Beyond the Pocket: A Large-Scale Survey on User Preferences of Bodily Placements of Wearable Technology

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Abstract. As wearables become smaller and more capable, their integration into everyday life introduces new design challenges. Current placement strategies are often shaped by laboratory assumptions and algorithmic constraints rather than real-world, context-dependent use. It remains unclear whether designs evaluated in controlled settings adequately reflect users' everyday needs, routines, and preferences. To address this gap, we collect empirical data on how people carry wearables in daily life, providing a systematic investigation of placement preferences across contexts and routines. We developed a multilingual questionnaire to characterize real-world wearable placement practices. Responses from n=300 participants recruited through common research channels reveal how wearable usage patterns vary across users and contexts. Based on these findings, we propose user-centred guidelines for sensor placement and examine how they align with assumptions in related work. This study contributes to the development of more inclusive, adaptable, and context-aware wearable systems.

1 Introduction

Wearable technology has become increasingly ubiquitous, offering features supporting health monitoring, fitness tracking, and communication. Continued advancements in miniaturization and computing-power driven by trends such as Moore's Law [46], are enabling the creation of devices that are smaller, more powerful, and more seamlessly integrated into daily life [12, 63]. However, the success of these technologies hinges not only on functionality but also on how individuals choose to integrate them into their lived experiences. While Human-Computer Interaction (HCI) and Personal Informatics (PI) research has previously focused on (user perceptions of) visualisation design (e.g. [10, 3]), what user interactions look like with PI tools (e.g. [43, 19]), and motivations behind using wearable devices and their embedded metrics (e.g. [42, 54]), it remains under-explored how users' preferred wearing locations change throughout the day, and how cultural norms and individual preferences influence these choices. Furthermore, there is a lack of understanding on users' motivations for carrying choices, and their perceived accompanying usability implications.

Individuals exhibit diverse perceptions of their bodies, influencing how they adopt and use wearable technology, and vice versa (e.g. [18, 60, 69, 70, 13]). Where users wear their technologies on their bodies are shaped by social norms (e.g. fashion trends), environmental constraints (e.g. climate), personal preferences, age, and body shape (e.g. [15]). This heterogeneity makes it challenging to generalise findings from limited studies to broader populations. Although Zeagler [78] provided a set of guidelines for the positioning of on-body wearable through literature, it is fully constructed based on the anatomical, physiological, and perception compatibility. Still, there is a lack of empirical HCI knowledge on cross-cultural preferences, hindering the development of user-centred wearable designs that are comfortable, effective, socially acceptable, and adaptable to diverse contexts. The importance of adaptive health systems has also been echoed in prior work (e.g. [41, 17, 59]), though it remains under-explored how to design such systems in an effective manner, both from a hardware and software perspective. Consequently, there is a discernible disconnection between the requirements of inclusive design practices and the state-of-the-art wearable devices. In a field where each millimetre and gram counts in making wearables as comfortable as possible, designing wearables for a multitude of wearing locations can affect the device's usability.

Accurate on-body localization of wearable devices remains a persistent challenge for algorithmic models, particularly in the domain of Human Activity Recognition (HAR) [15]. Although deep learning approaches have shown promising performance when utilizing data from a single or limited number of devices [23, 34, 75], their effectiveness is highly dependent on sensor placement [15, 61]. Therefore, there is a need to understand contextual wearable habits among users to provide tailored experiences. Although some works focus on personal device interaction and usage (Busso et al. [6]), broader information is needed, including extended demographic categories and other aspects of interaction that affect sensor signals, such as device position.

As a first step in the direction of contextually informed design, we collected and analysed guidelines published in the past, combined their recommendations, and localized places for potential improvement. Then we conducted a survey among the participants recruited through typical research channels, with the aim to acquire insights from a wide array of wearable users on how they wear their devices and in what contexts. Furthermore, given the challenges posed by domain variability [8, 61], our survey highlights demographic differences (e.g. age, gender, country of origin and residence, level of influence by parents) of collected sample, thereby supporting the refinement of algorithms for broader applicability in real-world scenarios. From our findings, we derived a set of guidelines to inform the design of more inclusive and effective wearable technologies.

To this end, we make the following contributions: (1) a synthesis of past guidelines for wearable designs; (2) an empirical survey with $n = 300$ valid responses conducted in four languages through typical research channels in multiple countries; (3) insights into key user attributes influencing bodily wearable placement habits; and (4) design considerations for more inclusive designs of future wearable developments.

2 Related Work

Here, we review related work on previously conducted studies on mobile phone carrying behaviour and past hardware design guidelines for wearables.

2.1 Mobile Phone and Smartwatch Carrying Habits across Gender and Cultural Differences

Prior work has extensively studied mobile phone carrying behaviour across cultures. A large pre-smartphone study by Cui et al. [11] across 9 countries and over 1,500 participants found strong gender and cultural differences, with women primarily using bags and men favoring trouser pockets [11]. Hand-carrying was also common in cities such as Delhi, Seoul, Jilin, and Los Angeles [11], though device form factors have since changed significantly with smartphones.

Health-related work by Szyjkowska et al. [66] (approx. 600 participants in Poland) linked intensive phone use with increased symptoms such as headaches and fatigue, but did not consider broader user experience or perceived utility. Gender-focused studies further highlight carrying differences: Redmayne [52] found that among fewer than 200 women, 86% carried phones off-body (e.g., hand 58%, pocket 57%), while Zeleke et al. [79] studied 356 men and examined carrying positions in relation to RF-EMR risk perception. These works highlight demographic differences but do not generalize across device types such as wearables or tablets.

