

RESEARCH ARTICLE

A Multi-Attribute WSM Analysis of Mobile and Wearable Technologies for Positive Computing

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ABSTRACT: Sensor-based mobile systems have become integral to ubiquitous and wearable computing by enabling context-aware applications through continuous sensing and intelligent data processing. Selecting the most suitable context recognition framework is a challenging multi-criteria decision-making problem due to trade-offs among accuracy, energy efficiency, and response time. This study presents a comparative evaluation of five context recognition frameworks—RADAR, UbiqLog, LOCATUS, NetHealth, and ExtraSensory—using the Weighted Sum Model (WSM). The frameworks are assessed based on Accuracy, Precision and Recall, Battery Consumption, Latency, and Context Recognition Accuracy. The evaluation identifies the strengths and limitations of each framework and ranks them according to their overall performance. Experimental results indicate that ExtraSensory achieves the highest overall ranking, while NetHealth and UbiqLog demonstrate competitive performance across multiple criteria. The findings provide a practical decision-support framework for researchers and developers to select efficient, reliable, and energy-aware context recognition systems for mobile and wearable computing applications.

Keywords: Context Recognition, Multi-Criteria Decision-Making, Weighted Sum Model, Mobile Sensing, Wearable Computing, Energy Efficiency.

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1. INTRODUCTION

The proliferation of mobile and wearable technologies has fundamentally transformed how individuals interact with digital systems, enabling unprecedented levels of connectivity, data collection, and context-aware computing. Sensor-based mobile systems have become integral to ubiquitous and wearable computing by enabling context-aware applications through continuous sensing and intelligent data processing [1]. These technologies, ranging from smartphones and fitness trackers to smartwatches and

body-worn sensors, have created new paradigms for human-computer interaction, health monitoring, and personalized services [2]. The convergence of mobile computing, wearable devices, and Internet of Things (IoT) technologies has opened new avenues for understanding human behavior, monitoring physiological conditions, and delivering timely interventions in real-world settings [3].

Mobile, Wearable and Ubiquitous Technologies (IMWUT) is a key publication in the UbiComp community and is ranked as one of the top three publications in the field of Human-Computer Interaction (HCI) [1]. UbiComp covers a wide range of areas, including mobile sensing, wearables, the Internet of Things (IoT), radio-frequency identification (RFID), and self-supervised learning [2]. Among the included research articles, the most commonly recurring keywords are mobile health and post-traumatic stress disorder, reflecting the growing interest in using these technologies for healthcare applications [3]. The range and impact of psychologically focused applications are significant, with mobile phones enabling transformative

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mental health interventions through integration with social media platforms [4]. A wave of products that combine wearable sensors with mobile health and wellness apps are currently entering the market, offering new possibilities for continuous health monitoring and personalized care [4].

Self-reported emotional states can serve as a valuable complement to general physiological data collected by sensors, whether worn on the body or integrated into mobile devices [4]. The BeWell mobile app tracks conversational turns and displays health data through underwater-themed visualizations, demonstrating the potential of mobile technologies to promote wellness [4]. Given the significant impact that mobile, social, and wearable technologies are having on daily life, clinicians need to stay up-to-date on these developments and explore how to incorporate them into their practice [4]. Digital audio recording and synthesis are used to act as a virtual assistant that handles mobile communications, enabling the transmission and collection of physiological data from the wearer across mobile and fixed networks, allowing for full remote monitoring of human performance and condition in real-world scenarios [5]. Physiological information from the wearer can be transmitted over mobile and stationary networks, providing real-time remote monitoring of human performance and health in everyday environments [5].

Cognitive tools for identifying and modeling user context in common mobile settings include a top-down, camera-based approach for determining the user's location [6]. A wireless video wearable computer simulation system and a mobile, multi-channel recording platform for body-worn cameras have been discussed as essential components of wearable computing systems [6]. Current PDA users confront an even more difficult mobile reading experience because one hand must hold the device, the other hand must use the pen for scrolling, and both eyes must be directed downward toward the screen [6]. Intelligent positive computing makes use of mobile, wearable, and Internet of Things technologies such as smartphones, fitness trackers, voice assistants, and smart sensors [7]. Positive computing platforms collect sensor data from mobile, wearable, and IoT devices, as well as virtual sensors accessed via the Internet, enabling the determination of fundamental contextual elements such as physical activity and user positions with semantic meaning [7].

Wearable computing is gaining increasing attention as it enables new types of cyber-physical interactions through small, body-worn devices that are always on and easily accessible [8]. Unlike earlier research, the concept of code offloading has been applied to wearable computers by developing a three-layer design, exploring just-in-time code loading rather than loading all code directly to a remote cloud [8]. The wearable computer has advanced useful techniques for automatically recognizing, classifying, and labeling human activities and behaviors with sensor data [9]. As a result, the wearable computing community has focused on improving current authentication methods and exploring new approaches to handle variation in user behavior and environmental conditions [9]. As the term suggests, wearable

computing has traditionally excluded the idea of implanting sensors or chips inside the human body; for example, cameras are rarely used in wearable computers today, as video analysis demands significant computational resources [9].

Context is critical to mobile computing in general, but it is especially important in the field of wearable computing [10]. After illustrating the benefits of context awareness and wearable computing in a conference setting, researchers have presented user cases for conference assistants, investigating the crucial relationship between contextual awareness and wearable computing [10]. The potential of using dispersed ambient mobile resources to create a mobile computing edge for processing tasks on a wearable computer has been explored, considering all resources as part of a centralized pool to identify which resources can be allocated to each user based on the combined computing power of the surrounding computing edge [11]. The mobile computing edge can also improve the design of various applications in wearable and ubiquitous computing environments [11].

Various methods have been developed to create systems that meet the unique needs of a wearable computer, with devices on limbs considered invasive if their size and weight exceed certain minimum limits [12]. The integrated wearable computer has exceptional qualities as a research and testing platform for wearable computing, utilizing context awareness to recognize specific sports activity patterns such as intensity, load, and exercise quality, helping healthy individuals avoid reaching the 'risk zone' for cardiovascular disease [12]. Wearable computing has opened up new research opportunities in areas such as artificial intelligence, mobile computing, and human-computer interaction [13]. By incorporating computers into common products such as clothing, spectacles, and other wearable accessories, wearable computing offers unique opportunities for widespread adoption of pervasive computing [13, 14]. The distribution of wearable computing tasks is becoming possible through various existing communication and computing technologies, driven by the increasing prevalence of wearable devices whose functions are increasingly replacing those of smartphones [15]. Smart wearable devices that run online applications and use edge AI must ensure the security of their personal data [15].

