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THE RELIABILITY OF COMMERCIAL WEARABLE BIOSENSORS IN MONITORING TRAINING LOAD AND RECOVERY IN RUNNERS: A REVIEW OF CURRENT EVIDENCE

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ABSTRACT

Introduction: Wearable devices have become increasingly popular among runners for monitoring physiological and training-related parameters, including heart rate (HR), heart rate variability (HRV), resting heart rate, sleep, and training load. However, the reliability and practical interpretation of commercially derived metrics remain important considerations.
Objective: This review aims to evaluate the reliability and practical utility of commercial wearable biosensors for monitoring training load, recovery, and potential signs of overreaching in runners. A secondary aim was to compare scientific evidence with information provided by device manufacturers and the way wearable-derived metrics are presented in popular online content.
Methods: A review of scientific literature indexed in PubMed between 2016 and 2026 was conducted using keywords related to wearable technology, physiological monitoring, running, training load, overtraining, and endurance performance. Scientific evidence was considered alongside information provided on the official websites of selected wearable manufacturers and publicly available content from popular science sources and social media platforms, including YouTube, Instagram, and TikTok. Particular attention was given to the reliability of optical measurements, HR and HRV monitoring, and commercially derived training and recovery metrics.
Results: The reviewed evidence indicates that commercial wearable devices can provide useful information for monitoring physiological responses to exercise and changes in training load. However, measurement accuracy varies according to the device, measurement method, and conditions of use. Commercial algorithms and derived metrics should therefore be interpreted cautiously, as they may not fully account for individual and contextual factors such as sleep, psychological stress, illness, or other sources of fatigue. The available evidence supports the use of wearable-derived data as an adjunct to, rather than a replacement for, subjective assessment of fatigue and recovery.
Conclusions: Commercial wearable biosensors represent a useful and accessible tool for monitoring training load and recovery in runners. Their measurements and proprietary metrics should not be interpreted in isolation or regarded as diagnostic indicators of overreaching or overtraining. A comprehensive approach combining wearable-derived data with training history, subjective symptoms, sleep, recovery, and individual context may provide a more appropriate basis for training decisions and injury prevention.

KEYWORDS

Wearable Technology, Biosensors, Heart Rate Variability, Heart Rate, Training Load, Recovery, Overreaching, Runners

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1. Introduction

1.1. The Popularity of Running Among Physically Active People

Running is one of the most accessible and widely practiced forms of physical activity due to its relatively low cost and minimal equipment requirements. It can be undertaken for recreational, competitive, social, and health-related purposes, while positive affective experiences may also represent an important motivation for participation [1]. Despite its numerous health benefits, regular running is also associated with a risk of overuse injuries, particularly when training load is increased excessively or recovery is insufficient [2, 3]. Consequently, appropriate monitoring of training load and recovery has become an important component of contemporary running practice.

1.2. Training Load and Injury Risk Among Runners

Running-related injuries are predominantly overuse injuries and may be influenced by previous injury history, demographic and anthropometric characteristics, biomechanical factors, and training-related variables [2, 3]. In particular, excessive training loads and abrupt increases in running exposure may contribute to an increased risk of injury [3]. Trail runners may additionally be exposed to factors associated with variable terrain and elevation gain, which further increase the complexity of training-load management [4].

The relationship between training load and injury risk is complex and influenced by multiple individual and contextual factors. Therefore, monitoring training volume, frequency, intensity, and physiological responses may provide useful information for adjusting training and recovery strategies. However, no single metric can fully characterize an athlete's physiological state or independently predict injury or overtraining.

1.3. Training Load, Recovery, and Overreaching

Appropriate progression of training load is essential for improving endurance performance, while adequate recovery is necessary to facilitate adaptation to training [5, 6]. High-intensity training can effectively improve endurance performance, but its physiological demands also emphasize the importance of appropriate recovery and monitoring of the athlete's response to training [6].

Excessive or poorly managed training stress may be associated with different states of training maladaptation, including functional overreaching, non-functional overreaching, and, in some cases, overtraining syndrome [7–9]. These conditions differ in their duration, effects on performance, and recovery requirements. Consequently, changes in physiological parameters should not be interpreted as direct evidence of overtraining but may provide additional information about an individual's response to training and recovery.

Heart rate (HR), resting heart rate, and heart rate variability (HRV) are among the physiological parameters increasingly used to monitor training response and recovery. Changes in HRV, particularly when evaluated against an individual's habitual baseline and considered alongside other indicators, may provide information about autonomic regulation and recovery status [7, 8, 19].