Smartwatch research extends this perspective into longitudinal usage. In a 200-day study of 50 students, Jeong et al. [31] identified distinct user groups (*work-hour*, *active-hour*, and *all-day* wearers), showing strong context dependence. More generally, wearable design must consider proxemics, movement, and comfort constraints [78, 25], including risks of device wear, discomfort [62], and motion restriction [67].

Large-scale sensing datasets combine self-reports and passive data for behavioural modeling. Early work such as *MDC* [35] captured smartphone mobility and communication, while newer datasets like *EgoADL* [64], *SmartUnitn2* [37], and *Qwantify* [73] integrate multimodal sensing and experience sampling. Cross-country datasets such as *DiversityOne* [6] and *GLOBEM* [74] further enable generalization across populations. However, most datasets remain limited in demographic coverage and rarely capture device–body placement, despite its impact on sensing quality.

Prior surveys highlight persistent underrepresentation of non-WEIRD populations in mobile and wearable computing [77, 29]. While recent PI research increasingly addresses inclusivity for marginalized groups [47, 30, 20, 44, 7], this

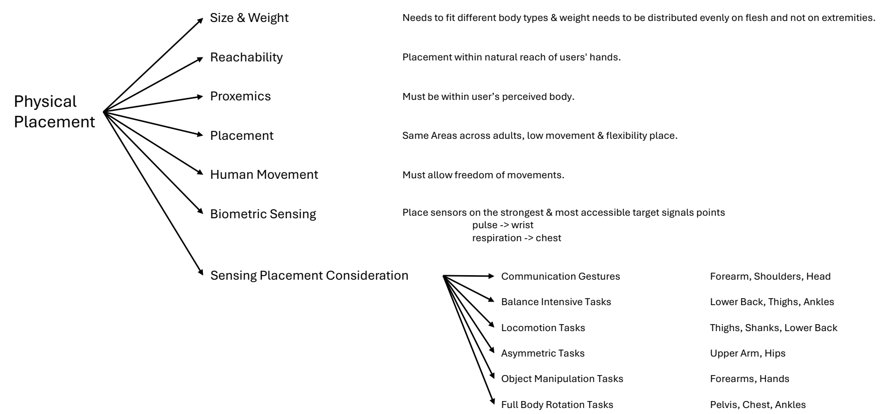

Fig. 1. Synthesis of wearable hardware design guidelines from past research.

focus is often limited to data visualization and metrics rather than hardware placement or form factor design [3, 42].

Building on this, our study examines real-world carrying habits across multiple wearable types, including smartphones and smartwatches, based on participants recruited through standard research channels.

2.2 Past Guidelines on Hardware Design of Wearables

Prior work has proposed several guidelines for wearable hardware design, summarised in Figure 1.

Gemperle et al. [25] introduced 13 early design principles covering placement, comfort, sizing, and adjustability, emphasizing human-centred design across body types. However, these guidelines remain broad, largely ignoring real user habits and being limited by the technological context of their time.

Building on this, Zeagler [78] extended wearable design guidance with body maps linking sensor placement to activity and context, and discussed aspects of social acceptability (e.g., avoiding sensitive body regions [78, p. 155]). While comprehensive, this work still does not incorporate how users actually wear devices in practice, which may lead to mismatches between assumed and real sensor locations and reduce data reliability.

A longitudinal study by Jeong et al. [31] examined smartwatch usage across 50 participants over 200 days, identifying distinct usage patterns and deriving UX implications. The study revealed real-world issues not considered in design (e.g., charging inconvenience), but was limited by sample size and device specificity.

More recently, Ray et al. [51] proposed the Where to Wear (W2W) framework, using simulation to identify optimal IMU placements for motion capture across six activity types. Although it accounts for motion noise, it does not consider incorrect or non-ideal placements that reflect real user behaviour.

Overall, while existing guidelines provide valuable design direction, they are rarely validated against diverse real-world populations. Their generalisability across demographic groups and typical user samples remains unclear, raising concerns about how well they reflect actual wearable usage and data collection conditions.

3 Methodology

Our inquiry was guided by two research questions:

- **RQ1:** *How are on-body placements for wearable technologies influenced by user attributes?*
- **RQ2:** *How do contextual factors influence users' on-body wearable placements?*

The first research question examines the influence of user demographics (e.g. age, gender, education) on the storage of wearable devices. The second question considers how contextual factors, such as time of day, activity, or environment, impact storage behaviour. Together, these questions investigate how context affects user behaviour.

To answer those questions, we conducted a demographically unrestricted, online questionnaire. Our study was approved by the ethics board of the primary researcher's affiliation.

In addition, the study is guided by a third research question:

- **RQ3:** *To what extent are assumptions about user characteristics, found in prior research, accurately represented?*

Through this research question, we examine which assumptions have been used in prior research, what types of guidelines exist, and how these relate to real-world data. To this end, we conducted a synthesis of related work (Section 2.2) and compared these findings with the results of our survey. In particular, we focused on identifying similarities, differences, and the extent to which assumptions are transferable to real-world contexts.

3.1 Survey Content

Our survey was offered in several languages (English, French, German and Polish) to mimic the way studies are performed in international groups that are taking advantages from different cultures and countries.

The time to complete the survey ranged from 2 minutes 40 seconds to 27 minutes 19 seconds, with an average duration of 9 minutes 32 seconds. The survey was divided into four sections, as seen in Figure 2: (1) smartphone usage; (2) smartwatch usage; (3) other wearable devices, and (4) demographic questions. The first and second sections of the questionnaire had the same structure, differing only in the type of device being addressed. For each device, participants were asked where they typically carry it. For each reported location, they

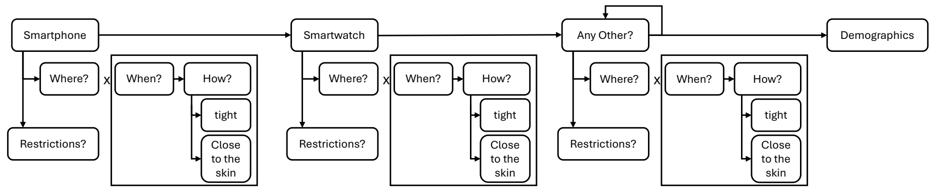

Fig. 2. Flowchart depicting the structure and contents of the questionnaire used in the study.

were then asked during which times of the day or night (e.g. at home, outside, while sleeping) they use that placement, as well as how tightly the device fits and how close it sits to the skin. The third section followed the same structure but was designed to repeat automatically, allowing participants to report additional wearable devices as desired. In the forth section, demographic questions are asked.

