JOURNAL OF SPATIAL INFORMATION SCIENCE
Number 32 (2026), pp. 95–116 doi:10.5311/JOSIS.2026.32.551

RESEARCH ARTICLE

A comparative analysis of positioning errors in 4G and 5G smartphones, and standalone GPS devices, in everyday mobility scenarios

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Received: October 20, 2025; returned: January 14, 2026; revised: May 22, 2026; accepted: June 24, 2026.

Abstract: The proliferation of location-sensing technologies, including smartphones and standalone GPS devices, has transformed human mobility studies. A central methodological concern in these studies is positioning accuracy, as errors in positioning can bias estimates of mobility patterns and environmental exposure. While the recent rollout of next-generation 5G technology promises sub-meter accuracy, most evidence comes from simulations or controlled trials, leaving everyday mobility performance largely untested, particularly in comparison with 4G smartphones and standalone GPS devices.

This study systematically evaluates the positioning errors of 5G New Radio (NR) smartphones compared with 4G smartphones and standalone GPS devices in everyday mobility scenarios. Data were collected from 27 participants across walking, biking, and driving routes on the Western University campus, encompassing five environmental contexts: *open space*, *between buildings*, *under tree canopy*, *in building*, and *underground*. Positioning errors were assessed using three complementary approaches: point-based, path-based, and area-based analyses. Results demonstrate that 5G smartphones consistently outperform 4G devices and standalone GPS in accuracy, particularly *in building* and *underground*, achieving lower median errors, higher spatial path fidelity, and improved indoor localization metrics. This advancement broadens the applicability of 5G smartphones across diverse research in health geography and urban planning.

Keywords: 5G smartphones, 4G smartphones, standalone GPS devices, positioning errors, mobility

1 Introduction

The rapid proliferation of location-sensing technologies, particularly smartphones and standalone Global Navigation Satellite System (GNSS) devices, has transformed how researchers capture and analyze human mobility [2, 8, 40, 44]. By enabling continuous, high-resolution tracking of individuals' movements, these devices have become indispensable in research across health geography, transportation, and spatial epidemiology. In such contexts, they are used to measure individuals' real-time interactions with environments that may influence health-related outcomes, for example, quantifying park engagement in relation to physical activity level [19], assessing exposure to retail food environments [22, 36], tracking children's air-pollution exposure along school commutes [14], and evaluating indoor co-location risks for communicable disease transmission [5]. A central methodological concern across these applications is positioning accuracy, as spatial errors can bias estimates of mobility patterns and environmental exposure.

The recent rollout of next-generation 5G cellular technology introduces features poised to substantially improve positioning in complex urban environments where 4G devices have often struggled to consistently provide accurate location information [1, 34]. Key features include multiple-input-multiple-output (MIMO) antenna systems, which leverage multiple signal paths to improve signal-to-noise ratios and reduce error rates, thereby improving positioning accuracy in interference-prone areas [55]. Time-of-Flight (ToF) technology enables more reliable distance estimation based on signal travel time, yielding greater accuracy in low-signal-quality environments. The low latency in 5G networks facilitates faster rates of real-time positioning, allowing for quicker responses to changes in a device's location [51, 52]. While reports suggest that 5G features can achieve sub-meter positioning accuracy [1, 43], most findings are derived from simulations or controlled trials rather than everyday mobility scenarios. In everyday mobility scenarios, various factors affect positioning accuracy, yet the performance of 5G devices in these scenarios has not been thoroughly investigated within the GIScience and transportation literature. Moreover, comparative evidence on positioning errors across 5G smartphones, 4G smartphones, and standalone GPS devices remains limited, as does understanding of how these differences may influence location-based studies of human movement and health. Here, GPS refers specifically to the U.S.-operated satellite constellation and one component of GNSS; the term is used colloquially throughout to denote standalone GNSS-based positioning devices.

Previous studies have identified factors, such as environmental conditions and transport modes, that may influence the positioning accuracy of smartphones (4G and earlier generations) and standalone GPS devices. Urban and natural environmental conditions, such as underground spaces, tree canopies, and urban canyons, can cause signal obstruction and multipath errors [21, 26]. For instance, standalone GPS receivers have been shown to achieve positional accuracy within 3 m in open fields but over 50 m in certain dense urban areas with high-rise buildings [32, 33]. Similarly, smartphone positioning accuracy has been reported to range from 5 to 20 m in areas with buildings and trees, largely due to multipath errors [26, 29]. Transport mode also affects positioning accuracy: slower or more consistent movements, such as walking or cycling, tend to produce more accurate location estimates, whereas faster or more erratic movements can increase errors [30]. Despite these insights for 4G smartphones and standalone GPS devices, it remains unclear how these factors influence the positioning accuracy of 5G smartphones. This study addresses this issue through a comparative analysis of positioning errors in 5G smartphones, 4G smartphones, and standalone GPS devices under everyday mobility scenarios.

Method-wise, previous studies investigating the positioning errors of location-sensing devices have traditionally adopted a point-based approach, comparing collected GPS points to ground truth locations [46]. While informative, the point-based perspective may overlook systematic deviations that accumulate along paths or lead to misclassification of individuals' presence within a specific area. Relatively few studies have evaluated device performance by examining positioning errors along paths (i.e., path-based) or within predefined spatial areas (i.e., area-based). These alternative perspectives are particularly valuable for health-related research where the path-based perspective enables more accurate assessment of environmental exposures that occur throughout a journey, such as visual exposure to advertisements or visits to retail locations [20, 49]. Similarly, the area-based perspective focuses on whether positioning data correctly capture the spatial extent of activity within predefined boundaries, such as distinguishing indoor from outdoor environments, a distinction particularly important in estimating health risks [54]. Together, these complementary perspectives highlight the need to move beyond point-based accuracy assessments when evaluating device positioning performance.

Building on these perspectives, we investigate positioning errors of 5G cellular devices in comparison with 4G cellular devices and standalone GPS devices, using three complementary levels of analysis: point-based, path-based, and area-based. At the point level, we examine individual GPS measurements from each device against a known ground truth to evaluate how positioning accuracy is influenced by environmental conditions and transport modes. At the path level, we evaluate movement paths to assess the alignment and divergence of paths recorded by different devices. Finally, at the area level, we focus on the spatial distribution of GPS measurements recorded within predefined areas, particularly indoors, to compare the positioning errors by each device type.