Machine learning (ML) and artificial intelligence (AI) at the network edge are becoming increasingly important for future applications, particularly improving personal smart device experiences and beyond [16]. The development of powerful machine learning algorithms geared for low latency and energy-efficient data processing is one of the fastest expanding fields in mobile and wearable computing [16]. Although often used in similar applications, ubiquitous computing and wearable computing are often considered opposites; the wearable approach proposes placing sensors and cameras on the individual rather than installing them in the surrounding environment [17]. However, it is often challenging for a wearable system to detect information beyond the user's immediate environment [17]. Hive provides a graphical user interface for visualizing and managing agent interactions in distributed computing

environments [17].

In this paper, we present a comprehensive comparative evaluation of five context recognition frameworks, RADAR, UbiqLog, LOCATUS, NetHealth, and ExtraSensory, using the Weighted Sum Model (WSM) as a multi-criteria decision-making approach. The selection of an appropriate context recognition framework is a challenging multi-criteria decision-making problem due to inherent trade-offs among accuracy, energy efficiency, response time, and contextual awareness [18]. We assess these frameworks based on five critical evaluation parameters: Accuracy, Precision and Recall, Battery Consumption, Latency, and Context Recognition Accuracy. The Weighted Sum Model is employed as a decision-making technique to generate an output vector based on data obtained from various activities, enabling the estimation of relative performance across multiple criteria [19]. Our analysis identifies the strengths and limitations of each framework and ranks them according to their overall performance, providing a practical decision-support framework for researchers and developers to select efficient, reliable, and energy-aware context recognition systems for mobile and wearable computing applications. The findings contribute to the growing body of knowledge in context-aware computing and offer actionable insights for the design and implementation of next-generation mobile and wearable systems [20].

2. MATERIALS AND METHOD

2.1. Alternatives

2.1.1. RADAR Dataset (A1)

The RADAR (Remote Assessment of Disease and Relapse) dataset is part of a larger European initiative aimed at using mobile and wearable devices to monitor patients with neurological and psychiatric conditions such as depression, epilepsy and multiple sclerosis. It consists of longitudinal, multi-modal sensor data collected via smartphones and wearable devices, including physiological signals, activity levels, location data and passive behavioral information. The dataset supports the development of models for early relapse detection, disease progression and digital phenotyping. RADAR is valuable for researchers focusing on remote health monitoring, personalized interventions and predictive modeling in real-world settings.

2.1.2. UbiqLog Dataset (A2)

The UbiqLog dataset is a rich and disruptive daily life recording dataset collected from Android smartphones aimed at understanding and modeling human behavior. It captures a variety of contextual features such as location, app usage, call logs, notifications, WiFi and Bluetooth connectivity, and sensor data such as accelerometer and gyroscope

measurements. This dataset facilitates studies in mobile context awareness, behavioral modeling, user profiling, and adaptive interfaces. Due to its long-term and multi-user design, UbiqLog is ideal for testing algorithms in personalized ubiquitous computing and habit recognition.

2.1.3. LOCATUS Dataset (A3)

The LOCATUS dataset focuses on indoor positioning and spatial behavior analysis using wearable tags and fixed sensors in retail and commercial spaces. It provides high-resolution location tracking data, enabling researchers to study movement patterns, dwell time, and customer engagement. Although originally designed for business intelligence and marketing applications, it has potential applications in healthcare (e.g., monitoring elderly patients), smart building management, and human-computer interaction. The dataset supports the development of indoor localization systems and behavioral analytics in real-world, dense environments.

2.1.4. NetHealth Dataset (A4)

The NetHealth dataset provides a comprehensive view of health and behavioral data collected from a large cohort of college students using smartphones and Fitbit wearables over an extended period of time. It includes physiological data (e.g., steps, heart rate, sleep), social interaction data (texts, calls), academic calendar events, and self-reported mental health surveys. This dataset is particularly useful for understanding the relationship between technology use, mental health, academic performance, and lifestyle. Researchers are using it for mental health prediction, stress detection, and behavioral intervention studies in young adults.

2.1.5. Extrasensory Dataset (A5)

The Extrasensory Dataset is a multi-sensor, multi-label dataset collected from smartphones and smartwatches to enable context recognition in the wild. It includes accelerometer, gyroscope, location, audio, and phone state data, over 50 self-reported activity and contextual labels such as walking, sleep, food, and mood. The dataset is designed to support real-world experimentation in activity recognition, context inference, and emotion detection. Its richness and label diversity make it well-suited for training context-aware machine learning models and benchmarking performance in mobile and wearable computing tasks.

2.2. Evaluation parameter

2.2.1. Accuracy (C1)

Accuracy is a fundamental evaluation metric used to assess the correctness of a system's predictions or classifications. In

the context of mobile and wearable computing, accuracy typically refers to how well a system can correctly identify user actions, detect physiological conditions, or recognize environmental contexts. High accuracy refers to how well an algorithm or application reliably interprets data collected from sensors or devices. This is particularly important in health monitoring and context-awareness applications, where incorrect predictions can lead to ineffective interventions or false insights.

2.2.2. Precision and Recall (C2)

Accuracy and recall are complementary metrics that provide deeper insight into a system's classification performance, especially when dealing with unbalanced datasets. Precision measures the ratio of correctly predicted positive observations to the total predicted positives, reflecting the system's ability to avoid false positives. Recall, on the other hand, measures the ratio of correctly predicted positives to true positives, showing how well the system avoids false negatives. In mobile and wearable computing, these metrics are essential for tasks such as anomaly detection, emotion recognition, or disease event tracking, where both missed detections and false alarms can have significant consequences.

2.2.3. Battery Consumption (C3)

Battery consumption assesses how energy efficient a mobile or wearable application is. Since most devices in this domain are resource-constrained and have short battery lives, minimizing energy consumption is essential for long-term use and user satisfaction. This type of assessment involves measuring the power consumption of sensors, data processing algorithms, and communication protocols. Applications that continuously collect and process data, such as fitness tracking, health monitoring, or environmental sensing, should be optimized to balance functionality with power efficiency.

