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ABSTRACT
Smartwatches have become widely adopted for everyday tasks, including activity tracking, notifications, and health monitoring, owing to their portability and ability to capture diverse data. While prior work has shown how smartwatches enrich multi-device systems and improve user experience, we still lack a systematic understanding of their roles, usage scenarios, and evaluation practices within these ecosystems. To address this gap, we conducted a systematic review of 106 studies on smartwatch-based multi-device systems. These studies were published across six leading Human-Computer Interaction conferences and five top-tier journals, with a cutoff date of November 2025. Our analysis identified two system configurations, seven smartwatch roles, common application contexts, and the evaluation methods employed across these studies. This work contributes to a clear understanding of how smartwatches function within evolving multi-device systems and offers guidance for future research on the design and integration of multi-device ecosystems.

KEYWORDS
Smartwatch; multi-device interaction; multi-device computing; survey; ubiquitous computing

1. Introduction

Smartwatches have evolved from niche novelties into important components of the personal computing ecosystem. Since the pioneering release of mass-produced devices like Pebble in 2013 (Pebble Technology, 2012; Pebble (watch), 2025), the landscape has been reshaped by major manufacturers such as Apple and Samsung. Today, smartwatches are no longer merely "miniaturized smartphones" for the wrist; they have matured into distinct artifacts with unique affordances, playing a critical role in the broader vision of Ubiquitous Computing (UbiComp) (Esakia et al., 2015).

The integration of smartwatches into multi-device ecosystems is driven by a fundamental tension between their unique capabilities and their inherent constraints. Unlike smartphones or tablets, smartwatches offer constant on-body presence and intimate sensing. Their wrist-worn nature enables "glanceable" interactions, allowing users to access information via micro-interactions without disengaging from the physical world (Schiewe et al., 2020). Furthermore, their rich sensor arrays allow for continuous, unobtrusive monitoring of physiological signals (Hänsel et al., 2016; Tan, Zhu, et al., 2025; Yang, Jiang, et al., 2024) and motion data (Leung et al., 2018; Mollyn et al., 2023; Xia et al., 2024), facilitating seamless data capture during physical activities where carrying larger devices is impractical. However, the smartwatch form factor imposes significant limitations. The "fat-finger" problem on small touchscreens (Darbar et al., 2016) and limited screen real estate hinder complex inputs and the visualization of dense information. Additionally, constraints in battery life and computational power often necessitate offloading heavy processing tasks to more robust devices.

This dichotomy—high availability and sensing power versus low input/output bandwidth—creates a natural imperative for cross-device interaction. Researchers have increasingly explored leveraging the smartwatch not as a standalone device, but as a complementary node within a multi-device system. Prior work has demonstrated the efficacy of this approach across various dimensions: (1) Efficiency, by using the watch as a secondary controller to accelerate tasks on larger screens (Horak et al., 2018); (2) Communication, by enabling subtle, non-verbal messaging for users with accessibility needs (Rocha

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et al., 2022); and (3) Interaction, by supporting remote interactions with large displays through gesture-based input (Siddhpuria et al., 2018).

Despite this growing body of work, the literature remains fragmented. Current research often focuses on isolated point solutions—treating the smartwatch purely as a controller in one context or a sensor in another—without a holistic view of its fluctuating identity within a device ecology. Designers and researchers lack a unified taxonomy and a clear set of design guidelines to understand when to distribute tasks to the wrist and how to orchestrate these devices effectively.

To bridge this gap, we conducted a systematic literature review to map the landscape of smartwatch utilization in multi-device ecosystems. We analyzed 106 studies (describing 116 distinct systems) from 11 top-tier Human-Computer Interaction (HCI) venues published up to November 2025 (see Section 3). The review aims to address the following research questions (**RQs**):

RQ1: What are the dominant configurations of smartwatch-integrated multi-device systems?

RQ2: What specific functional roles do smartwatches assume within these ecosystems?

RQ3: In which contexts are these multi-device systems deployed?

RQ4: How do researchers validate these multi-device systems?

By answering these questions, we further synthesize the gathered evidence to reflect on the field's evolutionary trends and identify key opportunities for future integration. This work makes the following contributions to the HCI community:

- An Exploratory Corpus Browser: We provide an open-source website that empowers the community to filter and analyze the literature corpus, fostering continuous knowledge discovery.
- A Structured Taxonomy of Multi-Device Systems involving Smartwatches: We propose a comprehensive taxonomy that systematizes the systems across four key dimensions: system configurations, the functional roles of smartwatches in cross-device interactions, application domains, and the validation methodologies.
- Critical Roadmap for Future Research: Beyond summarizing existing work, we trace the paradigm shifts over the past decade, identify emerging challenges, and outline high-impact opportunities for future technical and empirical advancements.

2. Related work

To situate our work within the research landscape, we examined existing surveys related to smartwatches. Existing reviews tend to fall into two extremes: they either examine the smartwatch in technical isolation—detaching it from the surrounding digital ecosystem—or subsume it as a generic component within broad wearable or multi-device surveys. Table 1 summarizes this literature, categorizing by research domain (computing or health) and its primary focus. Consequently, its unique architectural and interactional roles within complex multi-device systems remain largely obscured.

In the computing domain, reviews often prioritize smartwatches' specific technical capabilities or include them into generalized frameworks. For instance, Gomes et al. (2024) and Castro et al. (2024) investigate smartwatch-based on-device input methods (e.g., gesture recognition) and specific prototyping integrations with virtual reality (VR), yet treat the device largely in isolation or with limited devices. Broader wearable surveys classify input modalities and system architectures across various form factors (Baiense et al., 2025; Siean & Vatavu, 2021; Yang, Amin, et al., 2024), or focus on specific utility issues like privacy and stress management in wearable devices (Salehzadeh Niksirat et al., 2024; van den Berg et al., 2025). Similarly, while foundational cross-device taxonomies (Brudy et al., 2019; Gryphon et al., 2023) propose unified terminologies for multi-display environments, they offer high-level conceptual frameworks without providing concrete, empirical analyses of how smartwatches specifically function within these ecosystems.

In the health domain, reviews are predominantly application-centric. Topics range from general wellness and research impact of smartwatches (Huhn et al., 2022; Reeder & David, 2016; Yen & Chiu,

Table 1. Summary of prior reviews categorized by research domain and primary focus.

Domain	Research focus/topic	References
Computing	Smartwatch interaction Detailed analysis of gesture recognition sensors and VR integration.	Gomes et al. (2024); Castro et al. (2024)
	Cross-device frameworks Taxonomies for cross-device interactions and multi-display visualization spaces.	Brudy et al. (2019); Gryphon et al. (2023)
	Wearable systems & applications Broad surveys covering IoT, specific user groups (motor/elderly), privacy, security, and stress management.	Siean and Vatavu (2021); Vargemidis et al. (2020); Yang, Amin, et al. (2024); Baiense et al. (2025); Anja Trkulja et al. (2022); Salehzadeh Niksirat et al. (2024); van den Berg et al. (2025)
Health	General Wellness & Research Use of smartwatches for health/wellness, weight control, and general research impact.	Reeder and David (2016); Yen and Chiu (2019); Huhn et al. (2022)
	Cardiac health & COVID-19 Diagnostics for arrhythmia, atrial fibrillation, and COVID-19 via HRV.	Nazarian et al. (2021); Narut et al. (2021); Sanches et al. (2023)
	Chronic conditions Monitoring systems for diabetes (glucose levels), epilepsy, and chronic pain intensity.	Diez Alvarez et al. (2023); Rukasha et al. (2020); Avila et al. (2021)
	Remote monitoring & safety Remote health delivery, detection of occupational stress biomarkers, and fall detection.	King and Sarrafzadeh (2018); Morales et al. (2022); Warrington et al. (2021)

We identified 23 relevant surveys. While prior work focuses on specific device capabilities or health outcomes, our review targets the smartwatch's role in multi-device interactions.

2019) to clinical applications like cardiac health (Narut et al., 2021; Nazarian et al., 2021; Sanches et al., 2023), chronic condition management (Avila et al., 2021; Diez Alvarez et al., 2023; Rukasha et al., 2020), and remote monitoring safety (King & Sarrafzadeh, 2018; Morales et al., 2022; Warrington et al., 2021). While these works highlight the sensing utility of smartwatches—often paired with smartphones—they typically conceptualize the device as a passive data logger. They rarely discuss how the smartwatch actively facilitates interaction or coordinates with other devices beyond simple data transmission.

Overall, a clear gap remains: the lack of systematic, empirical studies investigating how smartwatches are positioned within multi-device interaction systems.

3. Methodology

Our review follows the *Preferred Reporting Items for Systematic Reviews and Meta-Analyses* (PRISMA) framework (Page et al., 2021). This process comprises four stages: *Identification*, *Screening*, *Eligibility*, and *Inclusion* (see details in Figure 1). After establishing the corpus, we conducted data extraction and coding. To ensure objectivity in the screening and data extraction procedures, the *Screening* and *Eligibility* stages, as well as the data extraction process, were jointly completed by the three coauthors, who discussed and resolved any discrepancies in their judgments.

3.1. Identification

Our search focused on six leading HCI conferences and five top-tier HCI journals (see full list in Table 2) within Human-Computer Interaction (HCI). We prioritized major HCI venues because they maintain a consistent methodological focus, particularly in the integration of system design with empirical evaluation. While relevant work exists in adjacent communities—such as digital health, computer networking, and design research—their research objectives and evaluation methods often diverge significantly. By concentrating on the HCI domain, we ensure a cohesive corpus that allows for rigorous cross-study comparison, avoiding the confounding variables that would arise from mixing disparate disciplinary aims and reporting styles. This scope encompasses both archival full papers and short papers (e.g., Late-Breaking Work) published before November 2025, capturing both foundational theories and emerging prototypes.