1.4. Wearable Biosensors in Exercise Monitoring

The increasing availability of wearable technology has enabled continuous or repeated monitoring of physiological and training-related parameters outside laboratory settings. Commercial devices, including sports watches, wrist-worn sensors, and smart rings, can provide estimates of various physiological and training-related parameters [10–12].

Many consumer wearables use photoplethysmography (PPG) to estimate heart rate and related physiological parameters. Although PPG-based measurements can provide useful information during everyday activities and exercise, their accuracy may be affected by movement, sensor placement, skin characteristics, and exercise conditions [11, 13–17].

In addition to directly measured physiological parameters, commercial wearable systems use proprietary algorithms to generate derived indicators of training load, recovery, readiness, stress, and other aspects of physiological status. These metrics may be useful for supporting training decisions, but their interpretation requires consideration of the underlying measurement methods, validation evidence, and individual context.

The growing popularity of wearable technology has also resulted in increasing amounts of information about these devices being disseminated through manufacturers' websites, YouTube, Instagram, TikTok, and other online platforms. The way wearable-derived metrics are presented to consumers may differ from the way they are interpreted within the scientific literature. A critical comparison of these sources may therefore help identify potential discrepancies between scientific evidence, manufacturers' claims, and popular representations of wearable technology.

The aim of this review was to evaluate the current scientific evidence regarding the reliability and practical utility of commercial wearable biosensors for monitoring training load and recovery in runners. A secondary aim was to compare scientific evidence with information provided by selected wearable manufacturers and publicly available online content to examine how wearable-derived physiological metrics and their potential applications are presented to users outside the scientific literature.

2. Methods

A literature search was conducted in the PubMed database for scientific publications published between 2016 and 2026. The search strategy included combinations of English-language keywords related to wearable technology, physiological monitoring, running, training load, overtraining, recovery, and endurance performance. Examples of the search terms included "running economy," "microelectromechanical systems," "physiological monitoring," "overtraining," and "endurance performance."

In addition to the scientific literature, publicly available information concerning commercial wearable devices was reviewed to provide a broader perspective on their practical use and interpretation. Information available on the official websites of selected wearable device manufacturers was examined, with particular attention to the physiological parameters measured, methods of measurement, training and recovery metrics, and limitations reported by the manufacturers.

To assess how wearable technology and its physiological metrics are presented to the general public, publicly available content from online platforms was also reviewed. The analysis included 20 YouTube videos and 20 posts from selected social media platforms, specifically TikTok and Instagram. English and Polish search terms, as well as their simplified equivalents, were used to identify relevant content. Examples included "sports watches for running," "smartwatch heart rate monitoring," and "is a smartwatch accurate."

The collected material was analyzed descriptively and thematically, with particular attention to heart rate (HR), heart rate variability (HRV), resting heart rate, training load, recovery, sleep, and indicators of overreaching or overtraining. Scientific evidence was considered separately from information provided by manufacturers and content available on social media and other popular online platforms. The purpose of including non-scientific sources was not to establish clinical validity, but to examine how wearable-derived metrics and their potential applications are communicated to users outside the scientific literature.

The findings from these different sources were subsequently compared to identify areas of agreement and discrepancy between scientific evidence, manufacturers' claims, and information presented in popular online content. Particular attention was given to the reported reliability and limitations of commercial wearable biosensors and to the potential role of these devices in supporting training-load and recovery monitoring among runners.

Of the analyzed online materials, only those directly cited or explicitly discussed in the manuscript were included in the reference list. The remaining materials were considered as part of the broader content analysis but were not individually referenced because they did not provide information directly used to support the statements presented in the manuscript.

3. Scientific Evidence on the Reliability of Commercial Biosensors in Runners

Sensors popular among physically active individuals, such as chest straps, wrist-worn sports watches, and smart rings, have become increasingly common tools for monitoring physiological status and training-related parameters. When used appropriately and with awareness of their limitations, these devices can provide useful information for exercise monitoring [10–12]. In addition, the increasing availability of wearable sensors has created opportunities for their use in physiological monitoring and potential medical and diagnostic applications [12]. Commercial wearable devices can measure or estimate parameters such as heart rate (HR), heart rate variability (HRV), blood oxygen saturation (SpO_2), and energy expenditure. Some devices also provide estimates of parameters such as respiratory rate and blood pressure using proprietary algorithms and indirect measurement methods [13].

