

Review and Content Analysis of Mobile Applications for Heart Rate Variability

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Submitted to: JMIR Cardio
on: September 25, 2025

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Review and Content Analysis of Mobile Applications for Heart Rate Variability

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Abstract

Background: Heart rate variability (HRV) is increasingly used in health and performance monitoring, though research on its practical applications and the accuracy and validity of these apps remains limited.

Objective: This study aims to systematically review and analyse the mobile applications that measure, analyse and provide feedback on HRV.

Methods: This study was a cross-sectional review of mobile applications for HRV measurement. A systematic search was conducted in the Google Play Store and Apple iTunes Store between October and November 2024. Data were extracted from app descriptions, screenshots, linked websites, and direct communication with developers.

Results: The search yielded 746 smartphone apps, with 231 meeting the eligibility criteria. Most HRV apps originated from the iTunes App Store (74.0%). While 38.3% of app information was publicly available in the app description or website, 46.7% was unobtainable. Most apps (87.0%) reported sensor location, including arm, chest, ear, finger and wrist, and 97.0% reported data storage methods. The majority (67.5%) were free with in-app purchases, and photoplethysmography (PPG) was the most common measurement method (61.5%). For only 71 apps complete data was extractable, of which 61 were unique apps without between-store duplicates. Many of these 61 apps used PPG sensors (39.3%) and time-domain HRV metrics like RMSSD (63.9%) and SDNN (60.7%), with most requiring user-triggered measurements and about 35% supporting continuous monitoring. A majority of apps offered personalized HRV reference scores (65.6%), self-reported stressor tracking (55.7%), and contextual insights or guidance like recovery and readiness scores (73.7%).

Conclusions: This study highlights the widespread availability but limited transparency and evidence base of heart rate variability apps, underscoring the need for improved data accessibility, measurement validation, and consistency across platforms to enhance their reliability and value for both users and researchers.

(JMIR Preprints 25/09/2025:84764)

DOI: <https://doi.org/10.2196/preprints.84764>

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Original Manuscript

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Conclusions: This study highlights the widespread availability but limited transparency and evidence base of heart rate variability apps, underscoring the need for improved data accessibility, measurement validation, and consistency across platforms to enhance their reliability and value for both users and researchers.

Keywords:

Smartphone applications, heart rate variability, apps, wearables

Introduction

Heart rate variability (HRV) is the variation in time intervals between consecutive heartbeats^{1,2}. This metric is a non-invasive indicator of autonomic nervous system activity, reflecting the balance between the sympathetic (fight-or-flight) and parasympathetic (rest-and-digest) branches^{1,2}. Generally, higher HRV is associated with greater parasympathetic influence, indicating effective recovery, adaptability, and overall cardiovascular health³⁻⁵. Conversely, lower HRV is often linked to increased sympathetic activity, which may result from physical stress, intense training, illness, or other physiological and psychological factors³⁻⁵. HRV metrics have been shown to correlate with a range of health outcomes, including cardiovascular fitness, stress levels, and overall well-being³⁻⁵.

The gold standard for measurement of HRV is an electrocardiogram (ECG), with traditional assessment protocols ranging from 5 minutes to 24 hours. Many smartphone apps now utilize photoplethysmography (PPG) technology to estimate HRV, by detecting changes in blood volume associated with each heartbeat, using light reflected from the skin via smartphone cameras or wearable sensors¹³. This enables an estimate of HRV through the pulse rate waveform. This a non-invasive, cost-effective, and accessible alternative to ECG, making it suitable for non-laboratory environments¹⁴. Recent advances, including the transition from single- to multi-wavelength LEDs¹⁵, and enhanced signal processing¹⁶ mean that PPG-based measures of HRV show reasonable accuracy compared to ECG¹⁴. Most smartphone apps and wearable devices have adopted (ultra)short recordings for measurement, typically under one minute, to increase usability in everyday settings.

This has led to the development of numerous mobile applications that use HRV measures to provide users with feedback and guidance related to health, stress, and performance, often through a smartphone or wearable device interface¹⁷, even though the evidence base underpinning such guidance is still evolving. This gap between research and practice raises questions about the validity of insights offered by these applications.

There is limited research evaluating these HRV apps, as well as the scientific validity of any advice they provide¹⁸. This is particularly concerning, as users may rely on these tools for health and performance monitoring without clear evidence supporting their utility and guidance.

To address this gap, the aim of this study is to review HRV smartphone applications and provide a content analysis of these applications.

Methods

Study design and search

The reporting of this study follows the Quality and Risk of Bias Checklist for Studies That Review Smartphone Applications¹⁹. A systematic search of HRV apps was conducted in the Google Play Store and iTunes App Store between October and November 2024²⁰. These account for approximately 99.3% of smartphone operating systems²¹. This was followed by a content analysis. Both initial searches were conducted in the Netherlands using the search terms “Heart Rate Variability” and HRV. App stores were searched through both a smartphone application and a web-based store.