3.2 Participants

As described in the introduction, considering realistic wearable placement during the design phase is essential. Failure to do so may result in user discomfort, as well as misleading assumptions and, ultimately, flawed findings. Therefore, in this work, we examine whether the populations typically recruited for scientific experiments exhibit device-carrying habits that align with prior work and existing guidelines. If these guidelines fail to accurately represent even this commonly studied population, their applicability to the wider general public is likely to be even more limited.

In scientific research, participant recruitment is commonly conducted via mailing lists, advertisements in public spaces, and word of mouth; accordingly, we used these channels as well. Participants were compensated by being entered into a raffle with prizes totalling 200 euros.

In total, $n = 449$ participants were recorded, of which we included $n = 300$ in our final analysis. Reasons for exclusion included failing to complete the survey or to provide valid answers to mandatory fields. The gender distribution of our sample consisted of 150 females (50%), 141 males (47%), 3 non-binary (1%), 1 other (0.33%), and 5 who preferred not to share (1.67%). The participants were between the ages of 18–80, with the age distribution skewed toward the younger generation ($M = 31.9$, $SD = 12.12$; see Figure 3).

Besides basic demographic information, we also asked participants about their background, such as highest achieved education, handedness, country of residence, and occupation, to collect insights into whether contextual and environmental factors influenced their wearable use.

In our survey, most participants were right-handed ($n = 268$), some left-handed ($n = 23$), and only a few ambidextrous ($n = 9$). Our sample had the following education levels: 21 (7%) practical, 52 (17.33%) high school, 96 (32%)

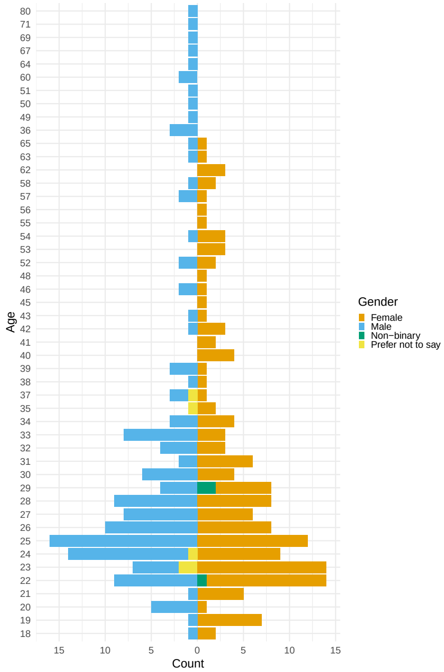

Fig. 3. Distribution of age of participants grouped by gender.

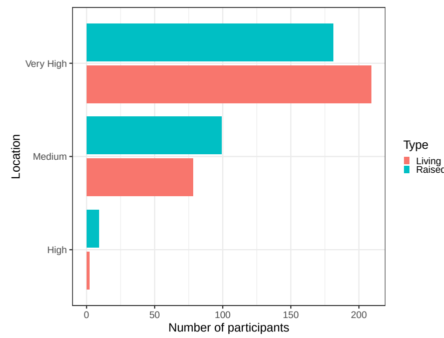

Fig. 4. Histogram of the number of countries in which participants ever lived, grouped by country of raised and living. The countries are categorised according to the Human Development Index.

bachelor's, 104 (34.67%) master's, and 27 (9%) PhD degrees. The reported types of occupations were divided into the categories presented in Table 1.

Participants originated from various countries, including Germany, Poland, Rwanda, the United States, India, Egypt, France, Japan, Australia, China, Sweden, and Indonesia (the distribution among countries has been removed for review anonymization).

Among participants of the survey, 153 (51.00%) reported living in the city, 135 (45.00%) in the countryside, and 7 (2.33%) in towns. Additionally, 5 (1.67%) participants reported living in a few types of settlements at the same time, likely reflecting the travelling nature of their work.

In our sample, 289 participants (96%) used smartphones, 92 (31%) smartwatches, 83 (28%) earphones, 18 (6%) headphones, 11 (4%) location trackers, 4 (1%) cardiac monitors, 2 (1%) tablets, 2 (1%) smart rings, 2 (1%) smart glasses, and 1 (0.3%) Coros pod[4]. It is important to note that some participants reported using more than one device at a time.

[4] `https://coros.com/coros-pod2`

Table 1. Number of participants by occupation type and gender; see Section 3.3 for the inclusion criteria.

Occupation type	Total participants	Female participants	Male participants
Medicine & Health	67	31	35
Computer Science	66	21	40
Humanities	33	27	6
Science	33	15	18
Engineering	33	9	24
Business & Economy	27	22	3
Education	14	9	5
Blue collar	11	4	7
Administration	12	10	1
Technicians	3	1	2
Architecture	1	1	0

3.3 Analysis

To identify associations between demographic characteristics of our sample and wearable device usage patterns, we employed an automated exploratory data analysis approach. It is important to note that all percentage data reported in this paper were calculated by dividing the number of occurrences of interest by the total number of participants.