The quality and accuracy of wearable-derived measurements may be affected by several factors, including movement, sweat, sensor placement, skin characteristics, and exercise conditions. Photoplethysmography (PPG), which is widely used in consumer wearables to estimate HR and SpO_2, is particularly susceptible to motion-related artefacts and changes in measurement conditions [11, 14–17]. Individual characteristics, including skin tone and other physiological factors, may also influence the quality of the optical signal and consequently the accuracy of the measurements [11].

Monitoring physiological parameters with commercial biosensors may facilitate continuous assessment of exercise intensity and training response. Wearable devices can therefore provide readily accessible information that may support training decisions and monitoring outside laboratory settings [17]. HRV has also been increasingly investigated as a potential marker of training adaptation and recovery. When interpreted relative to an individual's habitual baseline and considered together with other indicators, changes in HRV may provide information about autonomic regulation and the response to training [18, 19]. Sleep represents another important component of recovery, and wearable devices may provide estimates of sleep duration and nightly physiological parameters that can be considered alongside training load and performance-related measures [20]. In recreational runners, changes in HR and HRV have also been observed in response to intensified training, although the interpretation of these measures should account for the timing of measurements and individual variability [21].

Wearable technology may also contribute to injury prevention by providing information about training exposure and other potential risk factors. However, the availability of large amounts of physiological and training-related data does not mean that these measurements can independently predict injury or overtraining. Rather, wearable-derived information should be interpreted as one component of a broader assessment of training load, recovery, symptoms, and individual context [22, 23].

The practical use of wearable technology among coaches and athletes is increasing. A study by Düking et al. demonstrated that coaches use wearable-derived information to support decision-making, while also emphasizing the need for further improvement and validation of wearable measurements before their broader and more effective application [24]. Furthermore, wearable technology enables the collection of large amounts of data under real-world conditions. Prospective studies have demonstrated the feasibility of using wearable-derived data to investigate associations between training characteristics, biomechanics, and running-related injuries outside laboratory environments [25, 26].

The relationship between wearable technology use and running-related injuries is complex. Chowdhary et al. reported that runners using running-related technology were more likely to report running-related injuries; however, the conscious use of technology-derived information to guide training decisions was not associated with an increased risk of injury [27]. These findings suggest that the technology itself should not be regarded as either inherently protective or harmful. Rather, its potential value depends on how the information is interpreted and incorporated into training decisions.

Further research may therefore support the development of personalized, evidence-based digital interventions for injury prevention and self-management among runners [28]. Nevertheless, wearable technology should complement rather than replace established injury-prevention strategies. Early adoption of appropriate training and recovery practices and their consistent implementation remain fundamental, while wearable devices may provide additional information to support these behaviors [29].

It is also important to consider subjective measures of fatigue and perceived exertion alongside objective sensor-derived measurements. Combining subjective and physiological indicators may provide a more comprehensive assessment of an athlete's current training state and reduce the risk of relying excessively on a single metric [30].

Finally, the scientific evidence indicates that the reliability of commercial wearable devices is not uniform and varies according to the device, parameter measured, measurement conditions, and validation method. Recent validation studies of nocturnal resting HR and HRV have demonstrated that consumer wearables can provide useful estimates of these parameters, while differences between devices and measurement methods remain relevant when interpreting their results [31]. Understanding such differences is essential when evaluating manufacturers' technical specifications and claims regarding the capabilities of commercial wearable biosensors, which are discussed in greater detail later in this paper.

4. Characteristics of Selected Commercial Wearable Devices Based on Manufacturers' Specifications

Commercial wearable devices differ in their form, measured parameters, and proprietary algorithms used to process physiological and training-related data. This section summarizes information provided by the manufacturers of three selected devices or systems: Garmin, WHOOP, and Oura Ring. The information presented below reflects manufacturers' specifications and descriptions of device functionality and should therefore be distinguished from independent scientific validation.

Garmin watches provide a range of physiological and training-related measurements, including heart rate (HR), heart rate variability (HRV), respiratory rate, sleep-related parameters, stress, energy expenditure, and Body Battery™. Depending on the device model, Garmin watches also provide training-related metrics such as training load, recovery-related information, and estimates of maximal oxygen uptake (VO_2 max). These measurements are obtained using, among other technologies, a wrist-based optical heart rate sensor based on photoplethysmography (PPG), including Garmin Elevate™ technology. The manufacturer emphasizes that the accuracy of optical measurements may be affected by factors such as individual characteristics, device fit, movement, and the type and intensity of activity performed.

