From Hardware to Handovers: Mapping Smartphone Tiers to Mobility Diversity

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***Abstract*—Understanding mobility is essential for planning and optimization in mobile networks, requiring accurately learning mobility trends from the individuals moving within the area of study. The diversity of systems and mobility patterns present a challenge for such algorithms, as data and device heterogeneity has effects on fairness, specially for federated approaches. Unfortunately, most works lack resources to fully understand how mobility diversity manifests in real-world settings and how it correlates to system diversity. To address this gap, we present a large-scale measurement study quantifying system and mobility heterogeneity in cellular networks, leveraging data from a major mobile network operator. We calculate mobility statistics derived from the trajectories of over 50,000 devices across 178 distinct smartphone models to demonstrate not only the existence of mobility diversity, but also that it is intrinsically connected to smartphone diversity.**

I. INTRODUCTION

Mobility has been a fundamental characteristic of cellular networks ever since their inception. As networks become increasingly dense, they unlock new capabilities such as predictive handovers and multi-connectivity architecture that ensures uninterrupted services for users. This has enabled telecommunications data to serve as a valuable proxy for capturing end-user mobility patterns at a large scale. The co-existence of multiple generations of mobile systems translates into a heterogeneous landscape of connected devices, where high-end smartphones and wearables [1] operate alongside low-end feature phones limited to voice services, and large-scale IoT deployments.

In this work, we investigate the interplay between smartphone hardware tiers and end-user mobility in dense urban environments. This is particularly relevant in Federated Learning (FL), where mobility-aware approaches are used in next-location prediction [2]. In this context, device heterogeneity (*e.g.*, computing capacity, battery life, or connectivity) can lead to challenges in model training and accuracy, biased client selection or suboptimal model aggregation. Leveraging production Mobile Network Operator (MNO) data from a major European capital, we analyze mobility events from over 50,000 devices mapped to a geo-spatial grid. While smartphones comprise nearly 60% of devices globally [3], few works map hardware heterogeneity to real-world movement. We address this gap to inform network optimization strategies, including caching, handover management, and load balancing.

II. DATA COLLECTION AND PROCESSING

Network measurements. The studied cellular network supports 2G through 5G Radio Access Technologys (RATs). For each RAT, we utilize a passively collected signaling dataset containing control plane messages triggered by MNO subscribers (*e.g.*, Attach, Handover, and Detach). Each event record includes anonymized device-level identifiers (including an anonymized International Mobile Equipment Identity (IMEI)), the radio sector ID handling the communication, a timestamp, and the event result code. To distinguish smartphone models and exclude Machine-to-Machine (M2M) or Internet of Things (IoT) devices, we leverage a commercial Global System for Mobile communications (GSM) Association (GSMA) database to map the Type Allocation Code (TAC)—the first 8 digits of the IMEI—to specific device properties such as brand, model, and radio connectivity. Daily snapshots of the network topology are then used to geolocalize these device positions.

Data processing. We study a 14-day period (July 22 - August 4, 2024. The initial sample consists of 80,000 unique native MNO subscribers, excluding international roamers. We specifically include devices signaling within the metropolitan area for at least 80% of the 14-day observation window. After filtering for TAC values associated specifically with smartphone models, we retain 89% of the original sample, resulting in a final dataset of 178 unique device models and 53,253 unique User Equipments (UEs). We represent each anonymized device trajectory as a temporal sequence of radio cells traversed during successful handover events. These trajectories are mapped to a squared grid with $500m \times 500m$ cells (0.25 km²), as shown in Figure 1 (A1). This grid resolution is chosen because it exceeds 75% of the Base Station (BS) cell sizes in the studied area, ensuring spatial consistency.

Mobility indicators. To analyze macro-level user behaviors, we extract two key mobility metrics: *Entropy*, which measures trajectory randomness and predictability, and *Radius of Gyration* (Radius of Gyration (RoG)), which quantifies spatial dispersion around the center of mass. As illustrated by the two test UEs in Figure 1 (A2), these metrics effectively capture trajectory diversity. User A (orange) visits more cells over a larger area, exhibiting higher Entropy (4.76) and RoG (0.12), whereas User B (blue) follows a compact path with lower Entropy (1.68) and RoG (0.01).