Data Preprocessing & Filtering Prior to testing, categorical variables were consolidated where appropriate to improve statistical power and interpretability. We filtered out conditions that lacked sufficient responses to ensure the generalisability of our findings. For instance, for the *Device*, we first combined the categories *earphones* and *headphones* due to their similar purpose and usage. We then included only *smartphones*, *smartwatches*, and *earphones* in our analysis, as these were the only devices representing more than 10% of all responses.

For the *Gender*, only data from participants identifying as male or female were included, as the number of other reported answers were too low to draw any meaningful conclusions.

To analyse the influence of country while maintaining the full dataset, we used the Human Development Index 2025 (HDI) [49]. The HDI ranges from 0 to 1 and categorizes countries based on multiple dimensions, such as 'long and healthy life', 'knowledge', and 'decent standard of living'). It is updated each year by the World Health Organization (WHO). Depending on the HDI value, countries are divided into four categories: Very High ($>$0.800), High (0.700 - 0.799), Medium (0.550 - 0.699), and Low ($<$0.550). Most participants in our survey reported having grown up in Very High HDI countries ($n = 187$, 62.8%), followed by Medium HDI countries ($n = 102$, 34.2%), with only a few raised in High HDI countries ($n = 9$, 3.2%).

To obtain a more complete picture, we also analysed how many participants currently live in countries within those categories. The general trend remains similar, although 30 participants moved to countries in a higher HDI category and one person moved to a country in a lower HDI category (see Figure 4 for the distributions).

During the analysis of time-related wearing patterns, we examined only the categories: *Active time*, *During work hours*, *Sport*, *While in bed*, and *Outside*, as other times were not reported frequently enough to yield statistically meaningful results when dividing the data by different demographic variables. Some of those times were congregated from other responses of participant, thus:

- **Active time:** was created by combining two categories: *While not in bed* and *During the day* as those both describe a time that is spend actively doing tasks ranging from leisure, through house chores to work
- **Outside:** was combined from *on the way*, *outside*, *travelling*, *using public transport* as all of them combine notion of travelling in vehicles or being outside.

4 Results

This section presents the findings from our study, focusing on how user demographics—such as age, education, work background, country of origin and residence, and social influences (e.g. parents, friends, environment)—affect wearable device usage, on-body placement, and usage time. We explore how these demographic factors interact with time-of-day and context to shape placement behaviour across daily routines.

4.1 Demographic Influence

Age. Across all age groups, smartphone was the most commonly used wearable device. However, age-specific placement patterns emerged. Younger participants (under 28 years) showed a stronger preference for earphones and were more likely to carry their smartphones in hand. Older individuals—especially women—were more likely to store their smartphones in purses or bags. Smartwatches were typically worn on the left wrist regardless of age, although younger users showed more placement variability.

Gender. Gender significantly influenced both device usage and placement. For smartphones, men primarily used front pants pockets throughout the day (33.9% men in opposition to 5.37% women), while women preferred back pants pockets or waist-level jacket pockets (14.1% and 9.73%, respectively). During work hours and physical activity, women tended to store their phones in purses (4.36%) or backpacks (3.69%), whereas men continued to use front pants pockets (16.1%) or held the phone in hand. At night, both genders reported holding the phone in hand, likely indicating active use in bed rather than passive storage.

Earphone use patterns were similar across genders during the day and while exercising. However, storage preferences differed: men favoured pants pockets,

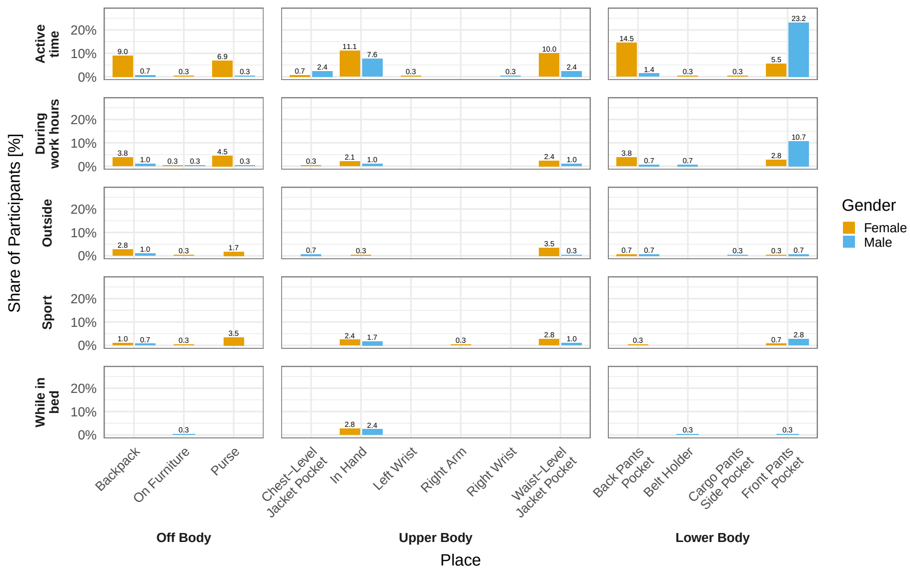

Fig. 5. Bar plot showing the distribution of smartphone carrying locations by time of day and gender; see Section 3.3 for the inclusion criteria. For each time period, percentages were calculated separately as the number of responses for each location category divided by the total number of study participants.

while women preferred purses and waist-level jacket pockets. Both used backpacks for storage. Smartwatch use showed comparable trends, most participants wore them on left wrist (28.6% of women, 41.9% of men), particularly during active or sport periods, with few choosing alternative placements.

Education. Educational background had little direct effect on device placement, with differences largely reflecting occupation and age. During active time, smartphones were mainly carried in front pants pockets by Bachelor's, Master's, and PhD holders (20.1%, 17.5%, and 17.1%), while high school graduates more often used back pockets (16%) or held them in hand (15%).