Garmin also states that its consumer wearable devices are not medical devices and are not intended to diagnose, monitor, or treat diseases [32]. Consequently, physiological and training-related metrics provided by these devices should be regarded as estimates intended primarily for fitness and wellness applications rather than as diagnostic measurements.

Another commercially available system is WHOOP. Unlike conventional smartwatches, WHOOP is designed as a screen-free wearable that continuously collects physiological and activity-related data and presents the resulting metrics through a dedicated mobile application. According to the manufacturer, the system organizes its main information into three areas: Strain, Recovery, and Sleep. Recovery incorporates physiological parameters including HRV and resting heart rate, while Strain is intended to represent the physiological demands associated with daily activity and exercise.

The WHOOP system also provides personalized recommendations and coaching based on the collected data. The manufacturer emphasizes, however, that WHOOP is not intended to diagnose or treat medical conditions. The availability and functionality of certain health-related features may also vary according to regulatory requirements, age, medical status, and geographic region [33].

The Oura Ring represents another approach to wearable physiological monitoring. According to the manufacturer, the ring can monitor multiple parameters related to sleep, cardiovascular function, stress, activity, recovery, and other aspects of physiological status. The manufacturer reports that Oura can estimate more than 30 biometric parameters and emphasizes its use for long-term monitoring of sleep and recovery.

The manufacturer also presents validation data indicating a high degree of agreement between Oura-derived measurements and electrocardiography (ECG) for selected parameters. In particular, the manufacturer reports high correlations for resting heart rate and HRV and describes additional metrics such as Cardiovascular Age (CVA) [34]. These results should, however, be interpreted as manufacturer-reported validation information and should not be considered equivalent to independent clinical validation unless supported by external scientific evidence.

Overall, the three systems differ in their form factor, primary applications, and methods of presenting physiological and training-related information. Garmin primarily combines wearable physiological monitoring with sports tracking and GPS-based training functions, whereas WHOOP emphasizes continuous monitoring of strain, recovery, and sleep. Oura focuses more strongly on sleep, recovery, and long-term health-related monitoring.

Table 1. *Comparison of selected commercial wearable devices (Garmin, WHOOP, and Oura Ring) in terms of form factor, primary applications, core data collection, and manufacturer-reported features*

Feature / Aspect	Garmin	WHOOP	Oura Ring
Form Factor & Display	Smartwatch with a physical display and, depending on the model, physical buttons	Screen-free wearable wristband	Smart ring without a display
Primary Focus & Target Use	Sports and endurance training, activity tracking, GPS-based training, and physiological monitoring	Continuous monitoring of strain, recovery, sleep, and daily physiological status	Sleep, recovery, cardiovascular, and general health-related monitoring
Data Tracking & Core Areas	HR, HRV, sleep, stress, respiratory rate, training load, VO_2 max, GPS, and other sport-specific metrics	Strain, Recovery, Sleep, HRV, resting HR, and other physiological parameters	Sleep, HRV, resting HR, stress, activity, cardiovascular parameters, and other biometric measures
Standout / Manufacturer-Reported Features	Broad sports functionality, GPS, training metrics, and physiological monitoring	Continuous data collection and personalized recovery and training recommendations	Long-term sleep and recovery monitoring and manufacturer-reported validation of selected cardiovascular parameters

5. Presentation of Wearable Technology in YouTube Content

The analysis of selected YouTube videos revealed that commercial wearable devices were commonly presented as tools for monitoring training load, fatigue, recovery, and physiological responses to exercise. The content frequently focused on heart rate (HR), resting heart rate, and heart rate variability (HRV) as indicators that may help users evaluate their current training status.

Several videos presented increases in resting heart rate and decreases in HRV as potential indicators of insufficient recovery or excessive training stress [35, 36]. In some cases, changes in HRV were described using specific percentage thresholds, including an approximately 15% reduction. However, these recommendations represented the interpretations presented by the analyzed content creators and should not be considered diagnostic thresholds for overreaching or overtraining.

Some of the analyzed videos also described overtraining as a consequence of repeated physical stress combined with insufficient recovery, emphasizing persistent fatigue and impaired physiological adaptation [37]. These explanations were generally presented in simplified terms and frequently focused on the importance of allowing adequate recovery between training sessions. Such content may be useful for communicating general training concepts to recreational athletes, but it does not replace the more complex definitions and diagnostic considerations used in the scientific literature.