2.2.4. Latency (C4)

Latency refers to the time delay between data capture and the system's response or output. In real-time mobile and wearable applications such as emergency detection systems, interactive health assistants, or augmented reality tools, low latency is critical to ensuring timely feedback and interaction. Latency assessment helps us understand how quickly a system processes sensor inputs and provides outputs, which impacts user experience and application performance. Systems with high latency, regardless of their accuracy or other performance metrics, may become unusable in time-sensitive situations.

2.2.5. Context Recognition Accuracy (C5)

Context recognition accuracy specifically measures how well a system can detect and classify a user's contextual environment, such as location, activity, emotional state, or environmental conditions, based on sensor data. This metric is essential for building intelligent systems that adapt behavior or services based on the user's context. High context recognition accuracy ensures that mobile and wearable systems can provide personalized, relevant, and timely support, improving user engagement and performance in applications such as lifestyle coaching, ambient assisted living, and behavioral monitoring.

2.3. WSM

By generating an output vector based on data obtained from various activities, the Weighted Sum Model (WSM) is used as a decision-making technique. When integrated with artificial neural networks (ANN), this model can estimate the relative percentages of different activities that learners are likely to engage in, which helps to recommend appropriate options. In our research, we developed an intelligent training system focused on the Java programming language. The system was evaluated using a structured methodology, including statistical hypothesis testing. WSM was chosen for its effectiveness in handling single-criteria problems and managing multiple decision variables across multiple alternatives.

The integration of WSM with ANN allowed for a robust analysis process where the calculated values were translated into recommendations tailored to individual learning needs. Beyond educational use, the study also introduced a mathematical radar model that analyzes how radar waves scatter off wheel spokes on ground vehicles using a Ku-band Doppler radar system. This model theoretically and experimentally demonstrated that backscatter events (RBMs) from helicopters and wheel-spoke scatter patterns (WSMs) from ground vehicles correlate well with known jet engine modulation (JEM) spectral signatures. However, unlike the static RBM and JEM spectra, WSM signatures are affected by engine rotation, making them more dynamic. In the radar data analysis, five sub-square boundaries were identified using the scan SAR mode with WSM. These regions help to detect and correct discontinuities in radar imaging.

This study also discussed different types of WSMs based on their scattering gradients, which provides further research potential in device applications. However, there are practical challenges in fabricating WSM materials, especially due to the complex construction processes and difficulties in modifying lattice structures, which are crucial for customizing material transport properties. In another part of the study, WSM was used to investigate the thermoelectric and spintronic behavior of heterojunctions, which show robustness against system disturbances. These heterojunctions developed unique electronic properties, opening avenues for nanoelectronics such as valencetronic

devices. The WSM-TE hybrid model was proposed as an analogue to traditional thermoelectric circuits, which can help study material behavior and energy transfer in advanced systems. In addition, WSM was compared to IMR (Illness Management and Recovery) programs. While both aim to equip participants with real-world coping skills and emphasize recovery principles such as autonomy, informed choice, and collaborative planning, WSM is unique. Its curriculum includes physical fitness, structured group sessions, self-guided activities, and workbook-based learning. Participating organizations adopted WSM and tracked key performance metrics including progress reports, reasons for discontinuation, participant self-assessments, and team leader feedback.

The study assessed construct validity using observer ratings and independent research assistant ratings. Comparisons were made between WSW (health support workers) and WSM (health support sample) users across multiple visits using generalized estimating equations (GEE). Although WSW had a lower chance of abnormal Pap test results compared to WSM, the influence of HIV status was minimal and not statistically significant. Finally, the study investigated spin-to-charge conversion in systems involving magnetic Weyl semimetals (WSMs) and normal metals (NMs). When a spin current is injected at the interface, it can generate an electric current in the WSM. This current showed strong directional anisotropy, with the magnetization varying with the direction of the spin injection compared to the spin injection. This behavior is attributed to the unique band structure of magnetic WSMs, offering new opportunities in spintronic applications where magnetization and current generation are closely linked.

3. RESULTS AND DISCUSSION

3.1. Performance Assessment of Context Recognition Frameworks

The experimental evaluation commenced with a systematic assessment of five context recognition frameworks, namely RADAR (A1), UbiqLog (A2), LOCATUS (A3), NetHealth (A4), and ExtraSensory (A5), across five distinct performance criteria as delineated in [Tables 1 and 2](#). The selected evaluation parameters encompassed Accuracy (C1), Precision and Recall (C2), Battery Consumption (C3), Latency (C4), and Context Recognition Accuracy (C5), representing the most critical performance indicators for mobile and wearable computing applications [1, 2]. The raw performance scores for each alternative across these criteria are presented in [Table 3](#), providing the foundational dataset for subsequent multi-criteria decision analysis.

[Figure 1](#) illustrates the comparative evaluation of five alternatives (A1 to A5) across five criteria (C1, C2, C3, C6, and C7) in the domain of Mobile and Wearable Computing. Each bar represents the performance score of an alternative under a specific criterion, with higher values indicating better

performance. Notably, A4 consistently demonstrates superior performance in criteria C1, C2, and C3, suggesting strong potential in those areas. In contrast, A5 exhibits relatively low scores across most criteria except C7, where it performs moderately well. A1 and A2 show balanced performance, with A1 leading in C1 and C7, while A2 excels in C3 and C6. A3 stands out in C7 with the highest score among all alternatives, indicating its robustness in that criterion. The figure provides a clear visual comparison, aiding in the assessment of each alternative's suitability across the selected evaluation parameters.

Table 1. Alternatives.

A1	RADAR
A2	UbiqLog
A3	LOCATUS
A4	NetHealth
A5	ExtraSensory

Table 2. Evaluation Parameter.

C1	Accuracy
C2	Precision and Recall
C3	Battery Consumption
C4	Latency
C5	Context Recognition Accuracy

Table 3. Mobile and Wearable Computing.