It is important to note that this research focuses exclusively on spatial positioning accuracy, i.e., how closely recorded coordinates conform to ground truth, rather than temporal movement dynamics such as speed, acceleration, or timing patterns. Because positioning errors in movement data can directly propagate into downstream analyses, biasing estimates of travel distances, misclassifying visited locations, distorting activity spaces, and introducing systematic errors in environmental exposure assessments along paths or indoors, understanding positioning accuracy is not merely a technical exercise, but a prerequisite for all valid movement analyses that rely on GPS or GNSS data.

2 Methods

2.1 Instruments

We leverage the latest advancements in mobile technology by exclusively using smartphones equipped with a 5G New Radio (NR) on a private network for data collection. Unlike Non-Standalone (NSA) 5G devices that also rely on 4G infrastructure, 5G NR smartphones operate independently from the existing 4G infrastructure, enabling a valid comparison between 5G and 4G devices. For the 4G cellular device, we directly take advantage of personal smartphones for the study, considering the widespread use of 4G smartphones in everyday life. The 5G devices were Google Pixel 6 smartphones, and the 4G devices represent a variety of models from major manufacturers such as Apple, Google, Samsung, and

Sony. Information on the specific devices used by each research assistant is provided in Table S1 in the Appendix. While hardware variation exists across 4G devices, this reflects the diversity of real-world smartphone usage and supports the generalizability of our findings. For the standalone GPS device, we use the Columbus P-10 Pro Submeter GPS/GNSS Data Logger. This device boasts high-precision positioning performance, with a probability of track points falling within a 0.5m circular radius greater than 50% of the time (0.5m/CEP: 50%) and a probability of track points falling within a 1.5m circular radius greater than 95% of the time (1.5m/CEP: 95%) [4]. The combination of 5G, 4G, and standalone GPS devices allows for a comprehensive evaluation of positioning errors across current technologies, providing a benchmark to assess the improvement by next-generation 5G infrastructure in everyday mobility scenarios.

2.2 Test routes

We conducted experiments around the campus of Western University during the summer months of 2022 and 2023. Three predefined test routes were designed to reflect distinct transport modes: walking (~15 min), driving (~10 min), and biking (~15 min). The walking route ("Figure 1") was specifically designed to traverse a variety of urban and natural environmental conditions to examine their influence on positioning accuracy. Five environmental conditions were delineated: *open space between buildings*, *under tree canopy*, *open space*, *in building*, and *underground*. *Open space* is defined as segments without buildings and tree canopy cover along the route, whereas *open space between buildings* refers to segments with buildings within 25 m on both sides [38] ("Figure S1"). The driving and biking routes largely overlapped ("Figure 2") and primarily traversed *open space* settings. The ground truth paths of each route were digitized using ultra-high-resolution (60 cm pixels) aerial imagery [13] in ArcGIS Pro 3.1 to provide precise reference points for error estimation. Georegistration error in this basemap is minimal in urban areas, as Maxar Vivid Advanced 30 cm HD imagery is available for metropolitan areas such as our study area [13]. Any residual geo-registration uncertainty constitutes a systematic offset applied uniformly across all check-in points, and does not differentially bias any particular device type or affect the validity of our cross-device comparisons.

2.3 Data collection

We asked research assistants to carry all three types of devices simultaneously while following predefined walking, biking, or driving routes. During data collection, the devices were placed separately in a pocket or backpack to replicate everyday use scenarios. In total, 27 unique research assistants volunteered their time, each completing four to six trips, resulting in 160 completed trips across the three transport modes (n = 130 walking, n = 14 biking, n = 16 driving). A greater number of walking trips was conducted to support a more detailed examination into the effects of various urban and natural environmental conditions on positioning accuracy.

To minimize the influence of cold-start errors on positioning accuracy, data collection protocols were designed to ensure steady state across all device types. For the 4G and 5G smartphones, no special startup procedures were required, as these devices maintain persistent background network connectivity in everyday use and rarely experience cold starts. For the standalone GPS device, each trip started only after confirming that the de-