III. RESULTS

Device Heterogeneity. Using TAC values, we identify 178 unique models. We categorize these into three tiers based on age (months), estimated price (as of July 2024), and Geekbench 6 multi-core performance: Low (99 models), Mid (38), and High (41). The tiers are distinguished by their

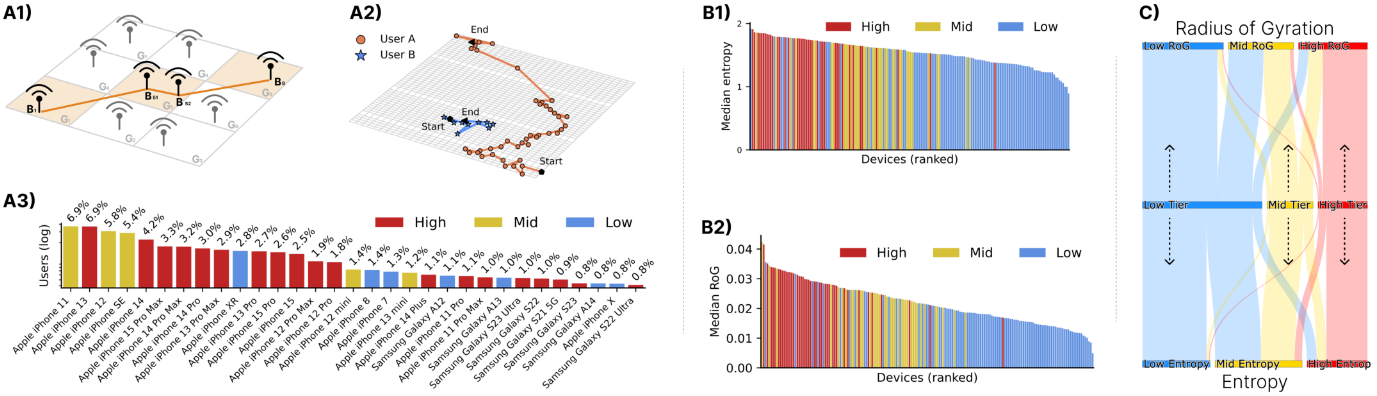

Fig. 1: (A1) The conversion from BS to grid locations; (A2) Example trajectories from two UEs with different Entropy and RoG levels; (A3) Top 30 smartphone models in this study, classified by their hardware tier; Ranking of median values for (B1) Entropy and (B2) RoG for each device; (C) Sankey diagram, showing how device tiers (middle) relate to mobility clusters, via the RoG (top) and Entropy (bottom).

centroids (age/price/computing score): High (21/689/5619), Mid (37/344/3248), and Low (51/117/1376).

The distribution of unique UEs remains stable throughout the study: High (48.5%), Mid (29.4%), and Low (22.1%). Figure 1 (A3) illustrates this stratification for the 30 most popular models. While older iPhones persist, the sample is dominated by premium Apple (Pro/Pro Max) and Samsung S-series flagships, followed by budget Samsung A-series devices. This highlights a clear bias toward high-end UEs in the studied metropolitan area.

Mobility Heterogeneity. We calculate the daily Entropy and RoG for each UE trajectory, aggregating median values per tier and device. Figures 1 (B1) and (B2) show a clear hierarchy: High-tier devices dominate the upper mobility ranks, while Low-tier devices occupy the bottom. We calculated the Spearman's rank correlation between the device features and mobility rankings, with positive correlation for both Entropy ($\rho_s = 0.762,\ p < 0.001$) and RoG ($\rho_s = 0.762,\ p < 0.001$).

Device-induced Mobility Heterogeneity. To determine if mobility patterns can reconstruct device tiers, we performed a Kolmogorov-Smirnov (KS) test across all 178 models for both metrics, using the results as features for hierarchical clustering. Silhouette score analysis confirms k=3 as the optimal number of clusters for both metrics, aligning with our device tiers. The resulting distributions for (High/Mid/Low) Entropy and RoG clusters are (50/72/56) and (57/54/67), respectively.

The Sankey diagram, presented on Figure 1 (C) visualizes the mapping between device tiers (middle) and mobility clusters (top/bottom). The tiers High and Low tiers show consistency: High-tier devices predominantly map to High-mobility clusters, and vice-versa. The Mid-mobility clusters exhibit greater variation, absorbing a significant portion of Low-tier and most Mid-tier devices. This is likely due to the high dynamicity of the Low tier, which contains both modern entry-level models and older, depreciated flagships. Notably, Low-tier devices with Mid-range mobility (e.g., iPhone X-series, newer Samsung A-series) are significantly newer than those in the Low-mobility cluster (e.g., iPhone 8, Samsung J-series).

Conversely, some Mid-tier devices appear in High-mobility clusters. This aligns with ”budget flagship” marketing (*e.g.*, Google Pixel A-series, Nothing, Poco) targeting younger, more mobile demographics.

IV. CONCLUSIONS AND FUTURE DIRECTIONS

We presented a study on how device and mobility heterogeneity are linked, by exploring large-scale measurements in the infrastructure of a MNO in an European capital. Mobility patterns vary significantly with device tier, with High tier devices showing higher Entropy and RoG, as well as having distinct mobility variations in time. Our future plan involves exploring how the correlation of system and mobility heterogeneity can affect the fairness of FL mobility models, evaluating client selection techniques and proposing changes towards improving model fairness. Our work has limitations due to our sample focusing on urban areas, as individuals from rural areas may have different patterns (*e.g.*, above average RoG and lower Entropy than urban settings).

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