Selection criteria

Apps were eligible for inclusion if their primary purpose was to measure or monitor HRV and were designed for consumer use. Apps had to be available in English, Dutch, or German, using either smartphone-based PPG for HRV or wearable device-measured HRV.

Apps were excluded if their primary purpose was not related to measuring or monitoring HRV (e.g. if they measured only heart rate), or if they were no longer accessible during data extraction. Additionally, apps were excluded if they focused on non-human subjects. One reviewer screened all identified applications for eligibility based on these criteria. For the content analysis, the duplicates between stores were taken together.

Data extraction

Data were extracted from the information provided on the app store, privacy statement and app website where relevant. When details were not available or unclear, developers were contacted via email with a request to provide information. If there was no response, a second email was sent at least one month later. If the second email also went unanswered, the data remained unavailable. Applications were downloaded only when providers instructed us to do so. Data extraction was started in the Netherlands but later transitioned to Ireland.

Application information included the app name, developer, release year, cost/payment model, and platform (iOS/android). Information was also collected on HRV measurement including the type of sensor used (camera/PPG, chest strap, wearable smart watch etc.), duration and frequency of measurement (e.g. on-demand/user prompted, continuous or periodic), reference ranges (present or not, based on what timeframe), metrics used (time domain; e.g. RMSSD, SDNN, or frequency domain; LF/HF ratio, pNN50 etc.), and additional features like the option to add self-reported stressors (e.g. stressful events, caffeine intake, comments), reminders, and whether or not scientific evidence underpinned the information or methods. Furthermore, information related to the feedback provided, such as training advice, stress scores, recovery guidance, or recommendations on how to improve HRV, was recorded, including the algorithms used to provide these metrics if provided. Data was extracted on whether the applications cite peer review validation of the methods/feedback provided. Finally, data privacy and security information were recorded, including data sharing, data export and data storage methods. A full list of extraction parameters and their descriptions can be found in the supplementary appendix.

Quality of information provided, and privacy and security

To evaluate the information provided to users' credibility criteria were developed from published information on the appraisal of traditional medical literature²²; authorship, attribution, disclosure, and currency. The disclosure criteria were left out however, a criteria on privacy and security was added. Authorship examined ownership, creators, contributors, and developers, considering professional affiliations, academic credentials, and other relevant expertise. Attribution assessed whether the app or website cited scientific references to support its content. Currency of information verified the date of the most recent update for the app.

Privacy and security information was extracted based on the type of personal data collected and how it was processed or stored. Information was extracted from both app stores, each of which uses its classification system. From the Google Play Store, apps were categorized based on whether data was only processed locally without being stored, or whether it was encrypted in transit. From the iTunes App Store data handling was categorized as one of the following: no data was stored only processed locally, data was collected but was not linked to the user's identity, data was collected and linked to identifiable users, or data was used to track users across other platforms (apps and websites).

Results

App selection

The initial search resulted in a total of 746 smartphone applications, of which 41 were within-store duplicates. Following eligibility screening, 231 apps were included for initial data extraction (Figure 1). Of these, complete data was extracted from 71 apps, of which there were 61 unique applications due to between store duplicates.

Metadata on all applications and missing data

Among the 231, 74.0% originated from the Apple iTunes Store, while 26.0% were from the Google Play Store. This indicates that more apps originate from Apple than from Google. In total 38.3% of data was found on the website or in the app descriptions, 15.0% was provided by providers via email and 46.7% of data was not provided at all.

An overview of the key characteristics of the 231 applications is displayed in Figure 2. Of the 231 apps, 201 (87.0%) had information regarding the sensor location and 224 (97.0%) described the data storage method. However, information on the ability to add reminders (n=85), and information on the

ability to add self-reported stressors ($n=85$) was less frequently available, which might be because the app did not support these functionalities. 67.5% were free with in-app purchases available. An additional 24.2% were free. The apps supported various devices. Most apps (61.5%) utilized photoplethysmography (PPG) via phone camera or wearable for measurements, while approximately 20.8% offered compatibility with different sensors using either PPG or electrocardiogram (ECG). A smaller portion (14.7%) relied solely on ECG wearables. Figure 2 presents an overview of these key characteristics of the included apps.