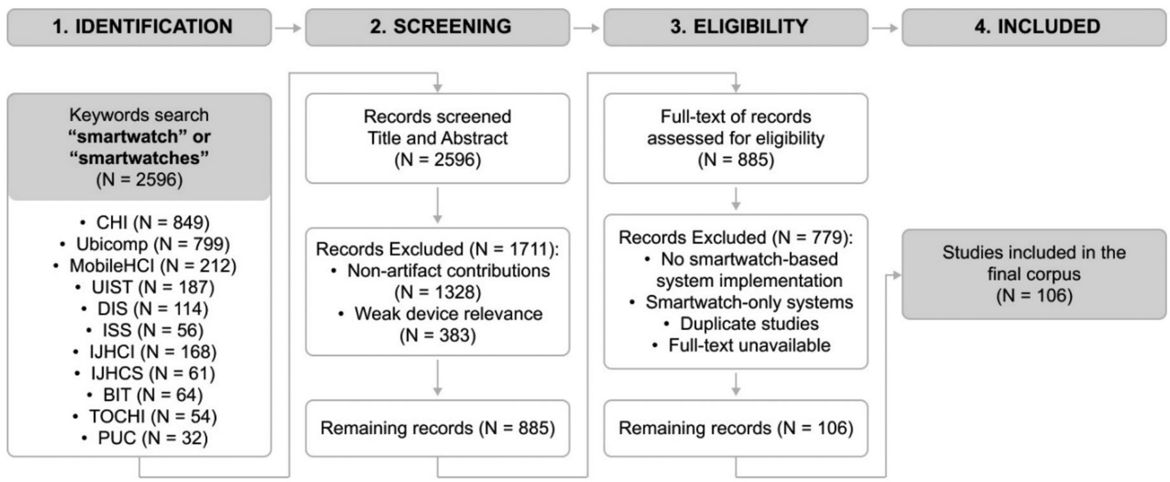

Figure 1. Overview of the PRISMA approach flow.

Table 2. Selected conferences and journals.

Conference	Journal
CHI: Conference on Human Factors in Computing Systems	IJHCI: International Journal of Human–Computer Interaction
UbiComp: Ubiquitous Computing	IJHCS: International Journal of Human–Computer Studies
MobileHCI: Human Computer Interaction with Mobile Devices and Services	BIT: Behavior & Information Technology
UIST: User Interface Software and Technology	TOCHI: ACM Transactions on Computer-Human Interaction
DIS: Designing Interactive Systems	PUC: Personal and Ubiquitous Computing
ISS: Interactive Surfaces and Spaces	

To ensure maximum recall, we employed tailored search protocols for journals and conferences. For journals, we accessed the respective publisher platforms and conducted keyword searches within each specific venue, restricted to the target timeframe. For conferences, as the six target venues are all ACM-indexed, we executed a dual-route strategy within the ACM Digital Library (DL) to account for varying indexing structures. First, we queried the conference-specific proceeding pages. Second, to capture full papers published under the journal-based model (where papers are indexed by journal issue rather than conference proceeding), we searched the corresponding journal within the ACM DL. In our scope, this primarily involved two ACM journal venues: IMWUT (*Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*) and PACMHCI (*Proceedings of the ACM on Human-Computer Interaction*). Notably, PACMHCI is organized into conference-specific issues (e.g., ISS, MobileHCI, and CSCW), so we scoped our searches at the issue level.

- IMWUT for UbiComp full papers (since 2017);
- PACMHCI (ISS issue) for ISS full papers (since 2020);
- PACMHCI (MHCI issue) for MobileHCI full papers (since 2022).

Prior to the formal search, the three coauthors performed a pilot study to optimize our keyword strategy. Our initial approach was to use terms describing the multi-device paradigm (e.g., "multi-device," "cross-surface"). However, we found that these terms primarily appeared in survey or theoretical papers, while artifact articles often omitted these high-level descriptions. A subsequent attempt to use action verbs describing device integration (e.g., "integrate," "combine," and "connect") proved inefficient due to the linguistic diversity of such terms and the excessive noise in results.

Consequently, we adopted a broad-funnel strategy prioritizing high recall over precision. We shifted our focus from interaction descriptors to the core device entity, employing only "smartwatch" and "smartwatches" as keywords. The search was applied to the full text (including title, abstract, and body) of the publications. While this approach deliberately increased the initial volume of records, it minimized the risk of omitting relevant studies that implement multi-device scenarios without explicitly labeling them as such in the metadata. This identification process yielded a total of 2596 records.

3.2. Screening

In the screening stage, three coauthors systematically reviewed the titles and abstracts of the 2596 records identified in the initial search. We established strict inclusion criteria based on the contribution taxonomy (Wobbrock & Kientz, 2016). Given our focus on the system architecture and implementation, we exclusively included studies offering *artifact contributions.* Records categorized solely as empirical research (observation/discovery), methodological, theoretical, dataset, survey, or opinion contributions were excluded.

Following the contribution check, we assessed device relevance using a conservative inclusion protocol to avoid false negatives:

- Explicit inclusion: Records explicitly mentioning “smartwatch,” “wristband,” “fitness tracker,” or “wearable bracelet” in the abstract were included.
- Implicit inclusion: Records not naming specific devices but mentioning hardware components commonly embedded in smartwatches (e.g., inertial measurement units (IMUs) on the wrist, wrist-worn microphones) were retained.
- Ambiguous cases: Abstracts that described a wearable or mobile artifact without specifying the device form factor were conservatively retained for the full-text review.

Studies explicitly stating the exclusive use of non-wrist-worn devices (e.g., head-mounted displays (HMDs) only, Smartphones only) were excluded. This screening process resulted in a total of 885 records.

3.3. Eligibility and inclusion

In the eligibility stage, we conducted a detailed full-text review on the remaining 885 articles based on three primary eligibility criteria (EC):

- **EC1:** The article must describe the implementation of an interactive system integrating a smartwatch with at least one other distinct device.
- **EC2:** Duplicate studies were excluded; if the same work appeared in both a non full-text publication (e.g., workshop or extended abstract) and a subsequent full-text article, only the full-text version was retained.
- **EC3:** The full text must be available.

For **EC1:**, we defined a “smartwatch” as “a wrist-worn computer capable of complex calculation and communication” (Esakia et al., 2015). We applied this definition flexibly to accommodate research prototypes:

- We included studies that conceptualized the device as a smartwatch during the design stage, even if the final implementation did not meet the standard definition. For example, some customized prototypes were built with only the hardware necessary for the study, such as IMUs (Azim et al., 2022) or microphones (Han et al., 2017), and omitted advanced computational or communication capabilities.
- We included studies that used terms like “wearable sensor” in the design phase but ultimately employed a commercial smartwatch in their experiments (Chow et al., 2016).
- We also included studies that used modified commercial smartwatches or customized smartwatches, as long as the devices retained computational and communication functionality.

Crucially, we established a boundary to distinguish a “multi-device system” from an “augmented single device.” We defined the “other device” based on *Physical Separability*. We included accessories like styluses (Hung et al., 2019; Schrapel et al., 2020) and smart rings (Yeo, Lee, et al., 2019; Zhang et al., 2016), as they could function as physically independent units, capable of interacting with devices beyond just the smartwatch. In contrast, we excluded enhancements that solely augmented the smartwatch itself, such as interactive wristbands (Klamka et al., 2020; Perrault et al., 2013) or additional displays (Seyed et al., 2016; Zhu et al., 2018), because these were considered extensions of the smartwatch rather than separate devices. In these cases, the “other device” effectively becomes a component of the smartwatch itself, augmenting its form factor rather than establishing a cross-device ecosystem.

The final corpus comprised 106 studies.

3.4. Data extraction and coding process

Following the full-text eligibility assessment, we identified that several articles reported multiple distinct systems. To ensure data integrity, three coauthors independently screened and cross-checked these systems. Upon reaching consensus, a total of 116 independent systems were extracted from the 106 eligible articles.

We then defined the unit of analysis for each RQ. For RQs concerning system configurations (**RQ1**), interaction (**RQ2**), and application contexts (**RQ3**), coding was conducted at the system level. Conversely, for experimental evaluation (**RQ4**), coding was performed at the article level, where a single experimental design or case study often serves to validate all system variants presented in one paper.

For RQ4, we restricted our analysis to 57 full papers, excluding short papers and works-in-progress. This decision was made because non-long papers often lack comprehensive evaluations due to page limits or typically present only preliminary, simple validations. Consequently, this restriction ensures that the assessment is based on rigorous experimental designs and validation procedures.

To ensure the reliability and validity of our classification, we adopted a hybrid coding approach combining deductive and inductive analysis. Initially, all coauthors jointly constructed a preliminary codebook based on the RQs and prior literature. To validate and refine this codebook, we conducted a pilot coding phase on a subset of the dataset ($N = 24$, approximately 20% of the systems). This pilot phase allowed us to stabilize the majority of the coding definitions and resolve early ambiguities. Following the pilot, the formal coding was carried out independently by three coauthors on the full dataset. Crucially, our process remained iterative: while guided by the stabilized codebook, coders were permitted to propose new codes or refine existing definitions when encountering novel patterns in the remaining data. Upon completion, the three authors convened to resolve disagreements, merge similar codes, and finalize the taxonomy through discussion and consensus. The detailed coding workflow for each RQ is outlined below.

- **RQ1 (Configuration)**: We focused on the hardware composition of the multi-device systems. Based on the preliminary codebook covering diverse interaction devices (e.g., smartphones, HMDs, computers), we coded all devices involved in the multi-device systems. Post-coding, system configurations were categorized into two primary groups: *pairwise* and *N -wise* ecosystems.
- **RQ2 (Interaction & Role)**: Coding was structured along two dimensions: the degree and mode of user engagement and the functional role of the smartwatch. We treated the “Smartwatch Role” dimension as non-mutually exclusive, allowing for multi-label coding. Ultimately, user engagement was clustered into three categories, while smartwatch roles were consolidated into seven. We conducted granular sub-coding on three key roles: (1) *Data collector*: types of data and sensors; (2) *Input device*: specific input modalities; and (3) *Notification device*: notification output modalities.
- **RQ3 (Context & Application)**: We adapted the cross-device taxonomy proposed by Brudy et al. (2016) to analyze four dimensions: Relationship, Proxemics, Dynamics, and Application Domain. While the codebook for the first three dimensions was directly informed by Brudy et al. (2016), we applied an inductive open-coding strategy for the Application Domain. Specifically, we assigned fine-grained, descriptive open codes (e.g., “navigation assistance for visually impaired people”) rather than relying on a fixed category set. We excluded generic enabling technologies that lacked specific

use cases; however, demonstration applications implemented within such papers were coded. As systems often address multiple areas, this dimension was also treated as non-mutually exclusive. These open codes were ultimately synthesized into seven high-level categories during the consensus meeting.