Earphones were typically worn during work and sport but stored elsewhere during active time. Smartwatches were predominantly worn on the left wrist across all education levels, especially among Master's (40%) and Bachelor's graduates (29.4%).

Occupation. Smartphone placement varied by occupation and activity. Medical and health professionals mainly used front pants pockets during work (42.9%) and active time (34.4%). Computer scientists preferred front pants pockets (36.4% work, 34.9% active) and in-hand use (25.4%). Engineers also relied on front pants pockets (46.2% work, 31.2% active) with frequent hand use (28.1%). Scientists

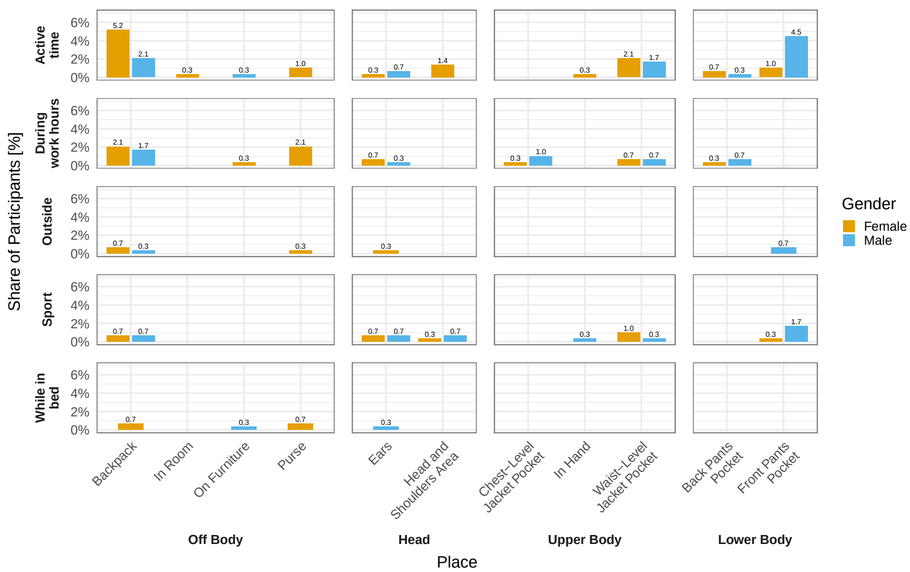

Fig. 6. Bar plot showing the distribution of earphones carrying locations by time of day and gender; see Section 3.3 for the inclusion criteria. For each time period, percentages were calculated separately as the number of responses for each location category divided by the total number of study participants.

split usage between front (33.3%) and back pockets (24.2%), while humanities and business participants showed more varied storage, including backpacks, jackets, and purses.

Earphone placement followed similar occupation-dependent patterns. Health professionals used front pants pockets (36.4%), backpacks (27.3%), and jacket pockets (27.3%). Computer scientists preferred front pockets (33.3%) and backpacks (28.6%), with frequent in-ear use at work. Humanities and business participants relied mainly on backpacks (42.9–55.6%) and purses (33–50%), while scientists used backpacks (33.3%) and jacket pockets (16.7%).

Smartwatches were consistently worn on the left wrist across occupations, especially during active time (computer science 85.7%, engineering and health 80%) and sport (health 83.3%, humanities 100%), with stable usage also during work and in-bed contexts.

HDI and Country of Origin. Participants from very high HDI countries owned more devices ($Mean_{\text{Very high HDI}} = 1.92$ vs $Mean_{\text{Medium HDI}} = 1.57$) and showed more diverse placement behaviours. During active time, they used front pants pockets (24.5%), but also back pockets (20%), jacket pockets (16.5%), in-hand use (15.5%), and backpacks (11.5%). Medium HDI participants were more uniform, mainly using front pants pockets (42.9%) and in-hand storage (28.6%).

Smartwatches were mostly worn on the left wrist, especially during active time (very high HDI 92.9%, medium HDI 69.2%) and sport (very high HDI 93.8%, medium HDI 75%), with stable usage across work and in-bed contexts. Earphone placement showed similar differences: very high HDI participants used backpacks (34.8%), front pants pockets (21.7%), and jacket pockets (19.6%), while medium HDI participants preferred front pockets (35.7%) and backpacks (28.6%). Hybrid participants showed mixed behaviours across contexts, including backpacks, purses, and in-ear use (up to 28.6%).

Participants who moved from medium to very high HDI contexts exhibited intermediate, hybrid patterns, with increased variability during work and sport. Higher device ownership was more common in very high HDI groups, particularly among Master's graduates and computer scientists.

Device Ownership. Most participants owned two wearable devices, a pattern strongest among urban residents, highly educated individuals, and those in very high HDI countries. Participants in technical and humanities fields also tended toward multiple devices. In contrast, individuals from medium HDI countries or with bachelor's degrees more often owned a single device. Among those who moved to higher HDI contexts, Master's graduates and computer scientists were more likely to own three devices. Within this subgroup, women more frequently reported three to four devices, while men typically owned two to three.

Urban vs. Rural Differences. Urban and rural participants showed similar primary smartphone placement, with front pants pockets most common during active time (City: 22.4%, Country Side: 38.1%) and work (City: 33.9%, Country Side: 41.9%). Urban users more often held phones in hand during active periods (24.3%) and in bed (87.5%), indicating higher direct device interaction. Rural participants more frequently used backpacks and purses, especially during sport (Backpack: 13.6%, Purse: 9.1%) and outdoor activities (Backpack: 20%, Purse: 20%).

Smartwatch placement was consistent across groups, with left-wrist dominance in urban (Active: 87.5%, Sport: 86.7%) and rural users (Active: 72.7%, Sport: 100%). Earphone use varied by context: urban participants used them throughout the day, storing them in backpacks (Active: 25%, Work: 35.3%) or front pockets (Active: 25%, Work: 11.8%), while rural participants mainly used them during sport and outdoor activities, often relying on backpacks or in-ear use (Backpack: 14.3%, Ears: 28.6%).