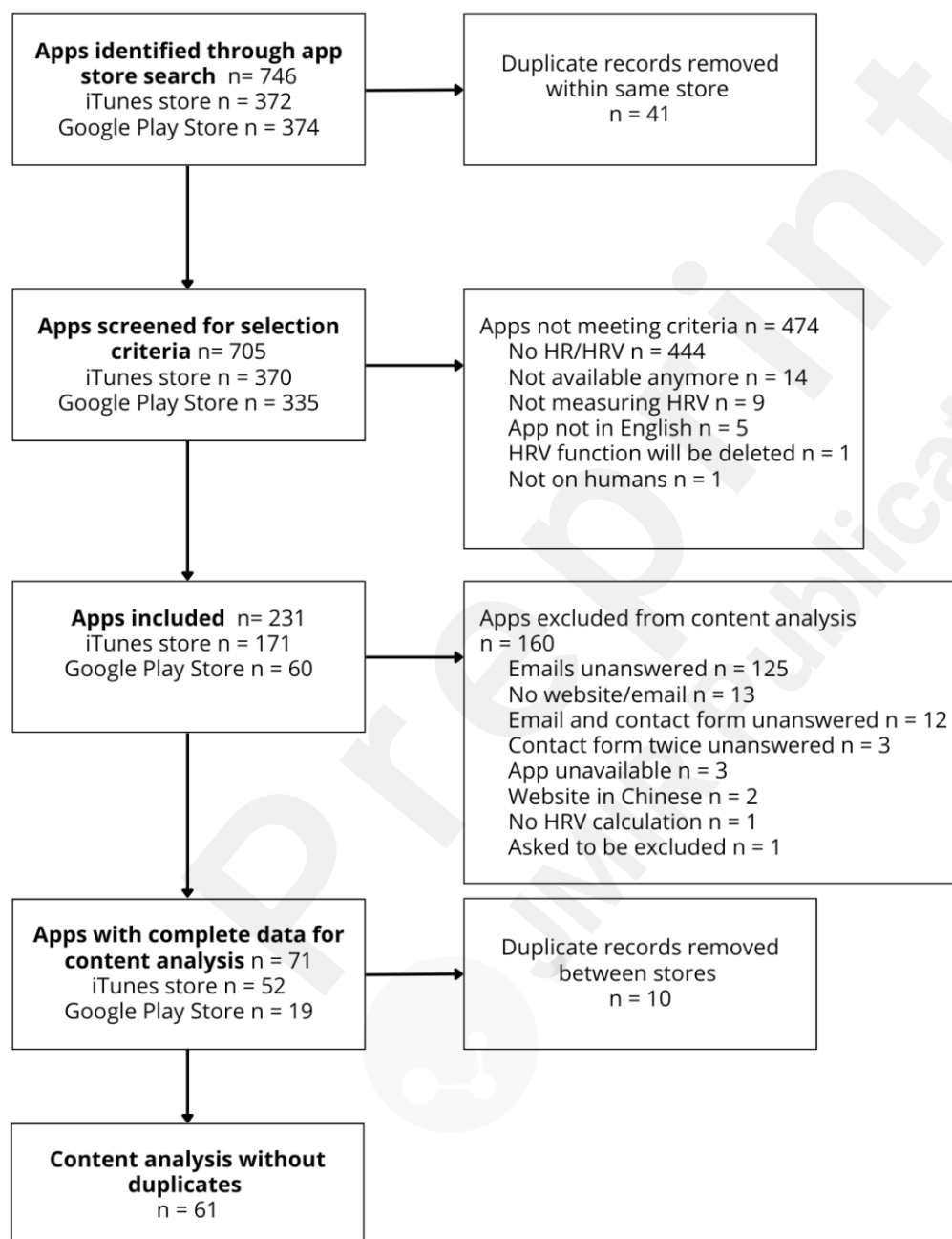


Figure 1: Workflow of the study process

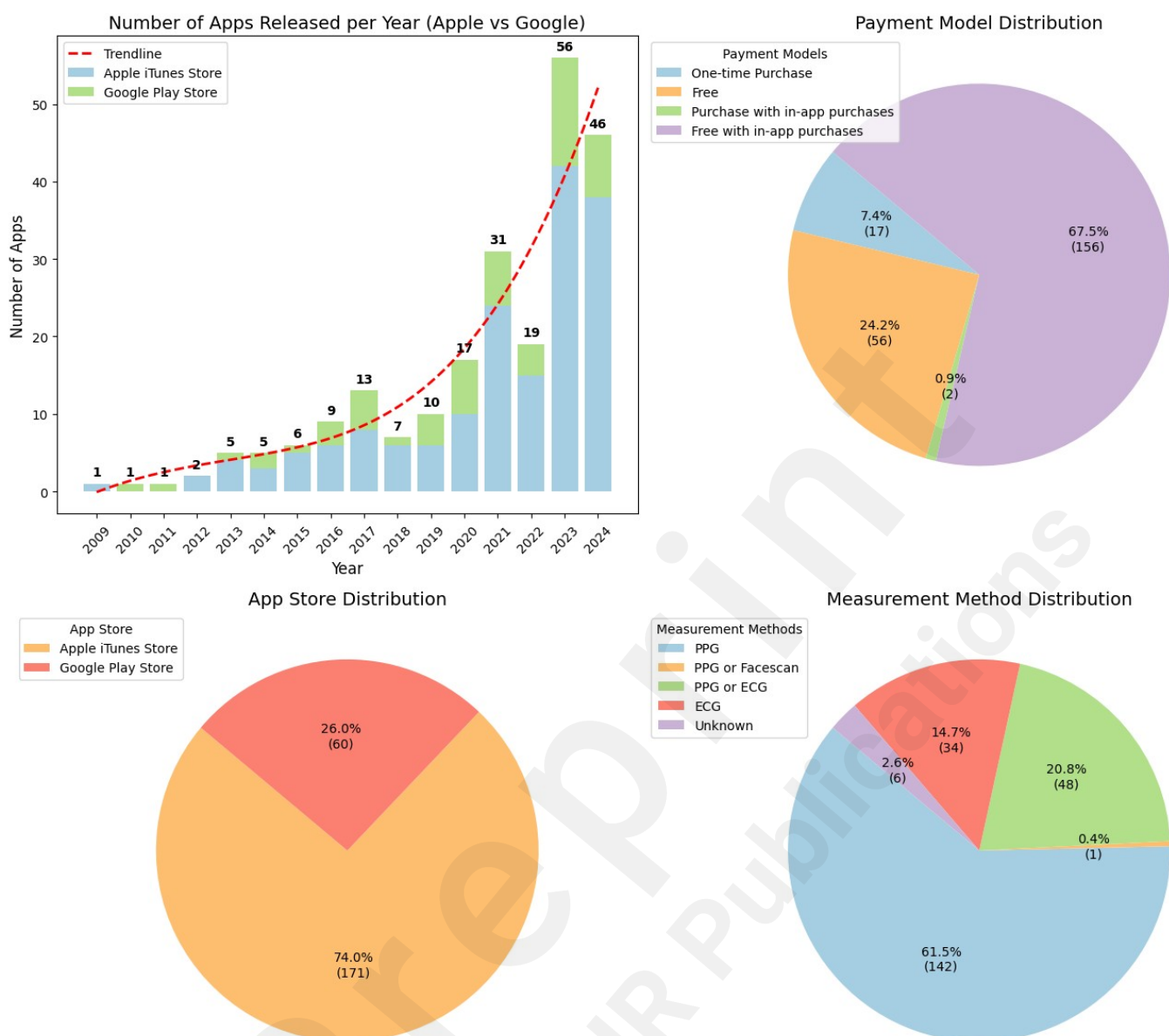


Figure 2. Key characteristics of all the unique smartphone applications (n=231) I. Bar chart of the number of apps released per year. An exponential trendline is plotted. The release date of two apps was unknown II. Distribution of the different payment models III. Distribution of the App Stores IV. Distribution of measurement methods. PPG = photoplethysmography, ECG = electrocardiography

Content of applications with complete extracted data

Of the 231 apps, complete data was successfully extracted for only 71 apps. Of these 71, there were 61 unique apps, with the rest being the same app identified on both stores (Figure 1). These 61 apps form the basis of the following reporting. Of the extracted data, 52.0% of the information was obtained from the app descriptions, in the app stores, or linked app websites, while the remaining 48.0% was collected via email. The summary findings are presented in Table 2.

HRV Measurement

In content analysis (n=61), PPG was the predominant sensor used for HRV measurement, with 39.3% of the apps using PPG from watches, smartphone cameras, or PPG devices placed on the finger or ear (Table 3 tabulates the sensor location by sensor type). 50.8% were free with in-app purchases, with 27.9% being free, and the remaining requiring payment, with or without in-app purchases. Most apps used multiple metrics to measured HRV, the majority used time-domain

metrics for reporting HRV scores like the root mean square of successive differences (RMSSD) (63.9%), the standard deviation of NN intervals (SDNN)(60.7%) or the percentage of adjacent NN intervals (pnn50)(23.0%), while others used time-domain metrics and frequency-domain metrics such as high frequency (HF) power (27.9%), low frequency (LF) power (27.9%), or the