- **RQ4 (Evaluation)**: Grounded in the frameworks of Lam et al. (2012) and Isenberg et al. (2013), we assessed whether articles reported three core evaluation types: Algorithm Performance (AP), User Performance (UP), and User Experience (UE). We also noted the presence of demonstration applications. We also performed deeper analysis on UP and UE, specifically documenting the metrics for UP, the methodological approaches for UE, and the setting of UE studies (e.g., lab vs. field).

The final coding distributions are presented in the Supplementary Materials.

4. Findings

The final corpus comprises 106 papers. Figure 2 shows their distribution by publication year and venue. The timeline begins in 2014 with the earliest identified study (Chen et al., 2014) from 2014, which explored joint interactions between a smartphone and a smartwatch. A significant increase in publication volume was observed in 2016. This trend closely mirrors the commercialization timeline of smartwatches. Following the launch of the Pebble in 2013 (Pebble Technology, 2012), major technology companies entered the market between 2014 and 2015, including the Samsung Gear Live (Samsung Electronics Co Ltd, 2025) (June 2014), LG G Watch (LG G Watch, 2025) (June 2014), the Motorola Moto 360 (Moto 360, 2025) (September 2014), the Apple Watch (Apple Inc., 2015) (April 2015), and the Huawei Watch (Huawei Watch, 2025) (September 2015). These hardware releases lowered the barrier to entry for researchers, stimulating an initial wave of academic interest in multi-device interaction. While the number of studies fluctuated in subsequent years, a notable resurgence is evident starting in 2023. This upward trend has been sustained, with year-over-year growth observed in 2023, 2024, and 2025. It is important to note that our search window concluded in late November 2025; thus, the 2025

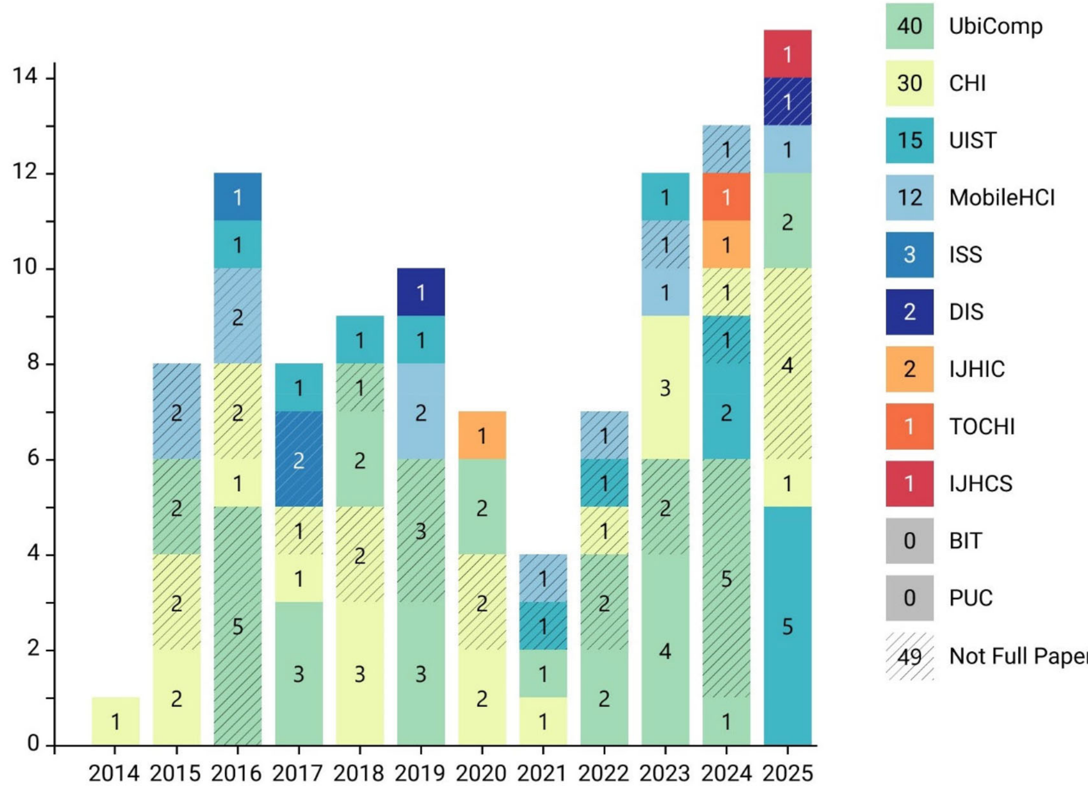

Figure 2. Number of published papers in each year.

data captures the most proceedings of the major annual conferences targeted in this review, with the exception of UbiComp.

Regarding publication venues, Figure 2 highlights that this research area is predominantly conference-driven, a characteristic typical of the HCI field. The vast majority of papers originate from top-tier HCI conferences, with UbiComp being the most prominent venue, followed by CHI, UIST, and MobileHCI. This distribution indicates that this research is situated at the intersection of several key HCI sub-fields: ubiquitous computing (UbiComp), general HCI (CHI), novel user interface technology (UIST), and mobile interaction (MobileHCI). In contrast, journal publications are sparse, reflecting the community's primary focus on conference dissemination.

4.1. Configuration

To address RQ1, we analyzed the device configurations of 116 systems and classified them into two primary categories: pairwise (78/116), involving a pairing of two devices, and *N*-wise (38/116), referring to systems that form a large network of three or more interconnected devices. Among the 78 systems with a pairwise configuration, the most common paired device is a smartphone (47/78). Other pairings involve HMDs (9/78), large displays (7/78), smart rings (6/78), computers such as laptops or desktops (4/78), smart glasses (2/78), keyboards (2/78), and styluses (1/78). In this review, we treat functionally integrated setups—such as a desktop computer composed of a monitor, system unit, keyboard, and mouse—as a single device, even though their components are physically distributed. In addition, "large display" refers to network-connected screens—typically larger than standard desktop monitors—often linked to a host device such as a laptop.

In contrast, *N*-wise systems go beyond simple pairings by integrating smartwatches into a broader ecosystem that includes laptops, desktops, smartphones, and various wearable devices such as smart rings, earbuds, and HMDs. In addition to these devices, some *N*-wise systems also incorporate a diverse range of external hardware components for data collection. These primarily include GPS devices for location tracking, spirometers for measuring respiratory function, microphones for capturing acoustic data, cameras for collecting visual data, and air quality monitors.

4.2. Roles

To address **RQ2**, we first classified the 116 systems based on the degree and mode of user engagement with the smartwatch. Direct Manipulation (53/116) follows Shneiderman (1983)'s principle of direct manipulation, wherein the smartwatch functions as an active control surface—users invoke system operations through taps, swipes, voice, or gesture commands on the smartwatch in real time. Peripheral Interaction (20/116) draws on Pousman and Stasko (2006)'s theory of ambient information, with the watch providing glanceable visual cues (notifications, glanceable widgets) or haptic/LED feedback that supports situational awareness without demanding explicit response. Background Sensing (43/116) is informed by Weiser and Brown (1996)'s Calm Computing vision, treating the smartwatch as an invisible sensor node: it silently collects or relays data in the background, unobtrusively supporting system-level functions without user intervention.

We also categorized the roles played by smartwatches in the 116 systems into seven categories. These categories are not mutually exclusive, as a single system could feature a smartwatch playing multiple roles:

1. a data collector (53/116), primarily functioning in conjunction with a smartphone, to gather physiological, motion, acoustic, or location data;
2. an input device (40/116), primarily designed to support interaction with smartphones or large screens, enabling users to control or interact with the system through touch, motion, voice, or physical buttons;
3. an extended screen (21/116), functioning as a secondary display for smartphones, computers, and large displays, presenting additional information from other devices;

4. a notification device (19/116), receiving information from processing devices (mostly smartphones) and delivering alerts to users through visual or vibrational cues;
5. a central device (8/116), acting as the primary computing unit when connected to peripheral devices such as smart rings and styluses;
6. a perceptual enhancer (2/116), acting as a supplementary wearable tactile perception to support smartphone or large displays;
7. an audio output device (2/116), functioning as the system's output channel by delivering audio content to the user, typically as part of a multi-device system involving earbuds, rings, or a smartphone.