4.2 Contextual Influences Across the Day

Device placement varies strongly across daily contexts, with activity type being the primary driver. This creates a clear distinction between active-use locations (hand, ears) and passive storage (pockets, bags, furniture), which is further shaped by demographic differences and informs HAR sensor placement considerations.

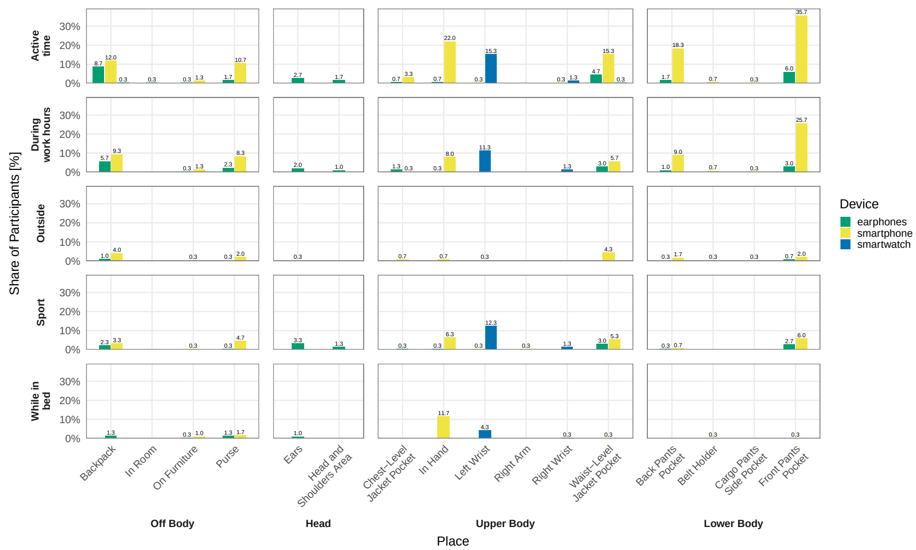

Fig. 7. Bar plot showing the distribution of device carrying locations by time of day. Percentages were calculated separately for each time period as the number of responses for each location category divided by the total number of study participants.

Active Time Habits During *Active Time*, smartphones are mainly carried in front pants pockets (29.6%), followed by in-hand use (18.3%), waist-level jacket pockets (12.7%), backpacks (9.97%), and purses (8.86%). Earphones are primarily stored in backpacks (29.9%), front pockets (20.7%), or jacket pockets (16.1%), indicating intermittent use. Smartwatches remain predominantly on the left wrist (86.8%).

During Work Hours Habits At work, smartphones are most often in front pants pockets (37.4%), followed by backpacks (13.6%), back pockets (13.1%), in-hand use (11.7%), purses (12.1%), and jacket pockets (8.25%). Earphones are mostly stored rather than worn, commonly in backpacks (28.3%), pockets, or purses, with limited in-ear use (10%). Smartwatches remain on the left wrist (89.5%), supporting continuous monitoring.

Outside Activity Habits During outdoor activities, smartphones are mainly placed in jacket pockets (26.5%) or backpacks (24.5%), with smaller shares in front pockets (12.2%), purses (12.2%), and back pockets (10.2%). Earphones are more frequently worn in the ears (23.8%), supporting communication and media use. Smartwatches remain consistently on the left wrist (90.2%).

Sport and Exercise Habits During sport, smartphones are split between front pants pockets (22.0%) and in-hand use (23.2%), with additional storage in purses (17.1%) and jacket pockets (19.5%). Earphones are often worn in the ears (23.8%) or stored in pockets and backpacks, reflecting active media use. Smartwatches remain on the left wrist (90.2%), serving as primary activity trackers.

While in Bed Habits In bed, smartphones are mostly held in hand (76.1%) or placed nearby (e.g., purses, 10.9%), reflecting pre-sleep usage. Earphones are typically worn continuously for media or sleep content. Smartwatches remain on the left wrist (92.9%), supporting passive monitoring such as sleep tracking.

5 Contextualizing Results in Culture and Society

Wearable and device placement is shaped by social, occupational, and environmental factors rather than random choice. Gendered clothing, professional requirements, and living environments influence which body locations are practical, explaining why theoretically optimal placements often differ from real-world usage.

Gender Differences Gender strongly affects available storage options. As shown by Diehm and Thomas [14] and Townsend [68], men's trousers generally provide larger and more numerous pockets than women's clothing. Consequently, women rely more on handbags, jackets, or backpacks, producing a broader distribution of device locations and a more uniform heat map. Men predominantly use front pants pockets, making this the most common placement overall despite greater variability among women.

Occupation and Professional Context Occupation further influences placement through functional requirements. Mobile professions such as medicine, construction, and technical trades favor secure, accessible locations, primarily front pants pockets (over 33% of participants), supported by standardized uniforms with gender-neutral pockets. In contrast, knowledge-based professions show greater variation, including desks, furniture, and handheld use; over 28% of engineers reported holding their smartphone while working. Earphone use similarly reflects workplace norms, being common in computer-based jobs but less so in occupations requiring continuous situational awareness.

Living Environment Living environment also affects device placement. Studies by Fan et al. [21], Christiana et al. [9], and Pelletier et al. [48] show that rural residents engage more in manual and household activities, encouraging storage in backpacks, purses, or on nearby surfaces. Urban users interact with their phones more frequently, with 24.3% carrying them in hand compared to 11.9% of rural residents, reflecting commuting and navigation habits.