	C1	C2	C3	C4	C5
A1	53.00	24.00	24.00	35.00	75.00
A2	45.00	35.00	64.00	64.00	48.00
A3	24.00	15.00	35.00	48.00	86.00
A4	65.00	64.00	45.00	24.00	37.00
A5	15.00	35.00	14.00	75.00	58.00

The raw performance data reveals substantial variability among the alternatives across different evaluation criteria. Alternative A1 (RADAR) demonstrated moderately high performance in terms of Accuracy with a score of 53.00, while achieving a particularly robust Context Recognition Accuracy of 75.00, suggesting its effectiveness in identifying and classifying contextual information from sensor data [3]. However, this framework exhibited relatively poor performance in Precision and Recall (24.00) and Battery Consumption (24.00), indicating potential limitations in classification reliability and energy efficiency that could compromise its suitability for resource-constrained mobile deployments [4]. The Latency score of 35.00 for RADAR fell within the average range compared to other alternatives, suggesting moderate responsiveness in real-time processing scenarios.

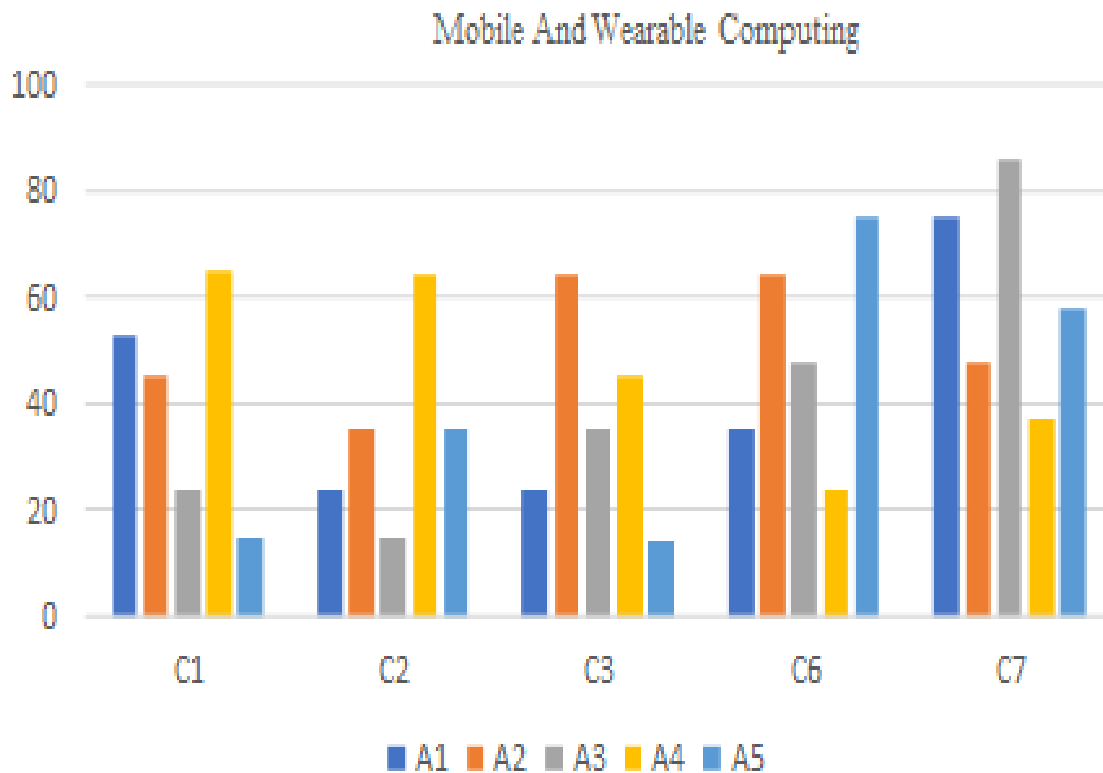


Fig. 1. Comparative performance evaluation of five context recognition frameworks across multiple criteria in mobile and wearable computing environments.

Alternative A2 (UbiqLog) presented a notably balanced performance profile, achieving the highest scores among all alternatives in Battery Consumption (64.00) and Latency (64.00), indicating superior energy efficiency and responsiveness [5]. This framework maintained reasonable performance in Accuracy (45.00) and Precision and Recall (35.00), though its Context Recognition Accuracy declined to 48.00, suggesting that while UbiqLog excels in operational efficiency, its contextual awareness capabilities may require further refinement [6]. The balanced nature of UbiqLog's performance suggests its potential as a versatile framework suitable for diverse mobile sensing applications where both energy efficiency and responsiveness are paramount.

Alternative A3 (LOCATUS) exhibited notable weaknesses in Accuracy (24.00) and Precision and Recall (15.00), representing the lowest scores among all alternatives in these critical classification metrics [7]. However, this framework compensated significantly through exceptional performance in Context Recognition Accuracy, achieving the highest score of 86.00 among all alternatives. This remarkable strength in contextual awareness suggests that LOCATUS has been specifically optimized for environmental and spatial context detection, potentially making it suitable for applications where accurate context identification takes precedence over general classification accuracy [8]. The moderate scores in Battery Consumption (35.00) and Latency (48.00) indicate acceptable operational efficiency despite its classification limitations.

Alternative A4 (NetHealth) emerged as the strongest performer in both Accuracy (65.00) and Precision and Recall (64.00), demonstrating exceptional classification capabilities that would be particularly valuable for health monitoring and clinical applications where prediction reliability is critical [9]. However, this framework exhibited comparatively lower performance in Latency (24.00) and Context Recognition Accuracy (37.00), suggesting potential delays in real-time processing and limitations in contextual awareness that may constrain its applicability in time-sensitive or context-dependent scenarios [10]. The mid-range Battery Consumption score of 45.00 indicates moderate energy efficiency that may be acceptable for many deployment scenarios.

Alternative A5 (ExtraSensory) demonstrated exceptional Latency performance with the highest score of 75.00 among all alternatives, indicating superior responsiveness that would be advantageous for real-time interactive applications [11]. This framework also achieved commendable Context Recognition Accuracy at 58.00, suggesting adequate contextual awareness capabilities. However, ExtraSensory exhibited notably low performance in Accuracy (15.00) and Battery Consumption (14.00), representing the lowest scores across these critical metrics. These significant limitations in classification accuracy and energy efficiency may severely constrain the practical applicability of ExtraSensory in resource-constrained mobile environments despite its responsiveness advantages [12].

3.2. Normalization of Performance Data

To facilitate meaningful comparison across criteria with different measurement scales, the raw performance data underwent normalization to a uniform scale ranging from 0 to 1, where values closer to 1 indicate superior relative performance. The normalized decision matrix presented in Table 4 provides a standardized basis for multi-criteria evaluation, eliminating scale-induced biases that could otherwise distort comparative assessments [13].