4.2.1. Data collector (53/116)

Smartwatches are widely used as data collectors in multi-device systems due to their built-in sensors and continuous on-body presence. The collected data primarily fall into the following four categories (the detailed data and corresponding sensors are summarized in the Supplementary Materials):

1. Motion (40/53): Smartwatches are commonly used in multi-device systems to collect motion data, typically through IMUs, which integrate multiple sensing components such as accelerometers, gyroscopes, and sometimes magnetometers. Beyond inertial sensing, recent implementations have incorporated electromyography (EMG) to capture subtle muscle activity (Xiao et al., 2025). Generally, the collected motion data facilitates detection across three granularity levels: (a) Physical Activity: Focusing on gross body movements and daily routines, such as running and walking (Hänsel et al., 2016; Zimmermann et al., 2019), primarily for health and fitness monitoring. (b) Upper-Limb Movement: Capturing fine-grained movements of the upper limbs, including hand gestures, arm postures, and finger postures (see identified postures and gestures in Figure 3), primarily used for input. (c) Peripheral Manipulation: Tracking the movements of paired accessories such as styluses (Schrapel et al., 2020) and smart rings (Yeo, Lee, et al., 2019; Zhang et al., 2016), to interpret input from peripheral accessories.
2. Physiological Data (12/53): Smartwatches are frequently employed in multi-device systems to collect physiological data, most commonly using photoplethysmography (PPG) and electrocardiography (ECG) sensors. Key metrics include heart rate (HR), heart rate variability (HRV), galvanic skin response (GSR), inter-beat intervals (IBI), and blood oxygen saturation (SpO2). These metrics are widely applied in assessing emotional responses (Chow et al., 2016; Dotch, 2024; Gadhvi et al., 2025; Hänsel et al., 2016), monitoring sleep (Wang et al., 2024), supporting breathing training (Tu et al., 2018), and providing general health-related assistance.
3. Acoustic Data (10/53): Smartwatches are also used to collect acoustic data through microphones. These signals may capture direct vocal content (Li et al., 2023) or be used to monitor environmental conditions (Han et al., 2017; Laput et al., 2018). They can also be combined with motion data

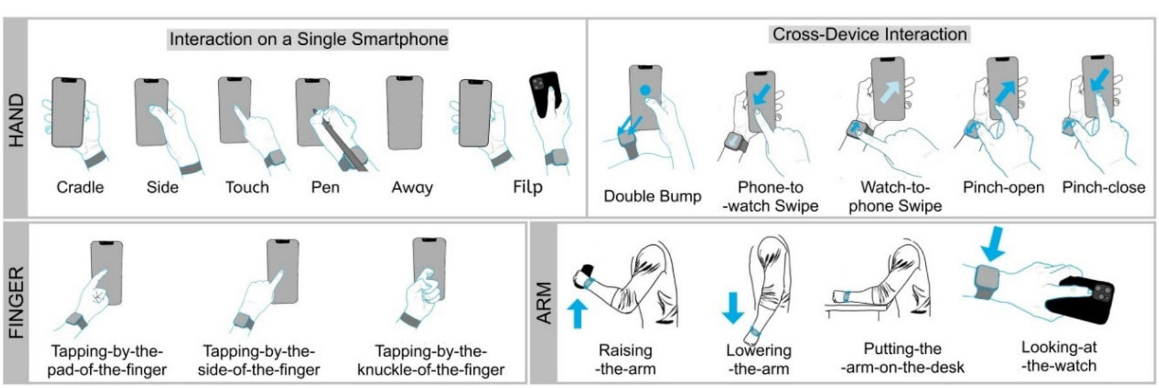

Figure 3. Identified gestures that can be recognized by integration of smartwatches and smartphones, including hand gestures (Chen et al., 2014; Kim et al., 2016; Kubo et al., 2017; Lim et al., 2016), arm postures (Kubo et al., 2017), and finger postures (Chen et al., 2014).

to analyze more complex actions, such as snapping, clapping, and knocking (Becker et al., 2019), as well as physiological symptoms, including coughing, wheezing, and sneezing (Chatterjee et al., 2019). Smartwatches are also used to detect inaudible ultrasound signals, leveraging acoustic ranging to achieve precise pose or limb tracking (Li et al., 2025; Zhou et al., 2020).
4. Location (3/53): Smartwatches equipped with Global Positioning System (GPS) modules are also used to monitor a user's location (Chun et al., 2025; Janaka et al., 2024; Yu et al., 2025). Location data can also be used to support caregiver monitoring of individuals with limited mobility or cognitive impairments (Chun et al., 2025).

When functioning as a data collector, the smartwatch is typically used as a passive device that does not require active user interaction. In this role, it collects data and transmits it to the system's computing unit, primarily a smartphone (Caceres Najarro et al., 2023) or computer (Laput et al., 2018), via communication protocols such as Bluetooth or Wi-Fi. A representative example is mLung++ (Chatterjee et al., 2019), where the smartwatch serves as a multi-modal data acquisition endpoint. It continuously captures audio, IMU, and PPG signals in the background and streams them to the patient's smartphone.

4.2.2. Input device (40/116)

Smartwatches frequently serve as input devices in multi-device systems due to their portability and their built-in touchscreens, sensors, and microphones. Five distinct input methods were identified (three of which are illustrated in Figure 4):

1. Touch (14/40): Touch interaction (Figure 4(a)) is one of the most common input methods when smartwatches are used as input devices. Due to their limited screen size, touch gestures are often simple, including basic one-finger actions such as tapping (Ahn et al., 2017; Gonzalez et al., 2024; Hirzle et al., 2018; Liu et al., 2021; Ohta et al., 2015; Siddhpuria et al., 2018) and double-tapping (Flores & Manduchi, 2018; Gonzalez et al., 2024; Hirzle et al., 2018), as well as simple gestures involving multiple fingers, like pinching (Chen et al., 2014) and swiping (Ahn et al., 2017; Chen et al., 2014; Gonzalez et al., 2024; Horak et al., 2018; Liu et al., 2021). These interactions are often used to send simple, direct commands, such as toggling the on/off state of other devices, including smartphones and smart home systems (Becker et al., 2019).
2. Spatial movement (23/40): Spatial movement enabled interaction (Figure 4(b)) is also common, which refers to the use of smartwatch sensors (such as accelerometers and gyroscopes) to capture and interpret users' hand and arm movements, translating them into input commands (Gomes et al., 2024). Specifically, the spatial movement of the smartwatch facilitated two main types of inputs:
   a. Input for shared/public large displays: Smartwatches are used to control cursors on large displays remotely, serving as an alternative to traditional mice (Siddhpuria et al., 2018; Yeo, Lee, et al., 2019). A representative example is WRIST (Yeo, Lee, et al., 2019), which employs a sensor fusion approach that combines IMU data from a smartwatch and a paired smart ring, enabling a specific user scenario: "macro–micro" pointing for large displays. The user's forearm controls a coarse "macro" cursor, while subtle wrist rotations control a precise "micro" cursor, effectively addressing the accuracy challenges of long-distance pointing.

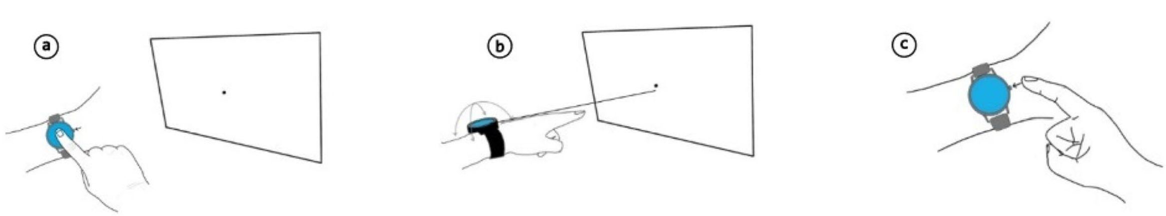

Figure 4. Illustrations for three common input methods of the smartwatch: (a) touch; (b) spatial movement; (c) physical button.

b. Shortcuts for controlling personal devices: Smartwatches are also used to execute shortcut commands on personal devices, such as smart furniture and smartphones, including toggling the on/off state of these devices (Becker et al., 2019; Rocha et al., 2022; Verweij et al., 2017). For example, GestEar (Becker et al., 2019) leverages the microphone and inertial sensors from smartwatches and employs a lightweight convolutional neural architecture to accurately recognize gestures that produce characteristic combinations of motion and sound, such as finger snapping, clapping, and tapping. This enables a range of hands-free interactions, including controlling smart home devices by clapping to toggle lights or speakers, snapping while walking to control music playback on a smartphone, or using specific gestures to unlock a personal device.

3. Acoustic Input (5/40): Utilizing the built-in microphone on smartwatches to detect sound signals is another input mechanism. This input method not only includes direct voice commands but also involves interpreting sound signals from external devices, such as recognizing typing sounds on a keyboard (Meteriz Yýldýran et al., 2022; Tan, Chan, et al., 2025) or analyzing sounds from user actions like clapping (Becker et al., 2019).
4. Physical Button (3/40): Interacting with physical components on the smartwatch, such as pressing buttons or rotating knobs, also serves as a form of input (Figure 4(c)). For example, Flores and Manduchi (2018) demonstrated the use of physical buttons on smartwatches, allowing users to scroll through a control menu by rotating the Digital Crown.
5. Vision (2/40): We also identified two innovative studies (Sridhar et al., 2017; Yeo, Wu, et al., 2019) that enabled gesture input by visually recognizing users' hand movements through modified or built-in cameras on smartwatches.

4.2.3. Notification device (19/116)

Smartwatches are commonly used for delivering notifications because they maintain skin contact and support multiple modalities, such as visual displays and vibration. Users can quickly glance at the watch to read messages and grasp information instantly, eliminating the need to locate the device. As a result, smartwatches have been used as notification devices in a variety of contexts, ranging from schedule alerts (Goto et al., 2015) and navigation cues (Lim et al., 2015) to assistive technologies (Doan et al., 2020). A representative system in this assistive context is the system proposed by Jain et al. (2020), designed to support sound awareness for Deaf and hard-of-hearing (DHH) users. The system helps users perceive important environmental sounds that they might otherwise miss, such as an alarm sounding or a microwave beeping. It relies on the microphone for continuous audio capture and uses a machine learning model to classify incoming sound. Upon detecting a target sound, the backend triggers a notification event via Wi-Fi, which the smartwatch delivers to the user through synchronized visual alerts and haptic feedback. In such systems, the user generally only needs to view or perceive the incoming signal, without being required to actively respond or initiate further interaction.

Furthermore, our analysis identified two main types of smartwatch notifications: *visual notifications* (9/19) (Cheng et al., 2024; Doan et al., 2020; Engelbrecht & Lukosch, 2020; Gonzalez et al., 2024; Goto et al., 2015; Hosseini-Toudeshky & Kersten-Oertel, 2023; Lee et al., 2016; Liu et al., 2021; Nguyen, 2023) and *vibratory notifications* (4/19) (Al-Taie et al., 2025; Arakawa, Nakagawa, et al., 2025; Lim et al., 2015; Zhong et al., 2025). Additionally, several studies (6/19) employed both modalities simultaneously to enhance the delivery of information (Chen et al., 2014; Chun et al., 2025; Engelbrecht et al., 2019; Golev et al., 2024; Jain et al., 2020; Wu et al., 2025).