Summary Overall, gendered clothing, occupational demands, and living environment explain much of the gap between optimal sensor placements and everyday practice. Rather than fixed body locations, device placement reflects a balance between comfort, accessibility, social norms, and clothing constraints, highlighting the need for context-aware wearable sensing algorithms.

6 Design Considerations for Usable Wearables

Based on the findings, we distilled a few recommendations to remember about while creating a new wearable device or designing an experiment with users.

6.1 Design Consideration 1: Adjust Sensor Placement to the Time of Day and Activities Performed

Mapping algorithmically recommended body locations to reported device usage identifies practical placements that balance signal quality, anatomy, and usability. The following recommendations summarize suitable placements across common daily contexts.

Active Time. As *Active Time* spans most waking activities, no single location fits all situations. Nevertheless, **the wrist** (via a smartwatch) is the most consistent primary placement. For smartphones, **the waist-level jacket pocket**, **back pants pocket**, or **front pants pocket** provide stable, practical alternatives. Although mapped from different anatomical regions, front and back pockets exhibit similar pelvis-coupled motion, making both effective for daily sensing. Together, wrist and pocket-level placements offer robust coverage while remaining comfortable and socially acceptable.

Work Hours. During work, **the wrist** remains the preferred location for continuous monitoring. Smartphones are best carried in **front or back pants pockets**, particularly in occupations requiring mobility. Where clothing or workplace policies limit these options, **waist- or chest-level jacket pockets** or nearby desks can serve as temporary locations. This combination balances signal continuity, accessibility, and workplace constraints.

Outside Activity. For outdoor activities, **the wrist** remains the primary location. Secondary placements include **front or back pants pockets** and **waist-level jacket pockets**, which maintain stable trunk motion while allowing easy access. **Earphones** provide complementary sensing for calls or audio but are not suitable as stand-alone sensors.

Sport and Exercise. During exercise, **the wrist** is the most reliable placement because of its stability and widespread smartwatch use. Smartphones may be briefly held in **the hand** but are better stored in a **waist-level pocket** during activity. This combination supports multimodal sensing without restricting movement.

While in Bed. During rest, **the wrist** remains optimal for continuous physiological and sleep monitoring. Smartphones are frequently used **in hand** before sleep for activities such as reading, messaging, or watching media, before being placed on nearby furniture. Consequently, the wrist is the preferred sensing location, while the hand and bedside furniture reflect realistic interaction and temporary storage patterns.

In summary, although temporal and activity contexts significantly influence user habits, wrist placement appears consistently across all the activities and time periods we analysed. Therefore, if the application allows, we recommend sticking to that placement. For other activities, we recommend careful consideration of stakeholders' needs.

6.2 Design Consideration 2: No Uniform Device Placement across Users

Our findings show that demographic factors, including gender, age, education, and culture, significantly influence how users carry wearable devices. For example, men predominantly use front pants pockets, while older users exhibit more consistent placement patterns.

Researchers developing wearable devices or training Human Activity Recognition (HAR) models typically either (1) use an existing public dataset or (2) collect a new one. Although new datasets provide greater experimental control, they are costly and time-consuming [40, 53]. Recruitment often relies on STEM student populations, introducing demographic biases in gender and age [22]. Public datasets are similarly biased, frequently over-representing young, male, STEM-affiliated participants [22], limiting the generalisability of wearable designs and HAR models.

These biases can lead to unrealistic placement assumptions. For example, Leng et al. [36] designed an emotion recognition system using IMUs in the front pants pocket, a location often unsuitable for women. Likewise, Liu et al. [39] proposed a wearable for monitoring eating behaviour in older adults despite not including older participants; its chest placement beneath the breast may also reduce comfort for women. Similarly, a panic attack detection system uses chest-worn sensors that may conflict with women's undergarments [55]. Finally, an activity recognition system based on headphone microphones may see limited adoption as many users now prefer earbuds [76].

To ensure real-world relevance, we recommend that future wearable designs consider diverse carrying preferences. Avoid defaulting to placements optimised for a limited subset of users, and instead design for flexibility and inclusivity across genders and age groups.

6.3 Design Consideration 3: Smartphone Availability During Sports and Throughout the Day

Our findings show that smartphone placement varies by gender and context. Men commonly carry phones in front pants or jacket pockets, whereas women often use purses or backpacks. During sports and some daily activities, users may not carry smartphones at all, creating gaps in sensing coverage. This variability challenges systems that assume consistent on-body smartphone availability.

Leng et al. [36] acknowledge limitations caused by relying on specific body locations that may be inaccessible or uncomfortable. For example, placing a smartphone in the front pants pocket may reduce adoption and affect performance when carried elsewhere. To avoid smartphone dependence, Bian et al. [4] combine a smartwatch with a custom earable for activity recognition. However, the earable relies on electrostatic sensors unavailable in standard earbuds, potentially limiting adoption, as users may prefer their own audio devices or find continuous wear uncomfortable. A shoe-mounted device improves movement recognition during sports [28], but our findings suggest such devices (e.g., Coros Pod) are rarely used outside sport-specific contexts. Similarly, [45] acknowledge that their multi-sensor audio-motion system is impractical for everyday use, highlighting the trade-off between recognition accuracy and real-world wearability.

> We recommend avoiding the assumption that smartphones are always carried on the body. People often set their phones aside during physical activity, at home, at work, or in social situations, which can lead to data gaps or missed interactions. Systems that rely solely on smartphones for sensing may miss important moments. Complementary wearables can help ensure more consistent data collection across a wider range of everyday contexts.

6.4 Design Consideration 4: Align with Users' Dominant Wrist Preferences

We found that most users wear smartwatches on their non-dominant wrist (typically the left), regardless of age or gender, due to comfort, ease of use, and minimal interference with daily activities. Systems requiring the dominant wrist may disrupt these habits, reducing comfort and adoption.