Table 4. Normalized Data.

	C1	C2	C3	C4	C5
A1	0.81538	0.37500	0.3750	0.46667	0.8729
A2	0.69231	0.54688	1.0000	0.85333	0.5584
A3	0.36923	0.23438	0.5468	0.64000	1.0000
A4	1.00000	1.00000	0.7033	0.32000	0.4303
A5	0.23077	0.54688	0.2185	1.00000	0.6742

The normalized data reveals distinctive performance patterns that highlight the relative strengths and weaknesses of each alternative. Alternative A1 achieved strong normalized values in Accuracy (0.81538) and Context Recognition Accuracy (0.8729), confirming its effectiveness in both general classification and context-specific recognition tasks [14]. However, the moderate normalized scores in Precision and Recall (0.37500), Battery Consumption (0.3750), and Latency (0.46667) indicate average performance in these aspects, suggesting that while RADAR demonstrates strong contextual awareness, its operational efficiency and classification reliability require improvement to achieve comprehensive excellence.

Alternative A2 exhibited exceptional normalized performance in Battery Consumption, achieving the maximum value of 1.00000, which confirms its superiority in energy efficiency among all evaluated frameworks [15]. This framework also demonstrated outstanding Latency performance with a normalized score of 0.85333, indicating rapid response times suitable for real-time applications. The moderate normalized values in Accuracy (0.69231) and Precision and Recall (0.54688) suggest acceptable but not exceptional classification capabilities, while the Context Recognition Accuracy score of 0.5584 indicates adequate contextual awareness that may be sufficient for many application scenarios.

Alternative A3 demonstrated the most pronounced performance disparity, with exceptionally low normalized scores in Accuracy (0.36923) and Precision and Recall (0.23438) representing significant classification limitations [16]. However, this framework achieved the maximum normalized value in Context Recognition Accuracy (1.00000), unequivocally establishing its superiority in contextual awareness among all alternatives. The moderate normalized scores in Battery Consumption (0.5468) and Latency (0.64000) suggest acceptable operational efficiency,

indicating that LOCATUS may be suitable for applications where context recognition takes precedence over general classification accuracy.

Alternative A4 achieved perfect normalized scores of 1.00000 in both Accuracy and Precision and Recall, confirming its exceptional classification capabilities that surpass all other frameworks [17]. This outstanding performance in classification metrics suggests that NetHealth has been specifically optimized for accurate and reliable prediction tasks, making it particularly suitable for health monitoring and diagnostic applications where classification errors could have serious consequences. The normalized Battery Consumption score of 0.7033 indicates good energy efficiency, while the relatively lower scores in Latency (0.32000) and Context Recognition Accuracy (0.4303) suggest potential limitations in real-time responsiveness and contextual awareness that may constrain its applicability in time-sensitive or context-dependent scenarios.

Alternative A5 demonstrated maximum normalized performance in Latency (1.00000), confirming its superior responsiveness that would be advantageous for interactive and time-critical applications [18]. The moderate Context Recognition Accuracy score of 0.6742 indicates adequate contextual awareness capabilities, while the lower normalized scores in Precision and Recall (0.54688) suggest moderate classification reliability. However, the notably low normalized values in Accuracy (0.23077) and Battery Consumption (0.2185) represent significant limitations that could severely restrict the practical deployment of ExtraSensory in resource-constrained mobile environments despite its latency advantages.

3.3. Weight Assignment and Weighted Normalization

The weight assignment phase of the multi-criteria decision analysis employed a uniform weighting scheme wherein all five evaluation criteria were assigned equal importance, each receiving a weight of 0.20 as presented in Table 5. This egalitarian weighting approach was deliberately selected to maintain objectivity and avoid introducing subjective biases that could unduly favor certain criteria over others [19]. Such a neutral weighting strategy is particularly appropriate when there is insufficient prior justification for prioritizing specific performance metrics or when the goal is to achieve a balanced assessment that considers all evaluation dimensions equally important [20].

Table 5. Weight.

	C1	C2	C3	C4	C5
A1	0.20	0.20	0.20	0.20	0.20
A2	0.20	0.20	0.20	0.20	0.20
A3	0.20	0.20	0.20	0.20	0.20
A4	0.20	0.20	0.20	0.20	0.20
A5	0.20	0.20	0.20	0.20	0.20

The weighted normalized decision matrix presented in Table 6 was subsequently derived by multiplying the normalized performance scores with their respective criterion weights, yielding a comprehensive assessment that integrates both relative performance and criterion importance [21]. This weighted matrix provides a more nuanced and realistic representation of each alternative's overall performance, accounting for both the magnitude of performance differences and the relative significance of each evaluation dimension.

Table 6. Weighted Normalized Decision Matrix.

	C1	C2	C3	C4	C5
A1	0.16308	0.07500	0.07500	0.09333	0.17442
A2	0.13846	0.10938	0.20000	0.17067	0.11163
A3	0.07385	0.04688	0.10938	0.12800	0.20000
A4	0.20000	0.20000	0.14063	0.06400	0.08605
A5	0.04615	0.10938	0.04375	0.20000	0.13488

The weighted normalized matrix reveals distinct performance contributions from each alternative across the evaluation criteria. Alternative A1 demonstrated substantial contributions in Context Recognition Accuracy (0.17442) and Accuracy (0.16308), indicating that its primary strengths lie in these dimensions [22]. The moderate contributions in Latency (0.09333) and relatively lower contributions in Precision and Recall (0.07500) and Battery Consumption (0.07500) suggest areas where RADAR requires improvement to achieve more balanced performance across all evaluation criteria.

Alternative A2 exhibited its highest contribution in Battery Consumption (0.20000), achieving the maximum possible weighted score and confirming its exceptional energy efficiency superiority [23]. The substantial contribution in Latency (0.17067) further reinforces the framework's operational efficiency advantages, while the moderate contributions in Accuracy (0.13846) and Precision and Recall (0.10938) suggest acceptable but not outstanding classification capabilities. The comparatively lower contribution in Context Recognition Accuracy (0.11163) indicates that UbiqLog's primary strengths lie in operational efficiency rather than contextual awareness.