4.2.4. Extended screen (21/116)

Smartwatches are also frequently used as visual extensions of other devices due to their portability within multi-device ecosystems. In personal, single-user scenarios, smartwatches are typically used in two main ways. First, a smartwatch may function as an auxiliary display that complements the primary device by expanding the usable screen or interaction area, and is usually operated simultaneously with the paired devices (Brudy et al., 2016; Hung et al., 2019; Kubo et al., 2017; Noh et al., 2016). Second, in certain contexts where rapid access to information is required, the smartwatch serves as a more convenient alternative in situ to the primary screen, enabling users to obtain relevant content without the need to physically retrieve or activate the main device (Zhong et al., 2025).

In multi-user or public settings, smartwatches transition into a personal screen, while large public displays act as shared interfaces. Here, it bridges the gap between public and private spaces, allowing users to store and check selected points of interest or personalize content views without disrupting the shared visual context (Banerjee et al., 2018; Horak et al., 2018). For example, Horak et al. (2018) operationalized this concept for collaborative visual analytics. In their system, analysts can "pull" specific data points from a shared wall-sized display onto their smartwatch for independent review. The smartwatch allows users to manipulate personal data subsets privately and asynchronously. Furthermore, these subsets can be "pushed" back to new regions of the public display, enabling personalized data comparison within a collaborative workspace.

Unlike notification devices, smartwatches functioning as extended screens typically require active user interaction rather than passive reception. Users are expected to respond quickly, make selections, or directly manipulate content, highlighting their role not only in information display but also in facilitating active engagement with the system.

4.2.5. Perceptual enhancer (2/116)

The smartwatch's constant contact with the skin allows it to deliver haptic feedback for enhancing sensory perception. A prime example is the Harmonious Haptics system (Hwang et al., 2015), which leverages a spatially distributed approach to enhance texture realism. The system employs a cross-device rendering technique: as the user explores an image on a tablet, the touchscreen renders vibrotactile feedback proportional to the visual luminance of the texture. Simultaneously, the smartwatch delivers a synchronized, inverted waveform to the wrist. This coordinated actuation exploits psychophysical masking to create a tactile illusion, significantly amplifying the user's perception of surface roughness and depth beyond what a single device could achieve.

As discussed in Section 4.2.3, some systems used the smartwatch's vibrator to deliver notifications. Similar to its role as a notification device, when functioning as a perceptual enhancer, the smartwatch also relies on passive perception rather than active user interaction. However, it is important to distinguish between these two roles. When used for notifications, the information conveyed is discrete and directive. For instance, a single 500-millisecond vibration might indicate that the user should turn left. The user interprets the signal, acts accordingly, and then awaits the next instruction. In contrast, when the smartwatch functions as a tactile display, the vibration serves as a continuous sensory channel. It simulates physical sensations and delivers nuanced haptic feedback that fosters a more immersive experience and deepens user engagement.

4.2.6. Audio output device (2/116)

Smartwatches equipped with built-in speakers are occasionally used for providing voice output. A representative implementation is Easy Return (Flores & Manduchi, 2018), a system designed to assist blind users with indoor backtracking (retracing steps) in map-less environments. The system employs context-sensitive audio routing to optimize information delivery. Proactive, high-level navigation cues (e.g., "turn left in seven steps") are broadcast via the iPhone's louder speaker to ensure audibility from the pocket. Conversely, when the user actively queries the system or browses menus, the guidance is routed to the smartwatch. This design leverages the proximal nature of wrist-worn devices, as users naturally bring the watch closer to their ear during active interactions, allowing for clearer and more discreet feedback from the smartwatch.

4.2.7. Central device (8/116)

In addition to functioning as auxiliary devices, smartwatches are sometimes deployed as central computing units when paired with accessories such as styluses (see the example in Figure 5(a)) or smart rings (see the examples in Figure 5(b,c)). Their integration primarily aims to enable precise and convenient input on the watch. A seminal example is SkinTrack (Zhang et al., 2016), which pairs a smartwatch with a signal-emitting ring to decouple input from the physical screen. The system transforms

Figure 5. Examples of integrating smartwatches with accessories: (a) enabling input on the back of the hand using a stylus (Schrapel et al., 2020); (b) tracking on-skin touch movements with a smart ring (Zhang et al., 2016); (c) utilizing watch-ring interaction to input on a large display (Yeo, Lee, et al., 2019).

the user's skin into an ad-hoc continuous touch surface. Technically, it leverages the human body as a conductive medium: the ring injects a high-frequency AC signal into the skin, which propagates toward the wrist. The smartwatch, acting as the sensing receiver, utilizes electrodes in its strap to detect phase differences in the incoming signals. By resolving these signals, the watch computes precise 2D touch coordinates on the arm in real-time, effectively expanding the interaction bandwidth beyond the device boundaries.

4.3. Application contexts

To answer RQ3, we categorized the application scenarios of the 116 reviewed systems using four dimensions: Relationship, Proxemics, Dynamics, and Application Domain. These dimensions and their corresponding classifications are adapted from the cross-device taxonomy proposed by Brudy et al. (2016).

4.3.1. Relationship

The relationship characterizes the mapping between users and devices within the ecosystem, specifically addressing whether the system is designed for an individual or multiple collaborating users. The 116 systems revealed two primary types of user-device relationships:

1. Single-user (109/116): a single person interacts with two or more devices (a 1-to-m relationship). Most systems leverage smartwatch integration to support individual tasks, including personal health management, knowledge work, and exploratory activities.
2. Multiple-users (7/116): multiple people interact with a set of interconnected devices (an n-to-m relationship), which in our corpus are primarily two-user, two-device (2-to-2) systems. These systems mainly focus on enhancing communication (Liu et al., 2021), particularly to foster social connection for vulnerable populations (referring to those at risk of poor physical, psychological, and/or social health (Aday, 1994)). Examples include systems designed for individuals with Alzheimer's disease (Chun et al., 2025) and children with ADHD (Doan et al., 2020; Silva et al., 2023). In addition, two systems were designed to support classroom activities (Das et al., 2021; Golev et al., 2024).

4.3.2. Proxemics

Proxemics describes the spatial distance between devices in a multi-device system. This dimension is inspired by and extends the concepts of Scale and Space proposed in Brudy et al. (2016)'s taxonomy of cross-device systems. The 116 systems in our corpus were categorized into four groups:

1. Near (80/116): All devices are positioned on the user's body or held in the user's hand. This category primarily includes single-user systems composed of wearable devices such as HMDs, smart rings, and earbuds, as well as handheld devices like smartphones when carried on the body.
2. Personal/Social (19/116): Devices are clustered within a localized area, such as a desk or table, typically within arm's reach, allowing users to interact with all devices while remaining seated or in place. These are typically single-user systems and include hardware that is placed on the desk, such as a laptop. Although this category can also include co-located multi-user social settings, our corpus did not contain such examples.

3. Room/Public (12/116): Devices are distributed across a shared physical environment, such as a room, and require users to walk or move to access all of them. This category includes systems where a smartwatch is used to control a distant large display (Becker et al., 2019; Zhu et al., 2025), or smart home systems where devices are spatially dispersed within a room (Hosseini-Toudeshky & Kersten-Oertel, 2023; Jain et al., 2020).
4. Remote (5/116): Devices are located in different geographical locations. These systems focus on facilitating communication between users across remote environments (Chun et al., 2025; Doan et al., 2020; Liu et al., 2021; Silva et al., 2023).

4.3.3. Dynamics

Dynamics refers to the mobility and potential for reconfiguration of the system setup, a characteristic closely related to its underlying device configuration. The 116 systems were categorized into three groups based on their dynamics:

1. Mobile (95/116): This category refers to systems composed of devices designed to be carried and used on the go, such as smartphones, tablets, and laptops. Mobile systems leverage the portability of smartwatches to support users in various aspects of daily life, including health, knowledge work, social interaction, and safety, as well as spatial exploration.
2. Semi-fixed (19/116): These systems remain stationary during use, but all devices are movable, detachable, and reconfigurable. Examples from our corpus include desktop setups (Yeo, Lee, et al., 2019), tethered HMDs (Siddhpuria et al., 2018) and detachable smart home devices (Jain et al., 2020; Meteriz Yýldýran et al., 2022).
3. Fixed (2/116): This category includes systems integrated into immovable, non-detachable wall displays or tabletops, such as public wall displays in museums (Banerjee et al., 2018; Brudy et al., 2016).

4.3.4. Application domain

The 116 reviewed systems cluster into eight distinct application domains, detailed in Table 3.

4.3.4.1. Health. Dominating the research landscape with 27 identified systems, the Health domain leverages the continuous sensing capabilities of smartwatches. We delineate two sub-themes: *Condition-Specific Support*, which assists vulnerable populations—such as those with chronic illnesses or disabilities; and *General Wellness*, which promotes everyday health management. Examples range from stress monitoring (Han et al., 2023; Wang et al., 2024) and exercise gamification (Gonzalez et al., 2024) to environmental sensing, such as detecting air quality (Nguyen, 2023).

4.3.4.2. Knowledge & creativity work. Closely following health, this domain explores how smartwatches can augment productivity and creative workflows. Rather than functioning in isolation, smartwatches often act as orchestrators in multi-device ecosystems. They streamline tasks ranging from visual content creation (Hung et al., 2019; Schrapel et al., 2020; Yeo, Lee, et al., 2019) to personal information management (Goto et al., 2015; Niforatos et al., 2015; Ye et al., 2016), effectively reducing friction in daily routines and enhancing interaction with smart environments (Verweij et al., 2017; Yeo, Lee, et al., 2019; Yeo et al., 2020).