Scholl et al. [57] require a smartwatch on the dominant (right) wrist, which may conflict with user preferences and reduce long-term compliance. Similarly, the wrist-worn systems proposed by Villa et al. [71] and Aiba et al. [1] may face adoption barriers unless they integrate with existing smartwatch ecosystems. Our findings suggest that ignoring established wrist preferences can hinder usability.

More adaptable approaches include the energy-aware system by [32], which uses smartwatch-compatible wrist sensors, although it does not consider wrist dominance. Emotion-tracking systems [72, 50, 27] also leverage standard smartwatch form factors, supporting comfort and long-term use. Likewise, Searle et al.

[58] collect data using a commercial smartwatch to enable real-world deployment, while Li et al. [38] use a compact sensor bracelet that can be worn comfortably alongside a smartwatch.

> To promote adoption, wrist-based systems should respect dominant wrist-wearing habits, offer wrist-agnostic designs, or ensure compatibility with prevailing smartwatch ecosystems.

6.5 Design Consideration 5: Evolving User Preferences Driven by Fashion and Technology Trends

Wearable device placement evolves with fashion, lifestyle, and technology. Our findings show that older users maintain more consistent placement habits, whereas younger users adapt more readily to changing trends.

Comparing our results with earlier studies highlights these shifts. In 2007, Cui et al. [11] found that 14% of men used belt clips, compared with just 1.9% in our study. Likewise, 11.5% of women carried phones in hand or around the neck in 2007, whereas today 40% carry them in hand and none around the neck. Phone placement in skirts, previously reported by 16.5% of women, has also disappeared. Some behaviours remain stable: both our study and Zeleke et al. [79] found that men commonly carry phones in front pants pockets at work, outdoors, and in vehicles. Nevertheless, these habits may change with evolving device designs, clothing, and cultural norms. Emerging sensing approaches, including conductive textiles [26], cosmetic-based sensing [5], and skin-compatible 3D-printed wearables [16], support seamless integration into daily life. However, as fashion continues to evolve, both sensing technologies and their algorithms must remain adaptable.

> Therefore, designers should avoid relying solely on historical norms or current standards. Instead, they must consider how emerging trends and generational differences may influence user behaviour over time. Wearables should be designed with flexibility and adaptability in mind, ensuring long-term usability across diverse and evolving contexts.

6.6 Design Consideration 6: Build Benchmarks that Reflect Real-World Device Placements

Wearable sensing benchmarks, particularly for HAR, often assume fixed or researcher defined device placements (e.g., front pants pocket or wrist). While this simplifies data collection and model development, it overlooks how users naturally carry devices. As early as 2015, Schlögl et al. [56] emphasized the need for in-the-wild studies to obtain representative data. Our findings support this, showing that gender, age, fashion, and comfort strongly influence device placement.

This mismatch between controlled benchmarks and real-world behaviour can reduce model performance and generalisability. Some datasets already address this issue by including multiple on-body positions, better reflecting natural usage [65, 24].

> To support fairer and more effective model evaluation, we recommend that future benchmarks prioritize capturing these real-world variations. This includes allowing participants to place devices where they typically would and annotating those locations. Benchmarks should also strive for demographic diversity to capture the full spectrum of carrying habits. Doing so will lead to more inclusive, realistic, and robust wearable sensing systems.

6.7 Limitations

While our study builds on prior guidelines and addresses gaps in the literature, several limitations should be acknowledged. Although the dataset includes 300 valid responses, it is insufficient for robust statistical analysis across intersecting demographic variables. Combining attributes such as country, education, and gender results in small subgroup sizes, limiting fine-grained comparisons. Consequently, our analyses identify general trends and indicative subgroup patterns rather than definitive conclusions.

The dataset also reflects demographic and geographic biases introduced by recruitment. Many participants were affiliated with universities, and respondents were concentrated in regions connected to the authors' professional networks. As a result, the sample largely represents the typical WEIRD (Western, Educated, Industrialized, Rich, and Democratic) research population [29].

As with all questionnaire-based studies, our findings are subject to recall and social desirability biases [2, 33]. Participants may misreport behaviours, and terms such as *"during the day"* or *"outside"* may be interpreted differently across cultures. Open-ended responses helped capture additional practices but cannot compensate for the sample imbalance.

Finally, the study is cross-sectional and cannot capture how wearable habits evolve over time. Longitudinal studies would help distinguish persistent behaviours from short-term trends and better understand changes in wearable use.

Despite these limitations, our study provides an empirical overview of wearable placement practices across gender, occupation, and limited cultural backgrounds, offering a foundation for future research and more context-aware wearable design.

7 Conclusions

Wearable technologies are becoming increasingly integrated into everyday life, yet their effectiveness depends on where and how people actually wear and carry them. Through a multilingual survey and a synthesis of prior work, we examined wearable placement habits across the typical research participant population and compared them with assumptions underlying existing designs. Our results reveal clear differences across gender, age, lifestyle, and cultural background. For example, men predominantly store smartphones in front trouser pockets, whereas women more often use handbags, backpacks, or jackets. Smartwatches are typically worn on the non-dominant wrist, reflecting established watch-wearing conventions. These findings motivate context-aware sensor placement recommendations that better match real-world routines and activities.

Our work highlights the importance of accounting for user diversity when designing wearable systems. We encourage future research with more diverse participant populations, longitudinal studies, and qualitative or mixed-method approaches to better understand the factors shaping wearable use. More broadly, we advocate engaging diverse users early in the design process and avoiding assumption-driven designs based on dominant user groups. By demonstrating the variability in wearable practices even within the research participant population, this work provides a foundation for more inclusive, context-aware wearable technologies.

Ultimately, **wearable systems should adapt to people—not the other way around**.

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