ratio between these two (LF/HF ratio)(18.0%). Most measurements were user-triggered, with the largest portion needing to be completed first thing in the morning (Figure 3). Continuous measurements (24 hours or overnight) (Figure 3) accounted for around 35%. Figure 4 shows the number of apps using ultra-short measurements (<5 minutes), short-term measurements (~5 minutes) and long-term measurements (>5 minutes) ²³.

Most apps (65.6%) provided HRV relative to a reference range or personalized baseline range, calculated as a range over a period of 7 days to multiple months. Over half allowed users to log self-reported stressors. Scientific references were cited in most cases, though some apps made unsupported claims. The majority provided contextual HRV insights, guidance, or additional metrics like recovery or readiness scores (Figure 5). Most apps support data export, with some offering it upon request or suggesting to export via Apple Health. Data storage practices varied, some apps stored no data, while others encrypted it, stored it anonymously, linked it to user identity, or a combination of these for different types of data.

Table 2. Results of content analysis of apps measuring HRV directly or with wearable devices (n=61)

Characteristics	Value, n (%)
Sensor type	
Wearable PPG sensor (e.g. watch/fitness trackers)	21 (34.4)
Bluetooth ECG HRM	16 (26.2)
Phone camera PPG	3 (4.9)
Multiple sensors possible	21 (34.4)
Year of app release*	
2010	1 (1.4)
2012	1 (1.4)
2013	4 (5.6)
2014	5 (7.0)
2015	3 (4.2)
2016	7 (9.9)
2017	5 (7.0)
2018	4 (5.6)
2019	4 (5.6)
2020	9 (12.7)
2021	7 (9.9)
2022	3 (4.2)
2023	11 (15.5)
2024	7 (9.9)
Payment model	
Free	17 (27.9)
Free with in-app purchases	31 (50.8)
Payment	11 (18.0)
Payment with in-app purchases	2 (3.3)
Third-party service used*	
Yes	34 (47.9)
No	35 (49.3)
Depending on the sensor used	2 (2.8)
Sensor location	
Arm	2 (3.3)