4.3.4.3. Social computing & safety. This category spans the spectrum from subtle social signaling to rigorous security protocols. Here, the smartwatch serves dual roles: as a discreet channel for interpersonal communication (Liu et al., 2021) and as a trusted token for biometric authentication (Leung et al., 2018; Mare et al., 2018; Wu et al., 2022), fraud prevention (Wu et al., 2025), and personal safety monitoring (Bi & Xing, 2019).

4.3.4.4. Games & installations. In this domain, the smartwatch transforms into an embodied controller. By translating wrist movements into in-game actions or multimedia effects, these systems enable

Table 3. A taxonomy of application domains.

Health (27)
→ Condition-specific support: Support for deaf or hard of hearing users (Jain et al., 2020; Jin et al., 2023; Zhang et al., 2022); Support for children with ADHD (Doan et al., 2020; Silva et al., 2023); Alzheimer's patients prevent getting lost (Chun et al., 2025); Assistance for people with noise sensitivity (Dotch, 2024); Diagnostic Reasoning System (Yang, Jiang, et al., 2024); Autistic people support (Dotch et al., 2023); Diabetic monitoring (Hosseini-Toudeshky & Kersten-Oertel, 2023); Physical therapy (Wang & Ma, 2023); Support for people with Aphasia (Rocha et al., 2022); Physical activity reminders for older adults (Zimmermann et al., 2019); Support for blind users (Flores & Manduchi, 2018).
→ General health support: Personalized Fitness (Xu et al., 2024; Zhao et al., 2025); Stress monitoring (Han et al., 2023; Wang et al., 2024); Environmental quality monitoring (Zhong et al., 2025); Running meditation (Tan, Zhu, et al., 2025); Exercising support (Gonzalez et al., 2024); Air quality monitoring (Nguyen, 2023); Mental health support (Caceres Najarro et al., 2023); Detection of abnormal lung sounds (Chatterjee et al., 2019); In-home breathing training system (Tu et al., 2018); Depression monitoring (Chow et al., 2016); Mood and stress self-assessments (Hänsel et al., 2016).
Knowledge & creativity work (26)
→ Management: Food journaling (Mirtchouk et al., 2016; Ye et al., 2016); Notification filtering (Kubo et al., 2017; Lee et al., 2016); Productivity (Arakawa, Patidar, et al., 2025; Gadhvi et al., 2025); Daily life monitoring (Yu et al., 2025); Logistical Management (Chen et al., 2021); Business schedule (Goto et al., 2015); Life logging (Niforatos et al., 2015).
→ Smart environments: Smart home control (Verweij et al., 2017; Yeo, Lee, et al., 2019, 2020); Cross-device unlocking (Becker et al., 2019; Houben & Marquardt, 2015); Presentation control (Zhu et al., 2025); Smart environment enhancement (Wu et al., 2022); Sound or light systems control (Becker et al., 2019).
→ Drawing: Multi-device drawing (Hung et al., 2019; Noh et al., 2016; Schrapel et al., 2020; Yeo, Lee, et al., 2019; Zhang et al., 2016).
→ Media: Cross-device reading (Chen et al., 2014; Cheng et al., 2024; Kubo et al., 2017).
→ Information access: Cross-screen browsing (Cheng et al., 2024).
Social computing & safety (9)
→ Safety: Authentication (Choi et al., 2023; Leung et al., 2018; Mare et al., 2018; Wu et al., 2022); Data security (Wang et al., 2025a); Preventing fraud (Wu et al., 2025); Safe driving (Bi & Xing, 2019).
→ Communication: Communication between couples (Liu et al., 2021); Call (Chen et al., 2014).
Games & installations (9)
→ Games: Gesture-based game (Yeo, Lee, et al., 2019; Zhang et al., 2016; Zhu et al., 2025); Sports game (Xu et al., 2024); Cursor-based Game (Yeo, Lee, et al., 2019); Joystick-based game (Sridhar et al., 2017); Multi-user game (Han et al., 2017).
→ Museum: Museum gallery exploration (Banerjee et al., 2018); Content curation (Brudy et al., 2016).
Spatial computing (8)
→ Exploration: Map control (Grubert et al., 2015; Weigel & Steimle, 2017; Yeo, Lee, et al., 2019; Zhang et al., 2016); Cross-device map viewing (Chen et al., 2014; Kubo et al., 2017).
→ Navigation: Indoor navigation (Lim et al., 2015; Xu et al., 2024).
Education (7)
→ Individual support: English learning support (Arakawa, Nakagawa, et al., 2025; Cheng et al., 2024); Cycling simulation (Al-Taie et al., 2025); Tennis data tracking (Park et al., 2024).
→ Group support: Classroom support (Chen et al., 2021; Das et al., 2021; Golev et al., 2024).
Data Exploration (4)
→ 2D data exploration: General data exploration (Horak et al., 2018); Image exploration (Sridhar et al., 2017); Map exploration (Houben & Marquardt, 2015).
→ 3D data exploration: 3D model exploration (Han et al., 2017).

immersive interactions for casual gaming (Yeo, Lee, et al., 2019; Zhu et al., 2025) and public art installations (Banerjee et al., 2018; Brudy et al., 2016).

4.3.4.5. Spatial computing. Smartwatches in this category function as controllers. They allow users to navigate and manipulate virtual or physical environments simply by tilting or gesturing with their wrist. Examples include map control (Grubert et al., 2015; Weigel & Steimle, 2017; Yeo, Lee, et al., 2019) and indoor navigation (Lim et al., 2015; Xu et al., 2024).

4.3.4.6. Education. Educational applications utilize the wrist-worn form factor to support unobtrusive engagement. These systems facilitate both in-class coordination—such as delivering real-time feedback notifications (Chen et al., 2021; Das et al., 2021; Golev et al., 2024), and individualized learning through personal activity tracking (Arakawa, Nakagawa, et al., 2025a; Cheng et al., 2024; Park et al., 2024).

4.3.4.7. Data exploration. This domain investigates offloading navigation tasks to the wrist. These applications enable users to interact with complex 2D maps (Houben & Marquardt, 2015) or 3D models (Han et al., 2017) using touch or gesture input, thereby decluttering the primary visualization display.

4.4. Evaluation

To understand how the multi-device systems included in our review were evaluated (RQ4), we systematically analyzed the types of devices used in system implementations and quantified the presence of the three core evaluation types (AP, UP, and UE) reported in the papers.

4.4.1. Implementation device

To assist future researchers and developers in choosing the right hardware, we compiled and analyzed the smartwatch models used across the 57 archival full papers in our corpus. These details, summarized in the Supplementary Materials, serve as a practical guide for selecting developer-friendly platforms, since not all commercial smartwatches provide open access to sensor data or support custom application deployment.

In addition to commercial smartwatches, six studies employed custom-made prototypes. This was primarily because commercial devices at the time lacked the technical capabilities needed to support the specific requirements of these systems. One early example is the work by Houben and Marquardt (2015), which implemented a prototype based on a custom-designed smartwatch platform. The authors cited limited access to sensor data, lack of support for custom hardware and gesture design, and insufficient flexibility for prototyping cross-device interactions as key motivations for building their own device. Other studies also turned to custom hardware due to the absence of specific components in commercial models, such as electromyography (EMG) sensors (Xiao et al., 2025), impedance sensing electrodes (Zhu et al., 2025) and cameras (Sridhar et al., 2017; Yeo, Wu, et al., 2019). Some went further by integrating enhanced versions of common smartwatch components, including nine-degree-of-freedom (9-DOF) IMUs (Azim et al., 2022) and arrays of four microphones (Han et al., 2017).

4.4.2. Evaluation method

Among the 57 full papers in our corpus, we excluded a total of nine papers, including three (Houben & Marquardt, 2015; Hung et al., 2019; Ledo et al., 2019) that proposed frameworks and developed prototypes, showcasing cross-device interactions through application use cases, but without conducting any formal evaluation of the multi-device systems themselves. We also excluded six papers (Han et al., 2017; Laput et al., 2016, 2018; Sridhar et al., 2017; Yeo,Wu, et al., 2019; Zhu et al., 2025) that implemented cross-device interactions through application use cases. However, the evaluations in these studies focused exclusively on single-device smartwatch systems—for instance, assessing the watch's ability to localize and classify acoustic signatures (Han et al., 2017) or detect and recognize user gestures (Zhu et al., 2025). All six conducted AP experiments, and one additionally evaluated UE.

For the other 48 papers, evaluations were conducted by assessing AP, UP, or UE (the detailed coding is provided in the Supplementary Materials). In addition, apart from the nine papers excluded above for relying solely on use cases, we found that among the 48 papers that conducted evaluations of multi-device systems involving smartwatches, some also used use cases as part of their methodology. Among them, ten papers (Chen et al., 2014, 2021; Grubert et al., 2015; Huang et al., 2023; Wu et al., 2022; Xu et al., 2024; Yeo et al., 2020; Yeo, Lee, et al., 2019; Zhang et al., 2016, 2017) not only included experimental evaluations but also used use cases to support their systems' frameworks or design spaces. For example, Duet (Chen et al., 2014) introduced a novel framework for joint interactions across smartwatches and smartphones, enabling both sequential and simultaneous use of the two devices. It demonstrated this through multiple cross-device applications, such as map browsing, music control, and a slide deck controller. Such use cases complement formal experiments by exploring design spaces and inspiring future applications.

4.4.2.1. Algorithm performance (AP) (30/48). AP evaluation aims to provide quantitative measurements of a system's technical performance, primarily focusing on system performance (accuracy, recall, F1 score, confusion matrix) and efficiency (latency, power consumption, response time, peak GPU memory usage). Most AP evaluations were conducted in controlled laboratory environments, which ensure precision and reproducibility in performance measurements. To demonstrate the value of their systems, the vast majority of papers compared their results with prior work. These comparisons were conducted either by referencing performance data reported in previous publications (Mollyn et al., 2023; Wang et al., 2025a; Wang & Ma, 2023) or by reimplementing existing methods under the same devices and configurations (Li et al., 2025; Yu et al., 2025; Zhang et al., 2025). In addition, some papers examined the robustness of their systems by evaluating adaptability and reliability under varying real-world conditions (Chen et al., 2021; Leung et al., 2018; Lu et al., 2020). For example, Zhang et al. (2016)

evaluated smartwatch-based gesture recognition across conditions such as wearing thin clothing versus no clothing, changes in skin moisture, and placing a smart ring on different fingers, demonstrating the system's ability to operate reliably in more complex environments.