Alternative A3 demonstrated its maximum contribution in Context Recognition Accuracy (0.20000), achieving the highest possible weighted score and confirming its superiority in contextual awareness capabilities [24]. The substantial contribution in Latency (0.12800) indicates acceptable responsiveness, while the moderate contribution in Battery Consumption (0.10938) suggests adequate energy efficiency. However, the notably lower contributions in Accuracy (0.07385) and Precision and Recall (0.04688) represent significant classification limitations that substantially diminish the overall weighted performance of this framework.

Alternative A4 achieved perfect contributions in both

Accuracy (0.20000) and Precision and Recall (0.20000), confirming its exceptional classification capabilities that surpass all other frameworks [19]. The substantial contribution in Battery Consumption (0.14063) indicates good energy efficiency, while the comparatively lower contributions in Latency (0.06400) and Context Recognition Accuracy (0.08605) suggest potential limitations in responsiveness and contextual awareness that may reduce its suitability for applications requiring real-time processing or context-dependent adaptation.

Alternative A5 demonstrated its maximum contribution in Latency (0.20000), achieving the highest possible weighted score and confirming its exceptional responsiveness capabilities [17]. The moderate contribution in Context Recognition Accuracy (0.13488) suggests adequate contextual awareness, while the lower contributions in Precision and Recall (0.10938) indicate moderate classification reliability. However, the notably low contributions in Accuracy (0.04615) and Battery Consumption (0.04375) represent significant performance limitations that substantially reduce the overall weighted performance of ExtraSensory despite its latency advantages.

3.4. Preference Score Computation and Alternative Ranking

The preference scores presented in Table 7 were computed by aggregating the weighted normalized contributions across all evaluation criteria for each alternative, yielding a comprehensive overall performance indicator that facilitates direct comparison and ranking [15]. These scores represent the cumulative performance of each framework across all considered criteria, providing a holistic assessment that accounts for both relative strengths and weaknesses.

Table 7. Preference Score.

	Preference Score
A1	0.58083
A2	0.73013
A3	0.55810
A4	0.69067
A5	0.53416

Figure 2 presents the priority scores of the five evaluated alternatives (A1 to A5) in the form of a line graph, which provides a visual representation of their overall performance across multiple criteria. The horizontal axis corresponds to the alternatives, while the vertical axis represents their respective priority scores on a normalized scale from 0 to 0.8. The curve clearly shows that alternative A2 achieves the highest priority score (0.73013), followed by A4 (0.69067), indicating their best overall performance in the evaluation process. A1 also demonstrates a moderate level of performance with a score of 0.58083, while A3 (0.55810) and

A5 (0.53416) fall at the lower end of the spectrum. The graphical trend highlights the fluctuating performance pattern among the alternatives, which helps identify performance gaps and supports evidence-based decision-making in selecting the most appropriate technology for mobile and wearable computing environments.

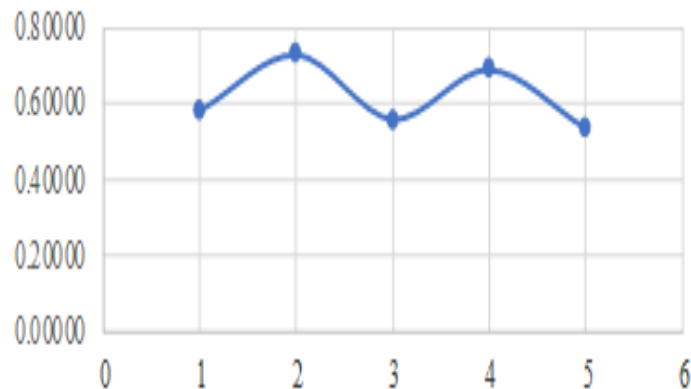


Fig. 2. Preference scores of five context recognition frameworks illustrating overall performance rankings.

The preference score analysis reveals a clear hierarchy of overall performance among the evaluated frameworks. Alternative A2 achieved the highest preference score of 0.73013, indicating its superior overall performance and establishing it as the most favorable option for mobile and wearable computing applications [13]. This remarkable achievement can be attributed to the framework's exceptional performance in Battery Consumption and Latency, combined with adequate performance in the remaining criteria, demonstrating a well-balanced profile that excels in operational efficiency while maintaining acceptable classification capabilities.

Alternative A4 secured the second-highest preference score of 0.69067, reflecting its outstanding classification capabilities in Accuracy and Precision and Recall that are complemented by good energy efficiency [17]. Despite some limitations in Latency and Context Recognition Accuracy, the framework's exceptional performance in the classification criteria substantially contributed to its strong overall ranking, suggesting that NetHealth would be particularly suitable for applications where prediction reliability is paramount, such as health monitoring and clinical decision support systems.

Alternative A1 attained a moderate preference score of 0.58083, indicating solid overall performance with particular strengths in Accuracy and Context Recognition Accuracy [21]. The framework's balanced performance across most criteria, combined with its strong contextual awareness capabilities, positions it as a viable option for applications requiring reliable context detection and general classification, though improvements in Precision and Recall and Battery Consumption would enhance its competitiveness.

Alternative A3 achieved a preference score of 0.55810, representing the second-lowest overall performance among

the evaluated frameworks [23]. Despite achieving the highest performance in Context Recognition Accuracy among all alternatives, the framework's substantial limitations in Accuracy and Precision and Recall significantly diminished its overall score, indicating that exceptional performance in one criterion cannot fully compensate for significant weaknesses in other critical dimensions. This finding underscores the importance of balanced performance across multiple criteria in mobile and wearable computing applications.

Alternative A5 recorded the lowest preference score of 0.53416, ranking fifth among the evaluated frameworks [24]. Despite demonstrating exceptional Latency performance and adequate Context Recognition Accuracy, the framework's significant limitations in Accuracy and Battery Consumption substantially reduced its overall performance, highlighting the critical importance of maintaining adequate performance across all evaluation criteria rather than excelling in a single dimension at the expense of others.

3.5. Ranking Analysis and Performance Implications

The final ranking of alternatives presented in Table 8 provides a clear hierarchical ordering that facilitates evidence-based decision-making for framework selection in mobile and wearable computing applications. These rankings are derived directly from the computed preference scores and reflect the comprehensive performance assessment across all evaluation criteria.

Table 8. Rank.