Chest	15 (24.6)
Ear	2 (3.3)
Finger	6 (9.8)
Wrist	14 (23.0)
Multi-site	22 (36.1)
HRV Baseline/ Reference range provided	
Yes	40 (65.6)
No	21 (34.4)
HRV metrics reported/displayed to users	
Coherence score	2 (3.3)
Frequency domain metrics	1 (1.6)
Time domain metrics	33 (54.1)
Frequency and time domain metrics	20 (32.8)
Frequency domain and non-linear measurements	1 (1.6)
Time and frequency domain, and non-linear measurements	2 (3.3)
Heart rate trace	2 (3.3)
User-logged self-reported stressors available	
Yes	34 (55.7)
No	27 (44.3)
Scheduled HRV Reminders Supported	
Yes	22 (36.1)
No	25 (41.0)
NA (continuously measured)	14 (23.0)
Capability for data export	
Yes	37 (60.7)
No	11 (18.0)
On request	6 (9.8)
Via the Apple Health application	7 (11.5)
Data storage*	
Data not collected	21 (29.6)
Data collected but not linked to your identity	9 (12.7)
Data collected and linked to your identity	6 (8.5)
Collection of both identifiable and non-identifiable data	10 (14.1)
Data collected but is encrypted in transit	15 (21.1)
Cross-application tracking permitted; identifiable data may be collected	1 (1.4)
Cross-application tracking permitted; non-identifiable data may be collected	4 (5.6)
Cross-application tracking permitted; identifiable and non-identifiable data may be collected	4 (5.6)
Information not provided	1 (1.4)

ECG = electrocardiogram, HRM = heart rate monitor, * duplicates between store were included n=71

Table 3. Cross table showing the sensor used and the sensor location (n=61).

		Arm	Chest	Ear	Finger	Wrist	Multiple sites
Wearable sensor	PPG	2		2	3	14	
Bluetooth HRM	ECG		13				3
Phone PPG	camera				3		
Multiple sensors			2				19