4.4.2.2. User performance (UP) (13/48). UP evaluation quantifies how users perform when interacting with a system through objective measurements. This line of research primarily relies on metrics related to time/speed ($N = 12$) and accuracy/error rate ($N = 12$). In terms of experimental design, many studies adopt controlled experimental comparisons to examine how different interaction conditions affect performance and to demonstrate the superiority of a new system relative to a baseline. For example, Easy Return (Flores & Manduchi, 2018) evaluates the effectiveness of its navigation assistance system by comparing task completion time and error rate under assisted and unassisted conditions. Some studies also employ additional performance metrics. For instance, SoundTrak (Zhang et al., 2017) uses throughput as a composite measure of user performance that captures both speed and accuracy when evaluating its 3D tracking system.

4.4.2.3. User experience (UE) (28/48). UE evaluation aims to collect users' subjective feedback and opinions about a system. It encompasses a broad range of assessment dimensions, including comprehensibility, usefulness, and satisfaction. This type of evaluation primarily relies on two methodological approaches: qualitative interviews and quantitative questionnaires. Interviews are most often conducted in a semi-structured format, which maintains focus while allowing deeper exploration of users' experiences. Regarding questionnaires, studies either use standardized scales or custom scales. Among standardized scales, the NASA Task Load Index (NASA-TLX) ($N = 7$), the System Usability Scale (SUS) ($N = 4$), and the User Experience Questionnaire (UEQ) ($N = 2$) are the most frequently employed. We also observe that many studies adopt domain specific scales ($N = 6$) to assess system impact in specialized contexts such as mental or physical health. For example, RunMe (Tan, Zhu, et al., 2025) employs the Multidimensional Assessment of Interoceptive Awareness 2 (MAIA 2), the Mindful Attention Awareness Scale (MAAS), the Intrinsic Motivation Inventory (IMI), and the Measure of Attention Focus (MAF). A substantial portion of studies rely on custom questionnaires ($N = 22$), typically using Likert scales (commonly on 1–5 or 1–7 scales) to capture user preferences and subjective ratings. Researchers also use diverse qualitative methods ($N = 5$) to capture user experience. For instance, Duet (Chen et al., 2014) uses the classic Think-Aloud protocol to gather participants' real-time thoughts. Easy Return (Flores & Manduchi, 2018) incorporates open-ended questions to elicit unrestricted feedback, and CurationSpace (Brudy et al., 2016) collects behavioral data to support analysis. In terms of evaluation settings, although most UE studies are conducted in controlled laboratory environments, six works adopt field studies (Arakawa, Nakagawa, et al., 2025; Huang et al., 2023; Jain et al., 2020; Liu et al., 2021; Silva et al., 2023; Yu et al., 2025). Field studies deploy systems in users' real daily environments to obtain feedback with higher ecological validity. These studies often run over longer periods, spanning days, weeks, or even months. Data collection in field settings typically combines interviews, questionnaires, and analyses of behavioral traces such as usage logs (Silva et al., 2023) and bookmarks (Jain et al., 2020).

5. Discussion

Building on the **RQs** introduced in Section 1, we addressed each in the preceding sections: Section 4.1 for **RQ1**, Section 4.2 for **RQ2**, Section 4.3 for **RQ3**, and Section 4.4 for **RQ4**. We now discuss broader trends, emerging challenges, and future directions for smartwatch-based multi-device systems.

5.1. The evolution of multi-device systems involving smartwatches

Over the past decade, the role of smartwatches within multi-device systems has undergone a significant transformation: an early phase dominated by pairwise configurations; and a recent phase marked by the emergence of N-wise configurations.

5.1.1. Phase 1: The pairwise era (pre–2018)

In the early development of multi-device ecosystems involving smartwatches, 86.4% of systems adopted a pairwise configuration, where the smartwatch functioned primarily as a secondary device tethered to a primary computing unit. Prior to 2015, these studies mainly relied on custom-built smartwatch prototypes (Houben & Marquardt, 2015). Since then, the majority of research has shifted toward using commercially available smartwatches, including those featured in **Phase 2** systems. This shift can be attributed to the rapid commercialization of smartwatches. Following the launch of the Pebble in 2013 (Pebble Technology, 2012), major technology companies began entering the consumer smartwatch market around 2014–2015, introducing devices from brands such as Samsung, LG, Apple, and Huawei. During this phase, a particularly common example was the use of smartwatches as extended screens or input devices for smartphones and large displays, enabling cross-display input/output interactions.

5.1.2. Phase 2: N-wise ecosystems and infrastructural maturity (2019–present)

Since 2019, an increasing number of system architectures have shifted notably toward *N*-wise configurations, accounting for 44.4% of recent systems compared to just 13.6% in the **Phase 1**. These systems integrate smartwatches with smartphones, HMDs, smart glasses, and Internet of Things (IoT) devices into more complex multi-node networks (Azim et al., 2023; Li et al., 2023, 2025). We attribute this proliferation to two key infrastructural developments. First, short-range wireless connectivity has become substantially more stable and energy-efficient, driven by advances in Bluetooth Low Energy (BLE 5.x) (Collotta et al., 2018). Second, recent years have seen significant enhancements in operating system-level support for cross-device coordination. Modern platforms now offer built-in mechanisms for device discovery, pairing, authentication, and state synchronization, substantially lowering the barrier to coordinating multiple devices without the need for bespoke communication pipelines. Frameworks such as Apple's Continuity (Apple Inc., 2025) and interoperability standards like Matter (Connectivity Standards Alliance, 2025) have standardized device discovery, state synchronization, and authentication, significantly lowering the barrier to implementing complex device topologies.

In parallel, the smartwatch's functional role has been shifting. Our statistical analysis reveals a decline in the use of smartwatches as Direct Manipulation devices—dropping from 61.4% in the pairwise phase to 36.1% in the recent phase. Instead, smartwatches are increasingly used as passive sensing nodes, capturing contextual data from users or environmental context (Arakawa, Patidar, et al., 2025; Lan, Li, et al., 2025; Yang, Jiang, et al., 2024). Furthermore, the complexity of usage has increased: 23.6% of **Phase 2** systems now assign multiple roles to the smartwatch, up from 15.9% in the **Phase 1**, reflecting a trend toward leveraging the device's versatility within distributed computing ecologies.

5.2. Opportunities for smartwatches to enhance haptic perception

The smartwatch's constant biomechanical contact with the wrist affords a unique, always available channel for delivering haptic feedback. However, its potential to augment haptic perception remains underexplored, with only two papers (Hwang et al., 2015; Terenti & Vatavu, 2025b) in our corpus explicitly investigating this utility. This scarcity highlights a critical opportunity to leverage wrist-worn devices for more immersive and context-aware interactions across a variety of domains. One promising yet underexplored direction is distal haptics—a technique that decouples the haptic actuation point from the interaction surface (Terenti & Vatavu, 2025a). In this paradigm, visual or touch input occurs on a passive surface (e.g., a standard touchscreen or physical object), while the corresponding vibrotactile feedback is rendered on the smartwatch. By exploiting cross-modal correspondence and pseudo-haptic illusions, this architecture can effectively endow non-haptic interfaces with rich tactile responses without requiring hardware retrofitting. For instance, in e-commerce scenarios, smartwatches could render "everyday haptics"—synchronizing vibration patterns with on-screen visual textures to simulate the frictional properties of fabrics.

Beyond such distal-haptics use cases, smartwatch-based haptics should evolve toward bio-adaptive closed-loop systems. Rather than delivering static rhythmic cues for workouts, smartwatches can leverage their sensing capabilities to modulate feedback parameters (e.g., intensity, frequency) in real-time based on the user's physiological state (e.g., heart rate variability). Such "neuroadaptive" approaches could dynamically regulate cognitive load or physical exertion in extended reality (XR) training and gaming applications, maximizing immersion while mitigating fatigue. Realizing these possibilities requires rigorous psychophysical studies to establish a standardized haptic vocabulary and determine optimal perception thresholds for wrist-based signaling.

5.3. From individual sensing to collective action and emotion

Our analysis reveals a significant "individual-centric" bias: only 7 out of 109 papers (6.4%) explore multi-user systems. We argue that this focus on the single user overlooks two profound opportunities for smartwatch-integrated systems.

First, we must bridge the gap between "sensing" and "acting" for vulnerable populations. Smartwatches are ideal for children and the elderly because they are wearable and always-on. However, a critical problem exists: while these users can provide signals (like a fall (Fayad et al., 2019; Şener et al., 2024)), they often lack the ability to handle the resulting emergency. Currently, most systems are "closed loops" where the data stays with the wearer. We argue that for these groups, a single- user design is a missed opportunity. The true value of a multi-device system lies in its ability to distribute responsibility. Prior work (Şener et al., 2024; Usta & Şener, 2025; Wolff et al., 2025) acknowledges that caring for the elderly is a team effort involving caregivers and medical professionals. Yet, we have not yet seriously explored how to technically link the wearer's watch to the various devices held by these different people. Specifically, we lack a clear understanding of how to design alerts and displays that adapt to the unique needs and roles of each person in this care circle.

Second, for general social use, we should move from "data sharing" to "emotional metaphor." Beyond health, the vast amount of biosignals collected by smartwatches can serve as a new, quiet language for intimacy. However, sharing raw numbers (like 120 bpm) feels clinical and invades privacy. The deeper opportunity lies in symbolic expression: mapping cold data onto warm, social cues. For example, instead of seeing a heart rate, a partner might see the font of a chat message vibrate or change color to reflect the sender's excitement. This transforms a medical metric into a "digital vibe." Such symbols act as a privacy filter, allowing people to feel close without feeling watched. Despite this potential, our review shows this space is nearly empty; only one study used a symbolic "otter" avatar to represent a partner's emotional and physical state (Liu et al., 2021). We believe future research should focus on how to turn these invisible body signals into visible, meaningful metaphors that strengthen human ties across devices.

