we derived the empirical confidence interval for each tag type, calculated as the the percentage of matches where the spatial error (δ) is less than the tag's reported radius (σ_{tag}). Intuitively, this is equivalent to the percentage of GPS coordinates that fall within the circle centered at tag's coordinates with radius of σ_{tag}. This approach provides a straightforward measure of reliability: a higher confidence interval indicates that the ground truth location more frequently falls within the tag's estimated margin of error.

Fit to Rayleigh Distribution. In addition, we test a common assumption in location systems: that δ follows a Rayleigh distribution parameterized by σ – i.e., $\delta \sim \text{Rayleigh}(\sigma)$. This assumption relies on the premise that latitude and longitude errors are independent and normally distributed. If this assumption holds for BLE tags, users can leverage the reported σ_{tag} value in each location update to estimate the probability of the ground truth being within any specified distance (e.g., the likelihood of the ground truth being within X meters).

To evaluate Rayleigh distribution's goodness of fit to tags dataset, we conducted a Monte Carlo simulation. For each matched data point between a tag and GPS measurement, we generated two sets of 10,000 samples: (1) radii drawn from $r_1 \sim \text{Rayleigh}(0.68 * \sigma_{\text{tag}})$, and (2) radii drawn from $r_2 \sim \text{Rayleigh}(0.68 * \sigma_{\text{GPS}})$, where 0.68 reflects the expected confidence interval for σ in location systems. These sets represent the estimated margins of spatial error for the tag and GPS measurements, assuming their σ values conform to the standard confidence interval.

The fit of each matched data point was assessed by calculating the probability of overlap between pairs of sampled radii from the two distributions. As illustrated in Figure 13, overlap was defined as the condition where the sum of a radii pair exceeded δ. The average overlap probability for each data point thus quantified how well the tag's location update aligned with GPS measurements when their respective margins of error were considered under the Rayleigh distribution assumption. We determined the overall fitness for each tag type by averaging the overlap probabilities across all its valid matches. If the overall fitness is high for a particular tag type, it suggests that the Rayleigh distribution provides a strong model for its spatial errors, enabling users to make probabilistic estimates of the tag's true location based on the reported σ_{tag} value.

Spatial Error Distribution. The statistical distribution of spatial error δ is another useful metric for evaluating reliability, as it models tag's location reports in relation to the true position. To explore this, we tested whether common statistical distributions—including beta, gamma, logistic, cosine, log-normal, and skew-normal—can effectively model the spatial error distribution for each tag type. Parameters for each candidate distribution were estimated using maximum likelihood estimation (MLE) based on empirical position errors. We select the best-fit distribution for each tag type via Kolmogorov–Smirnov (KS) test, and additional measures such as skewness and kurtosis were analyzed to provide deeper insights into the distributions' characteristics.

2) Results: **Confidence Interval of σ.** The result revealed varying levels of σ confidence interval across different tag types, which we summarize in Table II. Out of 5,186 tuples, AirTags demonstrated a 68.7% confidence interval, comparable to Android GPS, which reports a 68% confidence interval according to its documentation [18]. In contrast, Tile tags had a lower confidence interval of 55.9% based on 764 tuples. SmartTags exhibited the lowest reliability, with only 29.8% of 4,573 tuples falling within the reported radius σ, suggesting that their location reports underestimate the distance from the ground truth.

As shown in Table II, while AirTag and SmartTag demonstrate similar ranges of observed spatial error (δ), they differ significantly in their accuracy of estimating the distances from

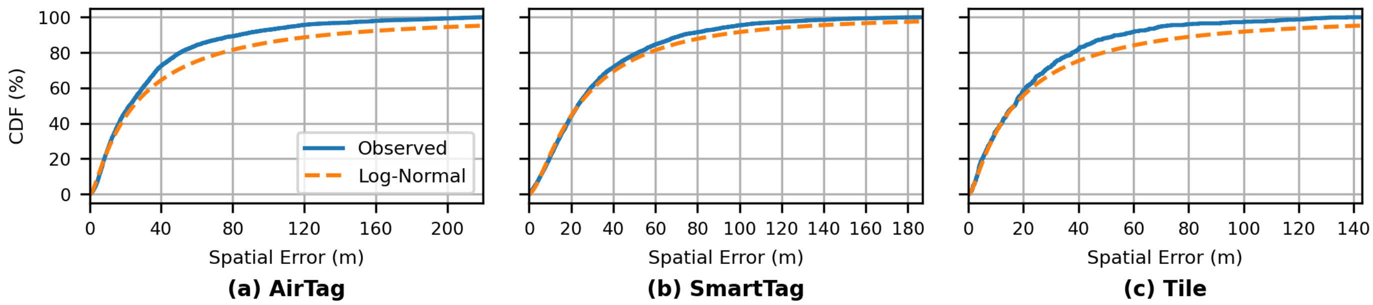

Fig. 15. CDF of observed spatial error compared to the best-fit log-normal distribution for each tag type.

ground truth. SmartTags tend to underestimate, with a median σ of 11.7 meters compared to a median observed spatial error of 22.82 meters. In contrast, AirTags make more conservative estimates, with a median σ of 36.15 meters, while the median observed spatial error is lower at 22.02 meters. This cautious estimation contributes to AirTag's higher σ confidence interval compared to other tags.