possible

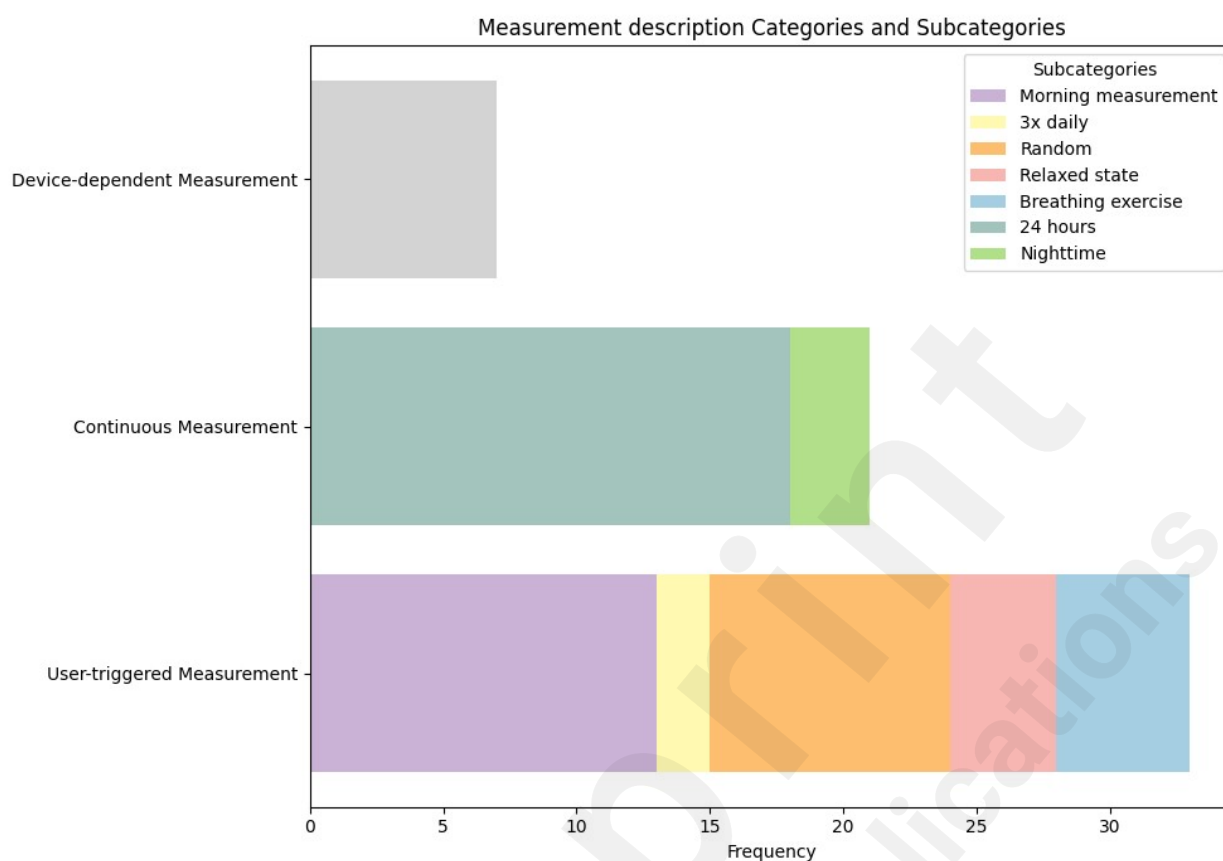


Figure 3. A stacked bar chart showing the frequency of different timing and conditions of measurement (n = 61). Device-dependent indicates that the app collected data from different devices and measurement was dependent on the device rather than the application.

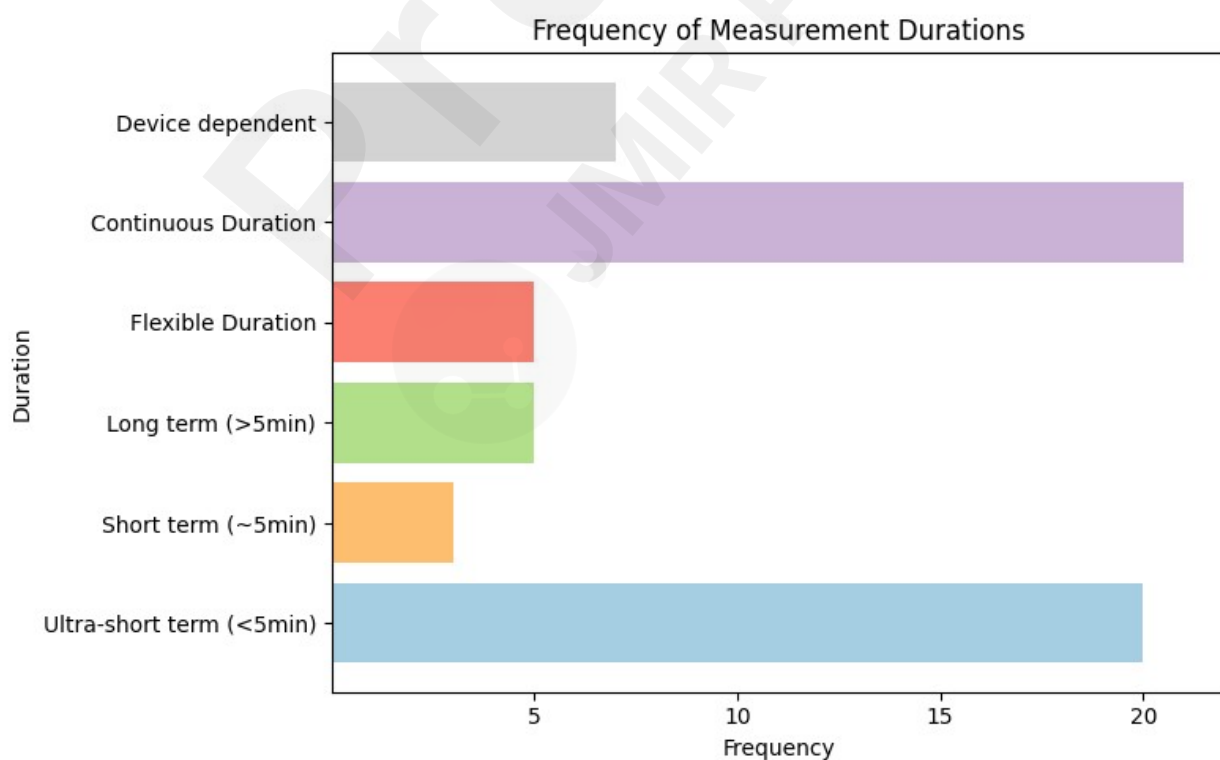


Figure 4. Measurement duration for measuring heart rate variability (n = 61). Device dependent indicates that the app

collected data from different devices and measurement was dependent on the device rather than the application.