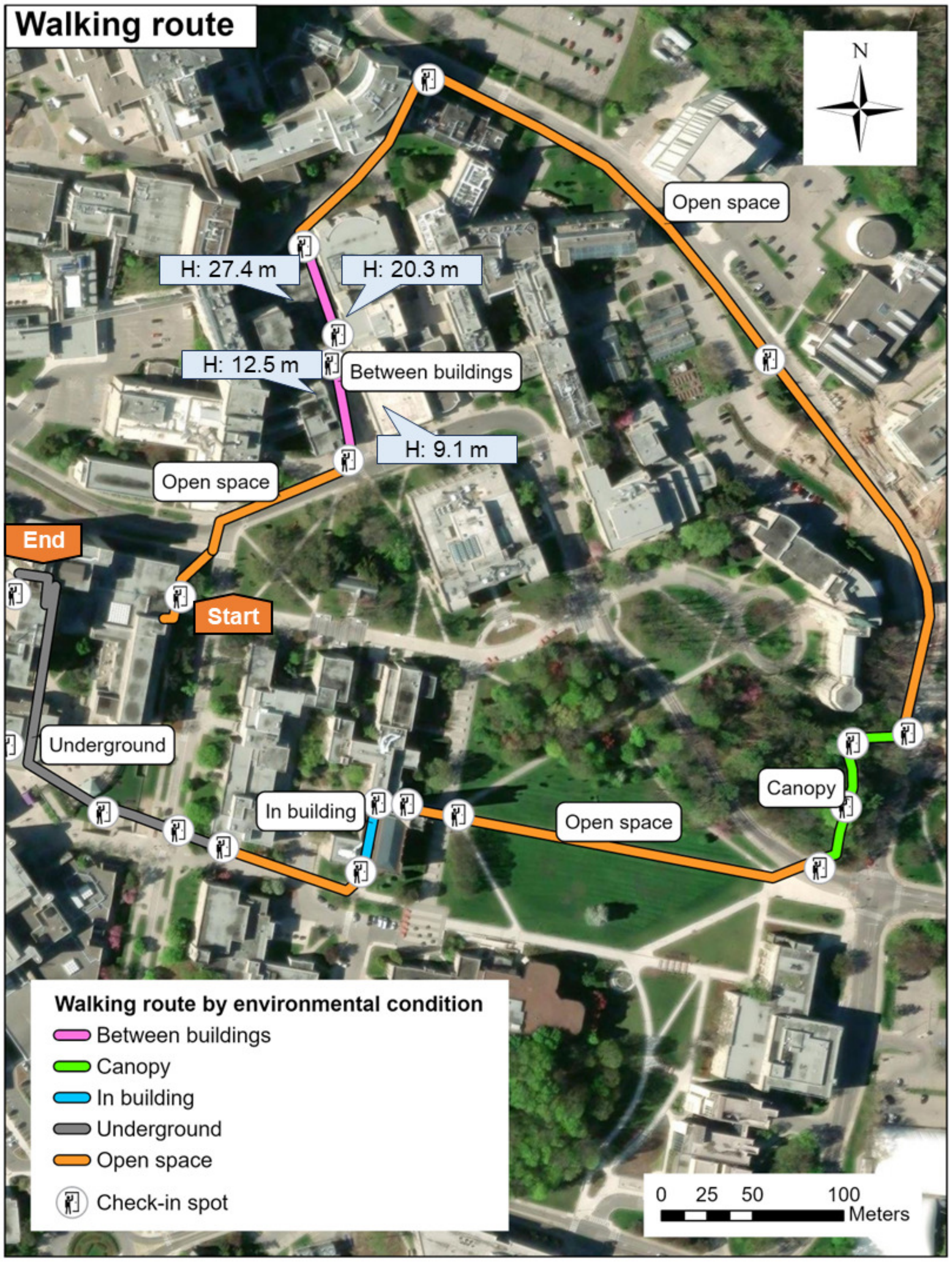

Figure 1: The walking route traversing five types of urban and natural environmental conditions on the campus of Western University.

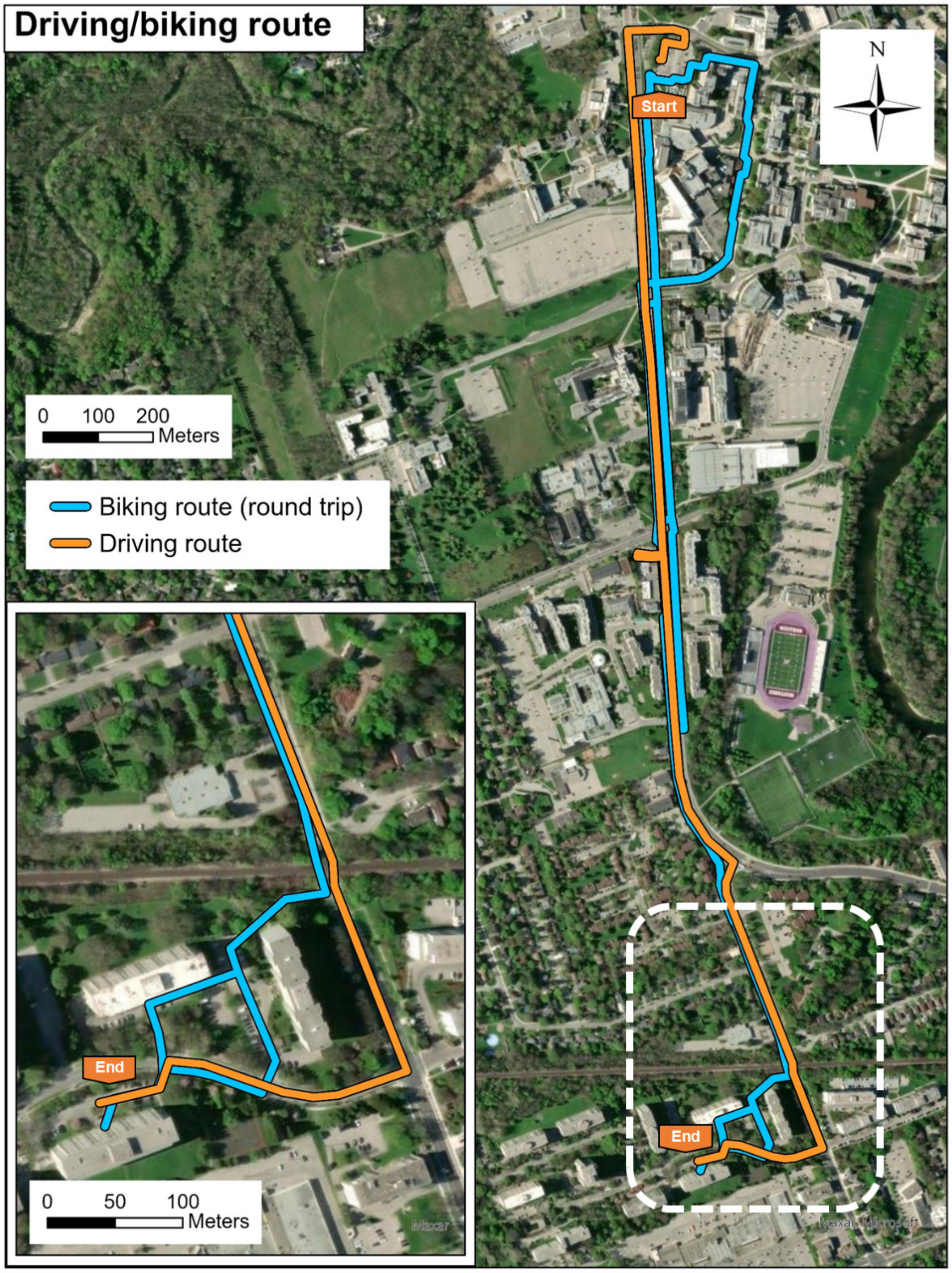

Figure 2: The driving and biking route on and around the campus of Western University.

vice had acquired a satellite lock and begun recording (as indicated by the flashing of the device's indicator light). These protocols ensured that cold-start errors did not contribute to the positioning data analyzed in this study, enabling a reliable comparison of positioning accuracy across devices. To minimize participant path deviation, the walking routes were physically flagged on the ground, and research assistants were instructed to follow the flagged path as closely as possible. Along the walking route, we designated four check-in spots for each of the five urban and natural environmental conditions (20 spots in total). At each check-in spot, research assistants briefly stopped to separately record a GPS location statement from each device. All check-in points were selected as clearly identifiable features that are easily locatable on both imagery and in the field, such as stop signs, staircase entrances, and crosswalks, ensuring consistent and reliable ground truth reference locations. Throughout the trips, GPS data were collected at a temporal resolution of 1 Hz with minimal missing points. This design ensured that all device comparisons were conducted under identical environmental and behavioral contexts, isolating device performance from other sources of variability.