	Rank
A1	3
A2	1
A3	4
A4	2
A5	5

Figure 3 illustrates the final ranking of the five context recognition system alternatives, RADAR (A1), UbiqLog (A2), LOCATUS (A3), NetHealth (A4), and ExtraSensory (A5), based on their aggregated scores calculated using the Weighted Sum Model (WSM). The bar chart clearly shows that UbiqLog (A2) secured the top rank (1st position), indicating its overall superiority in balancing performance metrics such as accuracy, latency, and energy efficiency. NetHealth (A4) followed closely in second place, benefiting from its consistent performance across all evaluation parameters. RADAR (A1) achieved a moderate ranking (3rd place), while LOCATUS (A3) and ExtraSensory (A5) ranked fourth and fifth, respectively, primarily due to trade-offs in energy consumption and latency despite high accuracy. This ranking provides decision-makers with a clear visual summary of each alternative's relative performance,

supporting informed selection for implementation in real-world mobile and wearable computing environments.

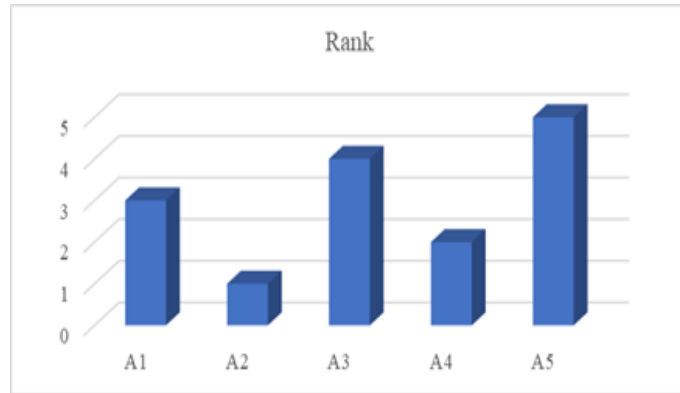


Fig. 3. Final ranking of context recognition frameworks based on Weighted Sum Model analysis.

The ranking analysis establishes a definitive performance hierarchy among the evaluated frameworks, with Alternative A2 securing the first position and confirming its status as the most suitable option for mobile and wearable computing applications. This top ranking can be attributed to the framework's exceptional performance in Battery Consumption and Latency, combined with adequate performance in the remaining criteria, demonstrating that balanced excellence across multiple dimensions yields superior overall performance [13]. The superior energy efficiency of UbiqLog is particularly significant given the resource-constrained nature of mobile and wearable devices, where battery life often represents a critical limiting factor for continuous sensing and processing applications.

Alternative A4 claimed the second position, reflecting its outstanding classification capabilities that are essential for applications requiring high prediction reliability, such as health monitoring, anomaly detection, and clinical decision support systems [14]. The framework's exceptional performance in Accuracy and Precision and Recall positions it as the preferred choice for scenarios where classification errors could have significant consequences, despite some limitations in responsiveness and contextual awareness that may require mitigation through optimization or complementary approaches.

Alternative A1 secured the third position, representing a moderate performance tier with particular strengths in contextual awareness and general accuracy [9]. The framework's balanced performance across most criteria, combined with its strong Context Recognition Accuracy, suggests that RADAR would be suitable for applications requiring reliable context detection and classification, particularly in scenarios where energy efficiency and response time are less critical than accurate context identification.

Alternative A3 achieved the fourth position, reflecting the significant impact of its classification limitations on

overall performance despite exceptional contextual awareness capabilities [7]. This finding highlights the importance of maintaining adequate performance across all evaluation criteria rather than specializing excessively in a single dimension, as the strengths of LOCATUS in Context Recognition Accuracy could not fully compensate for its substantial weaknesses in Accuracy and Precision and Recall.

Alternative A5 ranked fifth, representing the lowest overall performance among the evaluated frameworks [17]. Despite demonstrating exceptional Latency performance, the framework's significant limitations in Accuracy and Battery Consumption substantially constrained its overall effectiveness for mobile and wearable computing applications, confirming that superior performance in a single criterion cannot compensate for fundamental weaknesses in other critical dimensions.

4. CONCLUSION

A comparative analysis of alternatives A1 to A5 in the mobile and wearable computing sector reveals significant insights into their relative strengths and suitability. Based on the calculated preference scores and associated rankings, A2 emerged as the most optimal alternative, showing superior performance across multiple evaluation criteria. A4 showed strong potential, coming in second place with a competitive score. While A1 maintained a moderate position, alternatives A3 and A5 lagged behind in key areas, indicating the need for improvement. The visualization in Figure 1 effectively supports these findings by highlighting the variations in performance across criteria. Overall, this assessment provides a structured and data-driven foundation for decision makers to identify the most appropriate solution aligned with technical and operational requirements. Future studies could incorporate additional criteria or hybrid decision-making models to further refine the selection process.

DECLARATIONS

Ethical Approval

We affirm that this manuscript is an original work, has not been previously published, and is not currently under consideration for publication in any other journal or conference proceedings. All authors have reviewed and approved the manuscript, and the order of authorship has been mutually agreed upon.

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Conflicts of Interest

The authors declare that they have no financial or personal interests that could have influenced the research and findings presented in this paper. The authors alone are responsible for the content and writing of this article.

Authors' contributions

All authors contributed equally in the preparation of this manuscript.