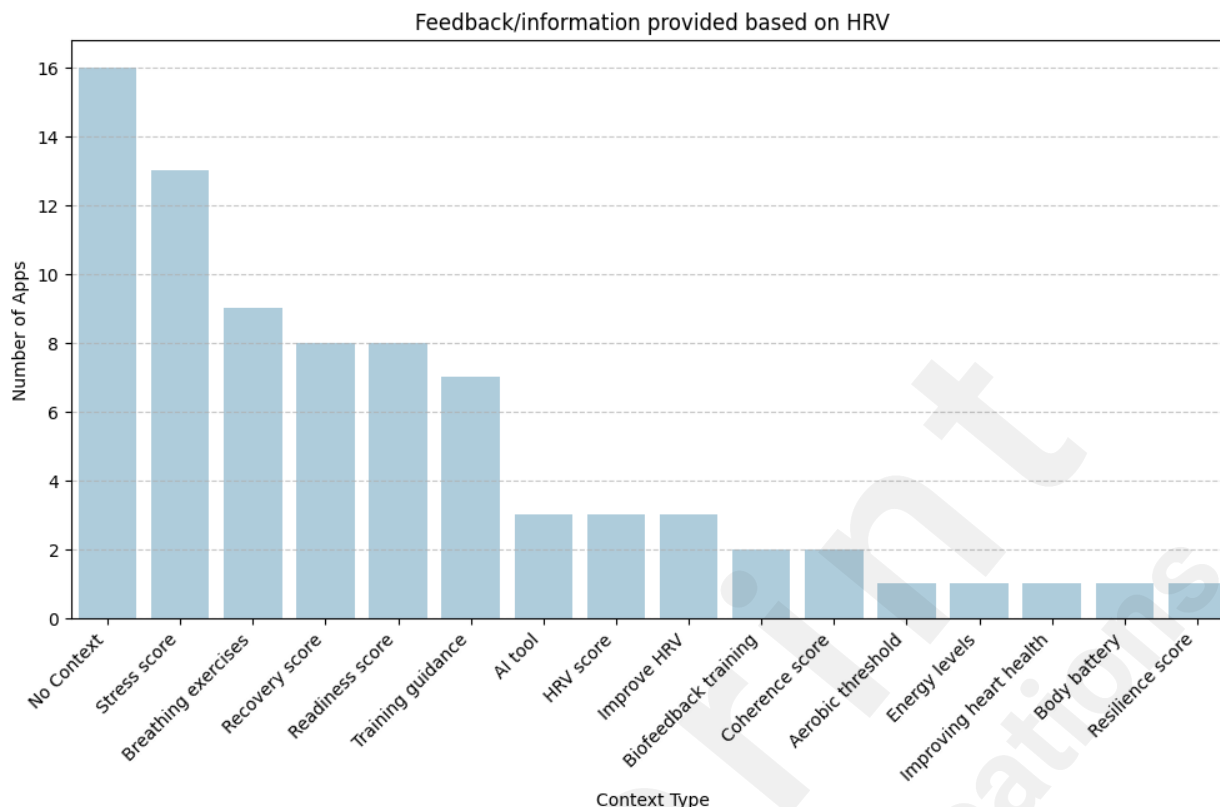


Figure 5. Feedback and information provided by HRV apps after measurement. Apps could offer multiple types of feedback (e.g. stress score, recovery guidance) (n = 61).

Quality assessment

For the quality assessment, the between-store duplicates were included because the last updated year, as well as privacy and security information for the application, differed between the Google Play Store and iTunes App Store versions. This resulted in a total of 71 different applications. A clear statement of authorship was provided by 38.0% of apps (27/71), while 66.2% cited peer-reviewed scientific evidence to support their use/information. In terms of currency of information, the majority (77.5%) were updated within the past two years.

Privacy and security of personal data were categorized into different levels provided by the app stores, with 21 apps (29.6%) classified as no data was collected only processed, 17 apps (23.9%) classified as data is collected but not linked to you, 16 apps (22.5%) classified as data is collected and linked to your identity, 14 apps (19.7%) classified as personal info may be collected but is encrypted in transit, 2 apps (2.8%) classified as data may be used to track you across other devices, and one app did not provide any details on privacy and security. The full results of this quality assessment are available in the Supplementary Appendix.

Discussion

This study aimed to assess mobile applications for HRV to provide an overview of how HRV is measured, how results and feedback are used (e.g. for feedback on stress or recovery), and whether apps report scientific evidence underlying these functions. The credibility of the information provided by apps and the data management and privacy practices of applications were also assessed. There was a steady increase in HRV-related app releases over time, with over two hundred now available. However, the majority of these lacked transparency regarding how HRV was measured, and the scientific evidence supporting the feedback they provided or the claims they made about their utility. Ultimately, complete data was successfully extracted from only 26% of available apps and was included in the content analysis. Only one app (Elite HRV: Wellness & Fitness), provided all

the necessary information in its app description and website, due to a user chat function. For all other apps, the information was acquired by direct contact with developers. Among the 61 apps analysed, two-thirds referenced scientific literature to support their methodology, often citing peer-reviewed studies on HRV measurement on their website. Several apps that rely on brand-specific sensors reported validation and demonstrated accuracy when compared to ECG-based measurements²⁴⁻²⁷. The root mean square of successive differences (RMSSD) is the most frequently used HRV metric in both the scientific literature²⁸ and in these apps (represented in 39/61 apps; 63.9%). RMSSD captures beat-to-beat variance and is primarily associated with parasympathetic tone²⁹. It is well validated for short-term, resting recordings³⁰ and is relatively simple to calculate¹⁷. The second most common metric was the standard deviation of NN intervals (SDNN) (37/61; 60.7%), SDNN reflects the ebb and flow of all factors that contribute to heart rate variability²⁹. This number of apps using SDNN was largely due to its default use in Apple Watch-based applications. Apple Watch validation studies primarily use its Breath app or Sleep Watch app to manually trigger a controlled HRV measurement, while HRV values obtained automatically from random daily measurements remain unvalidated³¹⁻³³. This raises questions about feedback based on Apple Watch HRV data collected outside the Breath or Sleep applications, as it is not known what measurement approach the applications use.