2.4 Data analysis

To evaluate positioning accuracy comprehensively, we adopted a three-level analytical framework: i) point-based, ii) path-based, and iii) area-based, building upon prior studies and extending the scope of analysis beyond conventional point-based comparisons. It is important to note that this three-level framework focuses exclusively on the spatial accuracy of recorded positions, that is, how closely recorded coordinates conform to ground truth, rather than the temporal dynamics of movement such as speed, acceleration, or timing patterns.

2.4.1 Point-based analysis

Investigating point-based errors is crucial because it captures the most basic unit of positioning performance, forming the foundation for path- and area-based analyses. Point-based positioning error was quantified as the Euclidean distance between each device-recorded coordinates and the corresponding ground truth coordinates. For walking routes, the ground truth coordinates were the 20 check-in spots across the five urban and natural environmental conditions, enabling direct comparison under controlled contextual variation. For biking and driving routes, the ground truth coordinates were derived from the waypoints along the digitized reference paths. Error distributions were summarized using the median, which is robust to outliers, and standard deviation, which captures variability and indicates the stability of system performance across environments. These metrics were preferred over mean-based metrics because GNSS positioning errors are typically characterized by extreme outliers, particularly in challenging environments such as underground and urban canyons [38, 50]. To examine differences in positioning errors across environmental conditions and transport modes, we employed two nonparametric analyses. Nonparametric methods were chosen because positioning data are typically non-normally distributed, often skewed, and can include extreme values.

First, we used the Kruskal–Wallis test to assess whether point-based positioning errors differed significantly among multiple groups (e.g., across the five environmental settings or across transport modes). This test ranks all observations and compares the distribution of ranks between groups, without assuming normality. When the Kruskal–Wallis test indicated significant overall differences, we performed post hoc pairwise comparisons using Dunn's test. The Dunn Z shows the direction and magnitude of the difference between the two devices in each pairwise comparison: positive Z = first device has greater error than the second; negative Z = first device has lower error, within the comparison pair. This procedure allowed us to identify which specific pairs of conditions (such as *underground* vs. *open space*, or biking vs. walking) accounted for the overall differences. A Bonferroni correction was applied to adjust the significance level for multiple comparisons, thereby controlling the family-wise error rate, i.e., the probability of making at least one Type I error (false positive) when conducting multiple statistical tests on the same dataset. This combination of descriptive and inferential statistics enabled both the quantification of central tendencies and the statistical assessment of systematic differences in positioning accuracy across devices, environmental conditions, and transport modes.

2.4.2 Path-based analysis

We evaluated how well the recorded paths reproduced the ground-truth routes. To do so, paths from the three devices were compared against the reference path using a geometric similarity measure. Specifically, we computed the dynamic time warping (DTW) distance [7]. Unlike direct point-by-point comparisons, DTW aligns two paths by flexibly warping the time dimension, thereby accommodating differences in speed, pace, and sampling intervals that are common in GPS data [44].

For implementation, each GPS point was first mapped to the nearest segment of the ground-truth path by calculating the minimum perpendicular distance from the point to the line. These assignments allowed us to compute DTW distances segment by segment, yielding a robust metric of how faithfully each device captured the overall shape and continuity of movement. To account for differences in segment length between the two paths being compared, DTW distances were normalized per 100 meters of segment length. This approach provides a more reliable assessment of device performance across varying environmental contexts than simpler distance-based metrics [17, 28, 45].

2.4.3 Area-based analysis

To evaluate positioning errors from an area-based perspective, we conducted two analyses: spatial correspondence and binary classification. For spatial correspondence, we quantified the proportion of overlap between each device-derived activity space and the ground-truth building footprint. Activity spaces were constructed from device point data using a concave hull, which preserves the true extent of movement more effectively than a convex hull. Unlike a convex hull, which is defined as the smallest convex polygon containing all points (often overestimating the true occupied extent), a concave hull can include inward curves and exclude empty areas by adapting to the actual shape of the point distribution, making it better suited for representing irregular movement patterns inside a building [10, 11]. The device-derived polygons were then compared against reference areas digitized from building footprints ("Figure 3"), which were derived using data collected by research assistants at the actual ground-level corners of the building exterior. The reference in-building area covers approximately 500 m^2 ("Figure 3(c)"). Because standalone GPS devices rely solely on satellite signal and provide little to no usable data indoors, this area-based analysis focused on comparing 4G and 5G smartphones. By assessing how well the device-generated activity spaces captured the true occupied areas, this analysis highlights differences in positioning capabilities under challenging indoor conditions, complementing point- and path-level evaluations.