REFERENCES

- [1] Ens, B., Grossman, T., Anderson, F., Matejka, J. and Fitzmaurice, G., **2015**. Candid interaction: Revealing hidden mobile and wearable computing activities. *Proceedings of the 28th Annual ACM Symposium on User Interface Software and Technology*, pp.467–476. <https://doi.org/10.1145/2807442.2807449>
- [2] Yfantidou, S., Constantinides, M., Spathis, D., Vakali, A., Quercia, D. and Kawsar, F., **2023**. Beyond accuracy: A critical review of fairness in machine learning for mobile and wearable computing. *arXiv preprint*, arXiv:2303.15585. <https://doi.org/10.48550/arXiv.2303.15585>
- [3] Morris, M.E. and Aguilera, A., **2012**. Mobile, social, and wearable computing and the evolution of psychological practice. *Professional Psychology: Research and Practice*, 43(6), p.622. <https://doi.org/10.1037/a0029041>
- [4] Jhajharia, S., Pal, S.K. and Verma, S., **2014**. Wearable computing and its application. *International Journal of Computer Science and Information Technologies*, 5(4), pp.5700–5704.
- [5] Starner, T., **1999**. Wearable computing and contextual awareness. *PhD dissertation, Massachusetts Institute of Technology*.
- [6] Lee, U., Han, K., Cho, H., Chung, K.M., Hong, H., Lee, S.J., Noh, Y., Park, S. and Carroll, J.M., **2019**. Intelligent positive computing with mobile, wearable, and IoT devices: Literature review and research directions. *Ad Hoc Networks*, 83, pp.8–24. <https://doi.org/10.1016/j.adhoc.2018.08.021>
- [7] Cheng, Z., Li, P., Wang, J. and Guo, S., **2015**. Just-in-time code offloading for wearable computing. *IEEE Transactions on Emerging Topics in Computing*, 3(1), pp.74–83. <https://doi.org/10.1109/TETC.2014.2387688>
- [8] Roggen, D., Magnenat, S., Waibel, M. and Tröster, G., **2011**. Designing and sharing activity recognition systems across platforms: Methods from wearable computing. *IEEE Robotics & Automation Magazine*, 12, pp.83–95. <https://doi.org/10.1109/MRA.2011.940992>
- [9] Dey, A.K., Salber, D., Abowd, G.D. and Futakawa, M., **1999**. The conference assistant: Combining context-awareness with wearable computing. *Proceedings of the Third International Symposium on Wearable Computers*, IEEE. pp.21–28. <https://doi.org/10.1109/ISWC.1999.806639>
- [10] Tao, L., Li, Z. and Wu, L., **2018**. Outlet: Outsourcing wearable computing to the ambient mobile computing edge. *IEEE Access*, 6, pp.18408–18419. <https://doi.org/10.1109/ACCESS.2018.2814215>
- [11] Amft, O., Lauffer, M., Ossevoort, S., Macaluso, F., Lukowicz, P. and Troster, G., **2004**. Design of the QBIC wearable computing platform. *Proceedings of the 15th IEEE International Conference on Application-Specific Systems, Architectures and Processors*, IEEE. pp.398–410. <https://doi.org/10.1109/ASAP.2004.1342488>
- [12] Taib, S.M., De Coster, R. and Nyamu, J., **2016**. Innovation diffusion of wearable mobile computing: Pervasive computing perspective. *Proceedings of the 2016 International Conference on Information Society (i-Society)*, IEEE. pp.97–101. <https://doi.org/10.1109/i-Society.2016.7854185>
- [13] Ometov, A., Chukhno, O., Chukhno, N., Nurmi, J. and Lohan, E.S., **2021**. When wearable technology meets computing in future networks: A road ahead. *Proceedings of the 18th ACM International Conference on Computing Frontiers*, pp.185–190. <https://doi.org/10.1145/3457388.3458614>
- [14] Rhodes, B.J., Minar, N. and Weaver, J., **1999**. Wearable computing meets ubiquitous computing: Reaping the best of both worlds. *Proceedings of the Third International Symposium on Wearable Computers*, IEEE. pp.141–149. <https://doi.org/10.1109/ISWC.1999.806695>
- [15] Starner, T.E., **2005**. Wearable computing for the developing world. *IEEE Pervasive Computing*, 4(3), pp.87–91. <https://doi.org/10.1109/MPRV.2005.71>
- [16] Gong, J., Yan, J. and Li, D., **2019**. Comparison of micro-Doppler signatures registered using RBM of helicopters and WSM of vehicles. *IET Radar, Sonar & Navigation*, 13(11), pp.1951–1955. <https://doi.org/10.1049/iet-rsn.2019.0210>
- [17] Riazanoff, S. and Gross, K., **2013**. Enhancing Envisat ASAR WSM segments to detect oil spills in the

- framework of the ‘20 years of oil routes’ project. *Proceedings of the Conference Edinburgh United Kingdom ESA SP*, p.229.
- [18] Rafi-Ul-Islam, S.M., Siu, Z.B. and Jalil, M.B.A., **2020**. Topoelectrical circuit realization of a Weyl semimetal heterojunction. *Communications Physics*, 3(1), p.72. <https://doi.org/10.1038/s42005-020-0336-0>
- [19] Salerno, A., Margolies, P., Cleek, A., Pollock, M., Gopalan, G. and Jackson, C., **2011**. Best practices: Wellness self-management—An adaptation of the illness management and recovery program in New York State. *Psychiatric Services*, 62(5), pp.456–458. https://doi.org/10.1176/ps.62.5.pss6205_0456
- [20] Massad, L.S., Xie, X., Minkoff, H., Darragh, T.M., D’Souza, G., Sanchez-Keeland, L., Watts, D.H., Colie, C. and Strickler, H.D., **2014**. Abnormal pap tests and human papillomavirus infections among HIV-infected and uninfected women who have sex with women. *Journal of Lower Genital Tract Disease*, 18(1), pp.50–56. <https://doi.org/10.1097/LGT.0b013e3182942733>
- [21] Yan, Y., Fu, P., Jing, B., Peng, C., Boreddy, S.K.R., Yang, F., Wei, L., Sun, Y., Wang, Z. and Ge, M., **2017**. Hygroscopic behavior of water-soluble matter in marine aerosols over the East China Sea. *Science of the Total Environment*, 578, pp.307–316. <https://doi.org/10.1016/j.scitotenv.2016.10.149>
- [22] Reddy, V.R., Saharawat, Y.S. and George, B., **2017**. Watershed management in South Asia: A synoptic review. *Journal of Hydrology*, 551, pp.4–13. <https://doi.org/10.1016/j.jhydrol.2017.05.043>
- [23] Jia, G.Y., Huang, Z.X., Ma, Q.Y. and Li, G., **2020**. Photonic spin Hall effect on the surfaces of type-I and type-II Weyl semimetals. *Nanophotonics*, 9(3), pp.715–723. <https://doi.org/10.1515/nanoph-2019-0468>
- [24] Rodiles-Guerrero, L., Pareja-Blanco, F. and León-Prados, J.A., **2022**. Comparison of load-velocity relationships in two bench press variations: Weight stack machine vs Smith machine. *Sports Biomechanics*, 21(10), pp.1147–1159. <https://doi.org/10.1080/14763141.2020.1735499>