Fit to Rayleigh Distribution. Figure 14 presents the median of the average overlap probability across all location updates for each tag type. The results show that AirTags and Tile achieved median average overlap probabilities of 81.2% and 80.3%, respectively. This indicates a reasonable fit between the observed errors and the Rayleigh distribution modeled on the reported σ_{tag}, demonstrating their potential to provide probabilistic estimates of the ground truth location at any given distance. In contrast, SmartTag exhibited lower average probabilities of 17.8% in median, underscoring the Rayleigh distribution's limitations in modeling its spatial errors.

Spatial Error Distribution Our analysis of 13 candidate distributions revealed that the spatial errors for all three tags are best modeled by a log-normal distribution. Figure 15 compares the cumulative distribution function (CDF) of the observed spatial error with the fitted log-normal model. For AirTag, the log-normal model closely aligns with the observed spatial error for approximately 50% of location updates, where the spatial error was 24.4 meters, before slightly underestimating the error compared to the empirical data. A similar pattern is observed for the other two tags, with the tailored log-normal models closely matching the empirical spatial error for over 60% of data points. These results suggest that the log-normal distribution provides a suitable statistical model for spatial errors in BLE tags.

Table III summarizes the statistics of the log-normal distributions for the three tag types. The results show that all three distributions are asymmetric (skewness > 0) and leptokurtic (kurtosis > 3), indicating heavier tails and sharper peaks in their spatial error distributions. These characteristics suggest that the devices occasionally produce location readings with significant deviations from the ground truth, as reflected in their high standard deviations which ranged from 56.76 (SmartTag) up to 124.87 (AirTag) meters.

Tag	# matches	δ (m)	σ (m)	CI_σ
AirTag	5,186	22.02 (10.0-48.56)	36.15 (29.33-43.16)	68.7%
SmartTag	4,573	22.82 (11.38-45.8)	11.7 (6.34-19.1)	29.8%
Tile	764	17.28 (6.60-34.68)	19.7 (7.92-35.0)	55.9%

TABLE II
SUMMARY OF MATCHED DATA POINTS ACROSS TAG TYPES. FOR OBSERVED SPATIAL ERROR (δ) AND ESTIMATED SPATIAL ERROR (σ), THE MEDIAN AND IQR ARE REPORTED. CI_σ IS THE PERCENTAGE OF LOCATION REPORTS WHERE $\sigma \geq \delta$.

Device	Mean	Std.	Skewness	Kurtosis	p-value
AirTag	58.27	124.87	16.33	1430.53	0.016
SmartTag	40.39	56.76	6.65	133.30	0.01
Tile	37.93	78.1	14.87	1111.08	0.04

TABLE III
STATISTICS OF THE LOG-NORMAL DISTRIBUTION MODELS THAT BEST FIT THE EMPIRICAL SPATIAL ERROR FOR EACH TAG TYPE.

VI. Conclusion

This paper evaluates the performance of three location tags–AirTag, SmartTag, and Tile–through both controlled experiments and real-world scenarios. Drawing on data collected in 29 countries, the study examines how factors such as user movement, companion device availability, and regional differences impact the usability of these tracking devices. The findings emphasize that the density of nearby compatible devices is a critical factor in determining their performance. Comparing our results to a prior study [1], we show that increased public mobility after pandemic restrictions may have benefited "in-the-wild" accuracy of AirTag and SmartTag. In particular, AirTag showed notable progress in location update frequency, attributed to recent software updates. Tile, on the other hand, seems to struggle due to relatively limited adoption on a global scale. We discover tendency for SmartTag to underestimate its margin of error from the ground truth, raising questions over its reliability. The empirical spatial errors across tag devices conform to log normal distribution, which suggests the need for refined methods to better handle occasional large inaccuracies in location reporting.

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APPENDIX

Table IV shows the percentage of ”urban” data points recorded, and the smartphone market share for Apple and Samsung across 29 countries visited by our vantage points. Note that any data points near the volunteers’ home locations were excluded from the analysis.

Country	Urban (%)	Apple (%)	Samsung (%)
AT	99.956498	42.33	34.42
BD	85.433607	4.72	20.05
CN	89.331057	22.37	1.39
CZ	100	33.62	24.02
DE	81.569309	38.67	34.23
EC	64.984699	16.77	31.74
EG	69.345351	12.95	25.83
ET	100	4.62	47.51
FR	69.297343	32.78	31.93
GB	91.472025	52.46	29.54
GH	99.600776	17.16	22.97
HK	2.018822	50.00	28.49
IN	88.748496	4.02	13.65
IT	57.399770	31.50	29.14
JM	74.990379	32.61	52.89
KE	60.791558	2.39	19.41
KR	94.232732	26.53	68.74
LB	96.190833	28.84	36.51
MD	98.750951	25.09	32.69
MY	100	29.93	14.75
NL	99.145458	43.39	36.17
NP	71.553505	12.25	24.92
OM	0	25.42	24.83
PH	82.753575	12.66	13.76
PK	99.909871	4.62	15.72
QA	65.222062	21.97	23.21
TH	100	33.69	20.12
TZ	52.004633	6.61	23.63
UZ	82.136526	10.01	27.66

TABLE IV
PERCENTAGE OF DATA POINTS LOCATED IN URBANIZED AREAS AND SMARTPHONE MARKET SHARE FOR APPLE AND SAMSUNG ACROSS COUNTRIES.