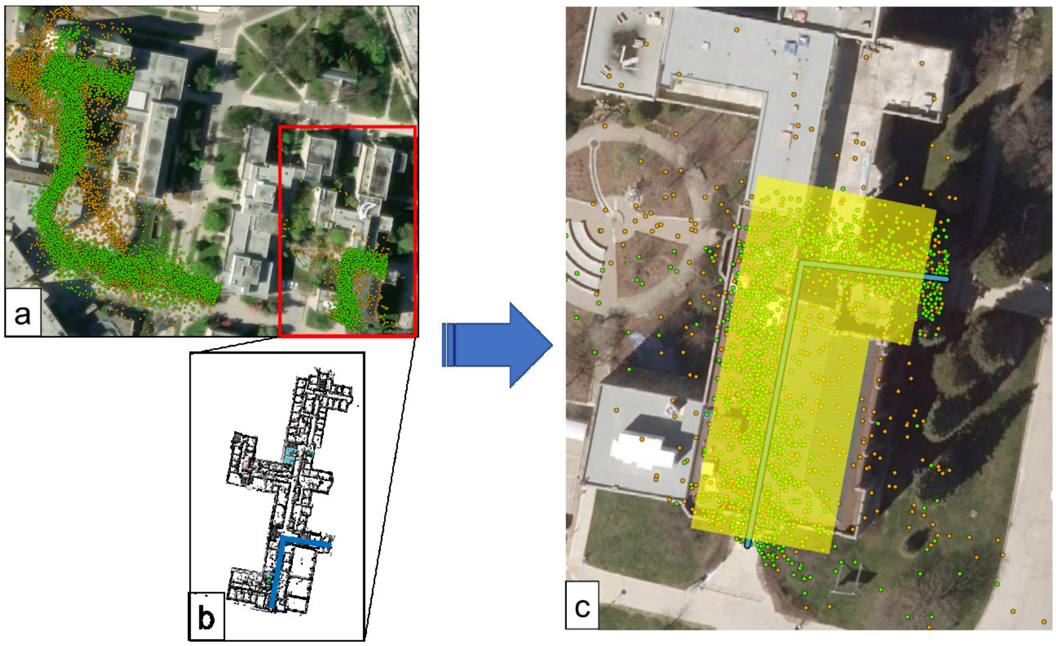

Figure 3: Illustration of indoor routes and tracking points: a) tracking points collected inside a building and underground from 4G (orange) and 5G (green) devices; b) the building floor plan; c) the indoor extent derived from the floor plan and georeferenced as an indicative activity range, which was used for binary classification (points falling within this extent were considered correctly identified as indoor).

We used spatial overlay to determine whether each device-generated point fell inside or outside the reference areas digitized from building footprints using a simple binary (i.e., in or out) classification ("Figure 3"). These classifications were compared against the true in-building or out-of-building status of each point when they were collected to compute performance metrics: precision, recall, and F1 score. Precision measures the proportion of points that ended up within the reference area that were actually collected indoors, reflecting the device's ability to avoid false positives. Recall measures the proportion of points that were truly collected indoors that ultimately fell within the reference area, reflecting how completely the device captures true indoor activity. The F1 score, defined as the harmonic mean of precision and recall, provides a single measure of balanced performance. Together, these metrics evaluate how reliably devices distinguish indoor from outdoor activity, offering a fine-scaled complement to the spatial correspondence analysis [35, 37].

3 Results

3.1 Point-based positioning errors

Positioning errors varied significantly by device type and environmental condition ("Table 1"). Note that for GPS devices, the results for indoor are missing because standalone GPS devices do not reliably produce data when indoors.

Environment	Device	Median (m)	SD (m)	Kruskal–Wallis p-value	Pairwise comparison	Dunn Z
Open space	GPS	2.3	9.7	<0.001	4G–5G	1.6
	4G	3.2	7.6		4G–GPS	-4.2*
	5G	2.0	6.1		5G–GPS	-6.5*
Underground	GPS	–	–	<0.001	4G–5G	16.2*
	4G	10.5	11.6		4G–GPS	–
	5G	5.5	8.0		5G–GPS	–
Between buildings	GPS	3.8	7.8	<0.001	4G–5G	7.5*
	4G	5.0	9.6		4G–GPS	8.5*
	5G	3.4	3.8		5G–GPS	-0.5*
Tree canopy	GPS	2.1	3.6	0.744	4G–5G	0.3
	4G	2.7	5.1		4G–GPS	-0.3
	5G	1.8	3.3		5G–GPS	-0.8
In building	GPS	–	–	<0.001	4G–5G	12.9*
	4G	4.8	12.1		4G–GPS	–
	5G	3.4	6.4		5G–GPS	–

* Statistical significance in Dunn post-hoc tests is indicated by an asterisk. Positive Z-values denote higher errors for the first device compared to the second, and negative values denote lower errors. P-values were adjusted using the Bonferroni correction.

Table 1: Point-based positioning errors (median and SD, in meters) for GPS, 4G, and 5G devices across different urban and natural environmental conditions. Statistical differences were assessed using Kruskal–Wallis tests followed by Bonferroni-adjusted Dunn post-hoc tests.

In open space, 5G smartphones achieved the lowest median error (2.0 m), followed by GPS (2.3 m) and 4G smartphones (3.2 m). Kruskal–Wallis tests confirmed overall differences among devices ($\chi^2 = 49.4$, df = 2, $p < 0.001$). Dunn post hoc tests indicated that 5G smartphones were significantly more accurate than GPS and 4G smartphones (Z=-6.5 and -4.2, $p < 0.001$), whereas the difference between 4G and 5G was not statistically significant in some comparisons (Z=1.6, p = 0.361). In challenging environments such as underground areas, 5G devices substantially outperformed 4G smartphones (median 5.5 m vs 10.5 m). GPS could not record indoor positions due to signal obstruction. Kruskal–Wallis tests showed significant differences across devices ($\chi^2 = 280.2$, df = 2, $p < 0.001$), with Dunn comparisons confirming superior performance of 5G over 4G (Z = 16.2, $p < 0.001$). Between buildings, 5G and GPS devices exhibited comparable median errors (3.4 m vs 3.8 m), both lower than 4G smartphones (5.0 m), with Kruskal–Wallis and Dunn tests supporting these differences ($\chi^2 = 79.4$, df = 2, $p < 0.001$). For *under tree canopy*, differences were not statistically significant (Kruskal–Wallis $\chi^2 = 0.6$, df = 2, p = 0.744), indicating similar performance across all three devices. In buildings, 5G smartphones again outperformed 4G devices (3.4 m vs

4.8 m). GPS data were unavailable indoors, but Kruskal–Wallis and Dunn tests highlight statistically significant improvements of 5G over 4G (Z = 12.9, $p < 0.001$).