5.4. The smartwatch's dilemma: Risks of redundancy and displacement

While the smartwatch's evolving role in multi-device interaction highlights its growing importance as a data hub, it leads to a growing vulnerability—being replaced by other micro-wearable devices. A growing number of studies have leveraged alternative wearables—such as smart rings, smart glasses, and earbuds—to collect physiological, behavioral, and acoustic data (Cao et al., 2024; Tang et al., 2026; Zhu et al., 2023). This trend challenges the smartwatch's position as the central sensing device and raises questions about its long-term indispensability. In addition, emerging evidence suggests that, due to substantial sensor redundancy across devices, lightweight wearables are increasingly capable of replicating sensing functions traditionally attributed to smartwatches. For example, Azim et al. (2023) demonstrated that correlated motion signals from smart rings and smart glasses could accurately recognize gestures with 90.9% accuracy without relying on a smartwatch. This points to a high degree of sensor redundancy in modern multi-device configurations. Furthermore, specialized form factors often outperform the wrist in specific contexts. Wang et al. (2025b) highlighted that smart rings can function not only as passive sensing nodes but also as sophisticated input and output devices. Lan, Sun, et al. (2025) found that face-worn haptics (via smart glasses) significantly reduced reaction times in autonomous driving takeover scenarios compared to wrist-based feedback. These studies indicate a paradigm shift: rather than defaulting to the smartwatch as a "catch-all" device, future systems may prioritize specialized wearables that offer superior anatomical placement or lower physical intrusiveness.

Concurrently, the utility of the smartwatch as a secondary or extended display is under pressure from advancements in smartphone hardware. With the advent of foldable devices and expandable screens—exemplified by the Huawei Mate XT (HUAWEI, 2025) and Samsung Z Fold series (Samsung Electronics Co., Ltd., 2025)—mobile devices now offer significantly larger and more flexible visual real estate. This evolution reduces the necessity of offloading visual tasks to the wrist. In scenarios demanding visualization or complex manipulation (e.g., digital drawing), the expansive canvas of a foldable phone negates the need for a supplementary smartwatch display. Consequently, the smartwatch risks losing its foothold as an auxiliary output surface, potentially relegating it to a purely passive role.

5.5. Disciplinary perspectives: HCI vs. Computer networking

Research on multi-device systems spans multiple communities with diverging priorities. While our reviews primarily focus on 11 HCI venues, flagship Computer Networking conferences—such as MobiSys[1], MobiCom[2], and SenSys[3]—offer vital complementary perspectives. To capture these perspectives, we applied the same methodology described in the Section 3 to these three Computer Networking venues. This process yielded 23 relevant papers (listed in the Supplementary Materials), including 10 full papers. Comparing this corpus with our HCI dataset reveals distinct patterns in how smartwatches are conceptualized and evaluated.

5.5.1. Role of the smartwatch: Sensor vs. interface

A primary distinction lies in the functional role assigned to the smartwatch. In Computer Networking research, the device is predominantly positioned as a *data collector* (17/23) and typically operates in the background (16/23). In these architectures, the smartwatch functions primarily as a passive sensing node within a distributed system, with limited emphasis on its role as a user-facing interactive surface. Conversely, while HCI research also utilizes smartwatches for sensing, it places significantly greater weight on direct user interaction (53/116) and foreground usage like acting Input Device (40/116). This distinction is reflected in system configurations: Computer Networking studies more frequently explore complex N-wise configurations (10/23) compared to HCI (35/116), likely driven by technical challenges in networking and synchronization rather than user interaction needs.

5.5.2. Application domains and "technical frontiers"

While both communities share a strong interest in health and social computing, their specific application foci diverge. HCI research broadly covers knowledge work, creativity, and education—domains requiring rich user input. In contrast, Computer Networking venues often target technically demanding scenarios that push the boundaries of connectivity and sensing, such as underwater communication (Chan et al., 2022; Yang & Zheng, 2024) or highly specific activity recognition tasks like toothbrushing monitoring (Huang & Lin, 2016). This suggests that Computer Networking research often serves as a pioneer for technical feasibility in extreme or novel contexts, while HCI focuses on refining user interactions in established contexts.

5.5.3. Evaluation priorities: Algorithm vs. experience

The most improved contrast appears in evaluation methodologies. Computer Networking research prioritizes technical robustness, with 90% of full papers (9/10) focusing on algorithm performance (e.g., latency, accuracy, energy consumption), compared to 62.5% (30/48) in HCI. User-centered evaluation shows the inverse trend: user experience assessments are more frequent in HCI (28/48) than in Computer Networking (5/10). Furthermore, when user studies are conducted in Computer Networking, they tend to be smaller in scale (typically 3–9 participants) compared to the broader range in HCI (5–46 participants). This indicates that Computer Networking studies often tend to prioritize technical performance, with user evaluation playing a secondary role, while HCI more deeply engages with how users interact with.

5.5.4. Summary

These patterns underscore a complementary relationship: Computer Networking research advances the *infrastructure*—optimizing how devices connect, sense, and preserve energy—while HCI research advances the *experience*—determining how these capabilities can be meaningfully designed for and adopted by human users.

5.6. Future opportunities for smartwatch integration in intelligent multi-device systems

Our survey of the existing literature has identified the smartwatch as a versatile component in multi-device systems. However, with the rapid adoption of immersive technology and Large Language Models (LLMs), we anticipate that the utility of smartwatches will expand significantly. Within the current landscape, smartwatches have only rarely been incorporated as input devices in XR ($N = 5$). We argue that by leveraging their unique form factor—being body-anchored and always-on—smartwatches can address critical limitations in current immersive and intelligent systems.

5.6.1. Immersive technology

Integrating smartwatches with immersive systems has the potential to improve both input robustness and feedback realism. Optical hand tracking in virtual reality (VR) or augmented reality (AR) often suffers from occlusion and lighting constraints (Mueller et al., 2017; Worrallo & Hartley, 2022). Smartwatches can mitigate these issues by providing continuous inertial data (IMU), offering a reliable fallback mechanism that maintains tracking stability even when hands are outside the camera's field of view. Furthermore, emerging "neuroadaptive" interfaces can utilize the watch's physiological sensors (e.g., heart rate) to dynamically adjust simulation parameters in real-time, such as lowering task difficulty when user stress is detected. Data from these physiological sensors can complement eye-tracking metrics to more accurately infer the user's cognitive or physiological state.

5.6.2. LLM

The integration of LLMs offers new possibilities for personalized assistance, but these models require rich context to be effective. Smartwatches serve as effective context providers due to their persistent access to user activity, location, and physiological state. By adopting standards like the Model Context Protocol (MCP) (Google Cloud, 2025), smartwatches can expose this sensor data as structured tools for AI agents. This data enables "context-aware prompt engineering," allowing systems to shift from reactive command-response cycles to proactive interactions. For example, detecting a physiological stress signal allows the system to offer timely interventions without explicit user input. To support these advanced features within battery constraints, future systems will likely employ a split computing architecture. In this model, the smartwatch handles low-power, real-time sensing (the "transient layer"), while computationally intensive tasks are offloaded to smartphones or other high-computing devices.

5.7. Limitation

There are several limitations to this review. First, our keyword strategy was centered on the terms "smartwatch" and "smartwatches." Although these terms are the most prevalent, this choice may have excluded studies that employ commercial smartwatches but refer to them exclusively through broader descriptors (e.g., "wrist-worn device") across whole papers. Second, by limiting our scope to major HCI venues, our evidence base represents a specific disciplinary perspective. As noted in the methodology, adjacent communities such as digital health, computer networking, and industrial design often provide specialized insights. Consequently, our synthesis may prioritize empirically-grounded user studies over purely system-level architectural optimizations or design-led explorations common in other fields. Therefore, our findings should be interpreted as a systematic mapping of patterns within the HCI community rather than an exhaustive census of all smartwatch-integrated systems across all technical disciplines. Future research could complement this work by adopting a more multi-disciplinary search strategy to capture these peripheral but valuable insights.

6. Conclusion

We presented a systematic review of 106 HCI papers to understand how smartwatches integrate within multi-device systems. Our analysis revealed that these systems have evolved significantly over time—ranging from early stages involving custom-built smartwatches, to a pairwise era characterized by device pairings, and more recently, to the emergence of networks comprising three or more interconnected components. In addition, we observed a shift in smartwatch usage—from direct manipulation devices toward passive, context-aware sensing nodes. Moreover, we found that smartwatch-based multi-device systems are primarily deployed in health and knowledge work domains, with validation efforts focusing mainly on algorithmic performance, followed by user experience and performance evaluations. Our review also discussed the dilemma for smartwatches: as their functionalities increasingly overlap with those of lighter, less obtrusive wearables such as smart rings and smart glasses, they may face the risk of functional redundancy and potential displacement. Looking ahead, we identify several promising directions for future research, including opportunities for smartwatches to enhance haptic perception, and pathways for more tightly integrating smartwatch-based multi-device systems with emerging technologies—particularly immersive environments and Large Language Models. We hope this review provides a foundation for future exploration at the intersection of smartwatches and multi-device interaction.

Notes

1. Mobile Systems, Applications, and Services.
2. Mobile Computing and Networking.
3. Embedded Artificial Intelligence and Sensing Systems.

Author contributions

CRediT: **Yihan Liu**: Conceptualization, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing; **Jiazhe Huang**: Visualization; **Yuchen Gu**: Visualization; **Fabiola Polidoro**: Writing – review & editing; **Lingyun Yu**: Project administration, Resources; **Yu Liu**: Conceptualization, Methodology, Project administration, Resources, Supervision, Writing – original draft, Writing – review & editing.

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