Different HRV metrics reflect distinct physiological processes and measurement approaches. Time-domain measures like RMSSD and SDNN are common in consumer apps, however, also frequency-domain and non-linear measures are prevalent. RMSSD is often preferred in PPG-based applications because it is less sensitive to respiration and artefact than other measures, making it particularly suitable for short, resting measurements^{23,30}.

Most apps use PPG to estimate HRV. Numerous studies support the validity of PPG-derived HRV under controlled conditions^{14,34,35}. In addition, some smartphone apps that use PPG via phone camera have undergone scientific validation for HRV measurements^{18,36}. Several studies report good agreement between PPG-derived pulse rate variability and ECG-derived HRV during rest or sleep, particularly in healthy young adults. However, results are less consistent in active, real-world conditions¹⁴, where motion and other uncontrolled conditions can reduce measurement accuracy. To address this, 32% of the apps included in this review implemented some form of standardization to improve reliability. This included measurements during sleep without distractions (n = 3), or during resting conditions (n = 17).

The accuracy of HRV is influenced by body position and external factors during recording^{37,38}. Wearable devices tend to underestimate HRV values when compared to ECG, the gold standard^{31,33}, and HRV values are not interchangeable across different postures. Although nighttime HRV measurements are typically recorded in a lying position (5%), only a small proportion of other apps (11%) reference specific posture requirements. This raises concerns about the validity of measurements from apps that lack such guidance. Without standardized protocols for recording posture, timing, and context, comparisons or interpretations of these values become problematic.

Many apps generated unvalidated proprietary scores such as body battery, coherence score, readiness or stress scores, the scientific evidence underpinning these remains limited. These composite scores (readiness, stress, and recovery) often integrate additional data such as resting heart rate, respiration rate, and user-reported stress. The underlying algorithms often remain proprietary, and the validity of the resulting health claims or insights is not always supported by established evidence³⁹.

The study revealed that, despite identifying 231 HRV apps, only 38.3% of all information was found on the website or in the app descriptions, highlighting a widespread lack of transparency. Additionally, only four apps received full scores across critical categories for quality assessment like Authorship, Attribution, Currency, and Privacy and Security. These factors are crucial for evaluating app credibility, both in the measurement methodologies they employ and in the scientific evidence supporting their claims.

Implications and limitations

One limitation of this study is that it captures the app landscape at a specific point in time. Given the changing market, some findings may become outdated. This accounts for apps identified in the initial search but which could not be located at the time of data extraction. The study was conducted in two geographic locations in Europe which may influence findings. Although the US app stores were used in both locations to ensure consistency, this shift may have affected app availability.

During data extraction, some apps were identified in only one app store search despite existing in both stores. This raises questions about app store algorithms and the visibility of applications. This may influence the discoverability and the comprehensiveness of the search. This situation is comparable to the rationale for searching multiple research databases, to mitigate bias and ensure complete coverage.

Another limitation is the language. By including only apps available in English, Dutch, or German, we may have excluded relevant applications designed for users in other regions, such as those using Chinese or Spanish-language platforms.

Conclusion

This study found over 230 apps for HRV measurement and monitoring, reflecting growing consumer interest in tools related to cardiovascular health and self-monitoring. However, most apps lack transparency regarding their measurement methods and supporting evidence, limiting their credibility and utility. Among those that do provide such details, there is considerable heterogeneity in measurement approaches, supported devices, data aggregation, and the nature of feedback provided. Notably, many apps generate proprietary scores that are not scientifically validated, raising concerns about the accuracy of cardiovascular risk interpretation and potential misguidance for users. Future studies should focus on evaluating the clinical relevance of HRV-derived feedback. Additionally, the development of standardized frameworks for app reporting, functionality and validation processes is critical to improve consistency, transparency, and integration of HRV apps into cardiovascular research and digital health practices.

Funding

No external financial support or grants were received.

Conflicts of interest

All authors declare no financial or non-financial competing interests.

Data availability

The data generated or analysed during this study are included in this published article and its supplementary information files.

Author contributions

Authors EDJ, BC, EA, and SH designed the study. Author EDJ did the app search and extracted the data. EDJ, BC, EA, and SH were all involved in the data analysis. EDJ wrote the first draft of the manuscript. All authors were involved in the interpretation of the data and approved the final version of the manuscript before journal submission.

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Supplementary Files

Multimedia Appendixes

Feature description for data extraction.

URL: <http://asset.jmir.pub/assets/5870fb43346c28deea942bcac96f8f39.docx>

Quality assessment table: results from the quality assessment.

URL: <http://asset.jmir.pub/assets/0d3258dd788cd2e9f77660d8aabda4fc.docx>

Full data set used in the study.

URL: <http://asset.jmir.pub/assets/ad1dd3ec98b4b69fd4b0dae4f436e099.xlsx>