Point-based positioning errors also varied across devices in different transport modes ("Table 2"). Overall, 5G smartphones exhibited the lowest median errors across all modes, with the lowest observed while biking (1.8 m) and walking (2.0 m). GPS devices had slightly higher median errors (biking: 2.0 m; walking: 2.4 m), whereas 4G smartphones consistently showed the largest errors, particularly during driving (6.3 m).

Transport Mode	Device	Median (m)	SD (m)	Kruskal–Wallis p-value	Pairwise comparisons (Dunn test)
Biking	GPS	2.0	4.1	<0.001	5G < GPS ($p < 0.001$)
	4G	3.5	9.4		5G < 4G ($p < 0.01$)
	5G	1.8	7.5		
Driving	GPS	3.7	12.0	0.001	5G < 4G ($p < 0.01$)
	4G	6.3	19.1		
	5G	3.9	12.8		
Walking (outdoor)	GPS	2.4	9.4	0.002	5G < 4G ($p < 0.01$)
	4G	3.2	7.0		
	5G	2.0	5.1		

Table 2: Positioning errors (m) of GPS, 4G, and 5G devices across transport modes. Statistical differences were assessed using Kruskal–Wallis tests with post-hoc Dunn pairwise comparisons.

Kruskal–Wallis tests revealed statistically significant differences among devices for all transport modes (Biking: $p < 0.001$; Driving: $p = 0.001$; Walking: $p = 0.002$). Post hoc Dunn tests indicated that 5G positioning errors were significantly smaller than 4G for all transport modes, and smaller than GPS while biking ($p < 0.001$). During driving, 5G errors were lower than 4G ($p < 0.01$) but comparable to GPS. These results suggest that 5G smartphones provide consistently improved accuracy, although all devices exhibited higher variability during driving, as reflected by larger SDs.

3.2 Path-based positioning errors

Path-based error also varied by device type and environmental condition, as shown by median DTW distances ("Table 3"). Across all environments, 5G smartphones consistently showed the lowest normalized DTW distances, indicating the highest fidelity to the reference paths. For example, in *open space*, the median normalized DTW distance for 5G was 80.2 m, compared to 120.5 m for GPS and 130.7 m for 4G. Similarly, 5G outperformed other devices *under tree canopy* (65.3 m), *between buildings* (75.4 m), *in building* (140.6 m), and *underground* (132.7 m). Notably, all devices exhibited the largest deviations within the in building environments, reflecting the ongoing challenges of maintaining path accuracy indoors even in the presence of reliable cellular connections.

Contrary to expectations, the median normalized DTW distance in *open space* (80.2 m) was slightly higher than that under tree canopy (65.3 m) and between buildings (75.4 m) for 5G smartphones. A similar pattern was observed for GPS and 4G devices, where *open space* segments exhibited slightly larger median DTW distances. The spatial distribution of positioning errors across all walking trips is further illustrated as a heatmap in the Ap-

Environment	GPS	4G	5G
Open space	120.5	130.7	80.2
Tree canopy	85.7	91.4	65.3
Between buildings	102.3	98.9	75.4
In building	200.8	180.2	140.6
Underground	150.4	145.9	132.7

Table 3: Median DTW distances (m) for GPS, 4G, and 5G trajectories across different environmental contexts, relative to ground-truth paths, normalized per 100 m segment length.

pendix ("Figure S2"), showing the concentration of high-error clusters in *underground* and *between-buildings* segments, particularly for 4G devices.

3.3 Area-based positioning errors

The concave hull areas derived from all three devices were substantially smaller than the reference area ("Figure 3"). Within the in-building segment, 4G devices exhibited a median concave hull area of 134.8 m² (IQR: 93.3–200.2 m²), with some outliers exceeding 500 m², whereas 5G devices showed a smaller median area of 122.8 m² (IQR: 94.6–151.0 m²), reflecting a more concentrated distribution of tracking points ("Table 4"). Similarly, in the *underground* segment, median activity space areas were 1089.8 m² for 4G (IQR: 995.2–1238.6 m²) and 918.5 m² for 5G (IQR: 844.6–1075.9 m²), indicating reduced spatial dispersion for 5G devices.

Environment	Device	Median (m^2)	IQR (m^2)
In Building	4G	134.8	93.3–200.2
	5G	122.8	94.6–151.0
Underground	4G	1,089.8	995.2–1,238.6
	5G	918.5	844.6–1,075.9

Table 4: Activity space area (m^2) derived from concave hulls for 4G and 5G devices across *in-building* and *underground* segments. Median, IQR, and range are reported.

Binary classification of points within building footprints further highlighted performance differences between devices ("Table 5"). For the in-building segment, 5G smartphones achieved higher precision than 4G devices (98% vs. 92%), recall (85% vs. 79%), and F1 score (91.0% vs. 85.0%), indicating that 5G more accurately identified points inside the reference area while capturing a greater proportion of true indoor points. Notably, both devices exhibited higher precision than recall. Similarly, in the *underground* segment, 5G

Environment	Device	Precision (%)	Recall (%)	F1 Score (%)
In Building	4G	92	79	85.0
	5G	98	85	91.0
Underground	4G	85	72	77.9
	5G	93	79	85.4

Table 5: Binary classification metrics (precision, recall, F1 score) for identifying points inside building footprints.

devices outperformed 4G with a precision of 93% versus 85%, a recall of 79% versus 72%, and an F1 score of 85.4% versus 77.9%.

4 Discussion

Overall, 5G smartphones demonstrated consistently improved accuracy across urban and natural environmental conditions, particularly in indoor and underground conditions where 4G performance degraded, while GPS remained accurate outdoors but limited indoors. We demonstrate that 5G smartphones provide improved positioning accuracy compared to 4G smartphones across diverse environmental contexts. Our findings are consistent with the stated benefits of 5G NR features, such as MIMO antenna systems [55], Time-of-Flight measurements [51], and low-latency signal processing [52]. The improved accuracy of 5G devices in between-building and in-building environments likely reflects the advantage of MIMO technology, which leverages multiple signal paths to enable more precise positioning in densely built or interference-prone areas [6,23]. In contrast, positioning errors in open-space environments were small across all devices, reflecting minimal signal obstruction and reliance on the same signals. Our results for 4G and standalone GPS positioning errors align with prior studies [12, 21, 26, 46], reinforcing the notion that GPS performs best outdoors but is limited indoors, while 4G smartphones experience substantial accuracy degradation in obstructed or indoor environments.

Across all transport modes, 5G smartphones outperformed 4G devices, with the smallest errors observed during biking and walking. This pattern likely reflects the advantages of 5G NR networks in mitigating multipath effects and enhancing signal reception through low-latency processing and MIMO-based diversity [55]. Higher errors and variability during driving are consistent with prior studies noting that dynamic, high-speed movement exacerbates positioning inaccuracies due to rapid changes in geometry and multipath propagation [38].

Collectively, these findings indicate that 5G smartphones are better suited for continuous tracking across mixed indoor–outdoor settings, bridging the gap between high outdoor accuracy of GPS and the convenience of smartphone-based mobility tracking. The use of 5G devices in future human mobility studies located within mixed semiurban contexts may experience an increase in spatial data accuracy and precision, resulting in better estimates of momentary exposures encountered in daily life. Future research should examine dense urban and heavily wooded areas, as well as temporal consistency, to further evaluate real-world performance.

Notably, 5G devices achieved the lowest median error under tree canopy (1.8 m) and the highest underground (5.5 m); a Mann-Whitney U test confirmed this difference was statistically significant ($p < 0.05$). The relatively high accuracy under sparse tree canopy conditions may be attributed to the limited canopy cover along the test routes, located on a small hill with minimal signal obstructions. These findings suggest that environmental factors can still influence 5G performance, highlighting the need for further studies in dense canopy or highly obstructed urban settings and also over longer distances. Also, the large standard deviations observed across environmental conditions reflect the characteristically right-skewed distribution of GNSS positioning errors, where most observations cluster near low error values but occasional extreme errors (arising from multipath interference, temporary signal loss, or between-trip variation in satellite availability) substantially inflate the standard deviation. This effect reinforces our use of the median as the primary measure.

It is important to note that the sampling frequency and accuracy level employed in our study provide sufficient accuracy for typical daily and health-related mobility tracking [42], rather than those in extremely high-precision navigation such as automotive or autonomous vehicle applications [24]. Such ultra-precise positioning requires continuous high-frequency updates, which are energy-intensive and impractical for long-term or large-scale human mobility studies. Our approach reflects the same accuracy and feasibility trade-offs that occur in human mobility research.

Path-based analyses using normalized DTW distances further illustrated that 5G devices maintain paths closer to ground-truth paths, which is essential for fine-scale mobility and exposure assessments [17,45]. Interestingly, the *open space* environment did not exhibit the lowest path errors, despite its unobstructed conditions. Several factors may explain this observation. First, differences in route length and sampling density can influence the normalized DTW distances. Although DTW distances were normalized per 100 meters, longer or less densely sampled paths in *open space* may accumulate slight deviations over distance, leading to relatively higher DTW values. Second, even in open areas, multipath effects and subtle signal interference from distant structures, vehicles, or other reflective surfaces can introduce small positional fluctuations, affecting both 5G/4G and GPS measurements. Finally, the nature of the DTW metric itself can amplify minor path deviations. DTW quantifies the overall shape similarity between paths, so slight misalignments along longer, relatively straight segments in *open space* can produce larger distance values, even if absolute positional errors are modest. These findings suggest that, while 5G significantly improves path fidelity, segment characteristics and local environment continue to affect measurement accuracy. The relatively large path-based errors observed in this study are worth noting. Primarily, the path-based errors are expressed as a normalized DTW distance per 100 m of path length, meaning errors accumulate along the entire route rather than errors at a single point. DTW is also known to accumulate small errors over long distances, resulting in larger aggregate values compared to point-based measures [15]. Secondarily, data collection while moving may introduce greater positional uncertainty than static measurements, i.e., check-in [25].

The area-based analyses demonstrated that both 4G and 5G devices exhibited higher precision than recall in indoor environments, indicating that outdoor points are rarely misclassified as indoors, whereas indoor points are more prone to misclassification as being outside due to signal attenuation, multipath effects, and limited network visibility [18]. This pattern highlights that even high-performance 5G smartphones tend to underestimate indoor activity areas rather than generating false positives. Area-based metrics further showed that 5G devices produced smaller, more concentrated concave hulls, reflecting fewer outlier positions and higher localization fidelity in constrained environments. Higher precision, recall, and F1 scores confirm that 5G more reliably identifies true indoor activity, reducing both false positives and negatives. It should be noted that the visible misalignment between the digitized boundary and the building outline in "Figure 3(c)" is attributable to two well-known imagery artifacts rather than an error in boundary definition. First, relief displacement causes building rooflines to appear laterally offset from their actual ground-level footprint due to the perspective projection of the satellite sensor, with greater displacement observed for taller structures farther from the image nadir [31].

Second, shadow effects at the time of image capture may further obscure the precise visual edge of building outlines [9].

These results have significant implications for health geography and environmental exposure research. Such accuracy is particularly valuable in health geography and spatial epidemiology, where precise location information enables dynamic assessment of behavioral and environmental exposures, identification of micro-scale disease transmission hotspots, and the design of targeted interventions [3,27,47]. Further, the superior indoor positioning performance of 5G may now enable analyses at a sub-building scale, supporting studies on pollutant exposure [56], facility usage [41], and micro-environmental health dynamics [48], which were previously limited to building-level granularity or required participants to carry multiple devices to record indoor and outdoor movement. Moreover, the consistent improvement of 5G over 4G suggests that 5G-enabled smartphones can serve as a reliable platform for longitudinal, high-resolution mobility tracking, with applications extending beyond health research to urban planning, environmental and wildlife management, smart building operations, and transportation studies [16,39,53].

Two limitations concerning data quality warrant acknowledgment. First, the ground truth reference data (digitized from 60 cm resolution imagery, see Section 2.2) can introduce positional uncertainty of up to 30 cm. While higher-accuracy reference approaches, such as Real-Time Kinematic (RTK) surveying, could provide sub-centimetre positional reference values, they were not adopted in this study as the specialized equipment and trained personnel required for deployment and calibration are beyond the operational scope of this research project. Second, while routes were physically flagged or infrastructure-constrained and participants were instructed to follow predefined routes, minor within-route deviations of up to 1–2 m cannot be completely avoided, particularly during driving. Importantly, as all devices were carried simultaneously by the same participant and evaluated against the same reference data under identical conditions, any positional uncertainty in the ground truth or within-route deviations affects all devices equally. In other words, these uncertainties do not favor one device type over another, and thus do not introduce systematic bias into the comparison between devices. Accordingly, findings should be interpreted as evidence of relative positioning advantages of 5G over 4G and standalone GPS devices, rather than as absolute accuracy estimates.

Furthermore, this study was conducted within an area of established 5G NR coverage; the behavior of 5G-enabled devices in regions with limited or no 5G coverage, where devices may fall back to 4G networks, warrants investigation. Future research could also examine GPS watches as a distinct device category alongside smartphones and standalone GPS devices. Although increasingly used in mobility research, GPS watches have a smaller evidence base in health geography and spatial epidemiology compared to other device types [21]. Such studies are valuable because GPS watches could enable tracking for smartphone-limited populations (e.g., children, older adults) or during field work and athletic activities, while their wrist-worn design may introduce unique positioning challenges that require dedicated validation.

5 Conclusions

This study provides a systematic evaluation of positioning performance across 5G NR smartphones, 4G smartphones, and standalone GPS devices, employing a three-level approach: point-based, path-based, and area-based analyses. By testing across five distinct real-world environmental contexts and three transport modes, we provide a comprehensive assessment of device accuracy under various real-world settings. Our results demonstrate a clear and consistent pattern: 5G smartphones outperform both 4G and GPS devices in terms of accuracy and reliability, particularly in challenging indoor and underground environments where conventional GNSS and cellular-based positioning often struggle.

These findings offer practical guidance for researchers in selecting appropriate data collection technologies, balancing factors such as data availability, device cost, and positional precision. Notably, 5G smartphones provide reliable tracking even in complex environments, supporting applications that require continuous, fine-grained movement data. Unlike controlled lab-based accuracy tests, data were collected during actual mobility trips across diverse urban environments, making findings directly applicable to real-world research design. Furthermore, as GNSS-derived data increasingly underpin big data mobility analytics and GeoAI models, understanding device-level positional accuracy is foundational, as errors from lower-quality devices may systematically bias downstream spatial analyses.

Our results have broader implications for urban mobility studies, activity space modeling, and location-based services, offering evidence for selecting the most suitable positioning technology based on study objectives, environmental context, and required precision. Overall, our comparative analysis underscores that 5G positioning is not merely a technical improvement in telecommunication technology, but also enhances the validity, applicability, and impact of location-based research across multiple domains. By demonstrating the advantages of 5G under real-world conditions, this study contributes directly to the evolving frontier of high-resolution human mobility research using mobile device technology.

Acknowledgments

This research was supported by the Bell-Western 5G Research fund. The funder did not have any involvement in the study design, analysis, or results reported in this manuscript. The funder provided in-kind five (5) 5G New Radio devices for use on the campus' private cellular network to the research team.

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A Appendix

Figure S1: 'Between buildings' environment along the walking route. Source: Google Street View (2024).

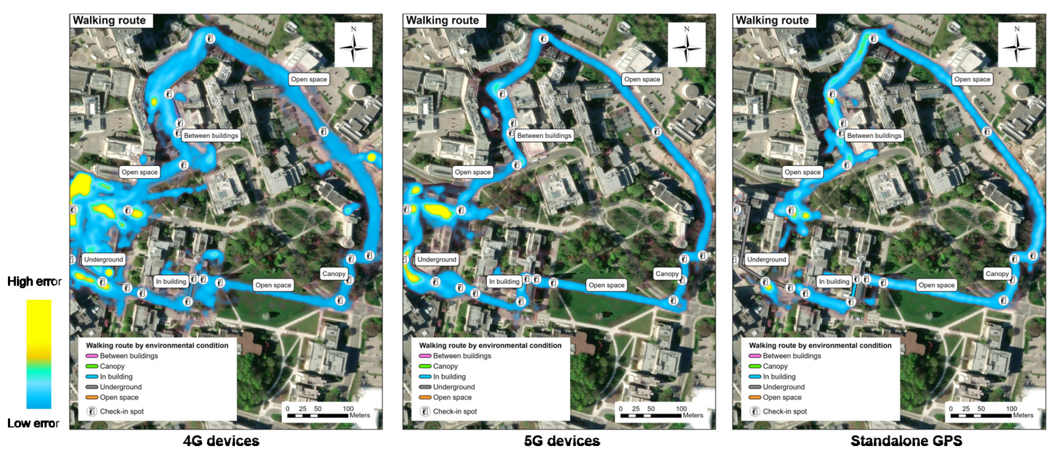

Figure S2: Heatmaps of positioning errors across all walking trips for 4G devices (left), 5G devices (middle), and standalone GPS devices (right).

RA ID	Device	Trips
1	iPhone 13	6
2	iPhone XR	6
3	iPhone 8	5
4	iPhone 12	6
5	iPhone 11 Pro Max	6
6	iPhone 12 Pro Max	6
7	iPhone 13	6
8	iPhone 11	6
9	Samsung Galaxy S10e	6
10	Google Pixel 6	6
11	Samsung Galaxy S21	6
12	Sony Xperia 1 III	6
13	iPhone XR	5
14	Samsung Galaxy S22	6
15	Google Pixel 5	6
16	iPhone 12	6
17	Sony Xperia 5 III	5
18	Samsung Galaxy A52	5
19	iPhone 11	6
20	Google Pixel 6 Pro	6
21	iPhone 8	5
22	Samsung Galaxy S21 FE	5
23	iPhone 12 Pro Max	5
24	Sony Xperia 10 III	4
25	Google Pixel 5a	4
26	Samsung Galaxy S20 FE	4
27	iPhone 11 Pro Max	5
Total		160

Table S1: Smartphone models of research assistants.