The analyzed YouTube content also emphasized that training adaptation depends on factors beyond exercise itself. Several creators highlighted sleep, psychological well-being, stress management, nutrition, and planned rest as important components of recovery [38–40]. This broader perspective is consistent with the concept that wearable-derived physiological measurements should be interpreted in the context of multiple factors rather than as isolated indicators of training status.

Garmin watches were also discussed in relation to the identification of excessive training stress and potential overreaching. Some videos described how changes in training load and deviations from an individual's usual physiological patterns may result in warnings or changes in device-generated feedback [41, 42]. The analyzed content recommended reviewing training history over several weeks, including periods of approximately 6–8 weeks, when evaluating whether changes in training load may reflect an excessive increase in training stress.

However, these recommendations should be regarded as interpretations or practical recommendations presented in the analyzed videos rather than established diagnostic criteria. The presence of a warning or an abnormal wearable-derived metric does not independently demonstrate that an athlete is overreached or overtrained. Instead, such information may serve as an additional signal that should be considered together with training history, subjective fatigue, sleep, performance, and other relevant factors.

Overall, the YouTube analysis indicated that wearable technology was generally presented as a practical tool for increasing awareness of training load and recovery. At the same time, the analyzed content varied considerably in the strength of the claims made about individual physiological metrics. This highlights the importance of distinguishing between practical recommendations communicated through popular online content and conclusions supported by independent scientific evidence.

6. Presentation of Wearable Technology in TikTok and Instagram Content

The analysis of selected TikTok and Instagram content showed that social media discussions frequently linked intense exercise and insufficient recovery with changes in physiological and psychological indicators. HRV, resting heart rate, fatigue, sleep, stress, and perceived recovery were among the parameters most commonly discussed.

Several posts and videos described decreases in HRV and increases in resting heart rate as potential signs of excessive training stress or insufficient recovery [43–49]. Some content also associated prolonged physical stress with sympathetic nervous system activation and changes in cortisol levels [43, 44]. However, these relationships were often presented in simplified terms, and the analyzed social media content did not consistently distinguish between temporary physiological responses to exercise, functional overreaching, non-functional overreaching, and overtraining syndrome.

The analyzed content also emphasized the importance of recognizing subjective symptoms of excessive training stress. Fatigue, reduced motivation, impaired well-being, sleep disturbances, and decreased performance were frequently presented as warning signs that should be considered alongside physiological measurements [47, 50]. This reflects a broader approach in which wearable-derived data are interpreted together with subjective perception and other contextual factors rather than used as an independent basis for training decisions.

Commercial wearable devices, including Garmin products, were also discussed in relation to monitoring training load and recovery [51]. Social media content described metrics intended to summarize recent training stress and fatigue and presented them as tools that may help users identify sudden changes in training exposure. Acute and chronic training load concepts, including the Acute-to-Chronic Workload Ratio (ACWR), were also mentioned in the analyzed content [52].

However, the presentation of training-load metrics on social media may imply a greater degree of certainty than is supported by the scientific literature. A calculated workload ratio or a change in a wearable-derived metric does not, by itself, establish that an athlete is overtrained or at increased risk of injury. Such measures should therefore be interpreted in relation to the individual's training history, performance, recovery, symptoms, and other contextual factors.

The analyzed social media content additionally emphasized sleep, nutrition, rest, and individualized training as important components of safe athletic development [53, 54]. Some posts also questioned the usefulness of standardized training plans and encouraged users to adapt training according to their current physical condition and individual capabilities [55].

Overall, the analysis of TikTok and Instagram content demonstrated that wearable technology is frequently presented as part of a broader self-monitoring approach to training and recovery. Nevertheless, social media content may simplify complex physiological relationships and may present wearable-derived metrics as more definitive than warranted by scientific evidence. This difference is important when comparing popular online information with evidence from peer-reviewed research and manufacturers' technical specifications.

7. Discussion

The findings of this review indicate that maintaining an appropriate balance between training load and recovery is an important component of safe and effective training among runners. Commercial wearable devices may support this process by providing repeated measurements of physiological and training-related parameters, including heart rate (HR), heart rate variability (HRV), resting heart rate, sleep-related measures, and estimates of training load. However, the available evidence indicates that the accuracy and reliability of these measurements vary depending on the device, parameter assessed, measurement method, and conditions of use.

When scientific evidence is compared with manufacturers' information, it becomes apparent that commercial wearables can provide useful physiological and training-related data but should not be regarded as medical or diagnostic instruments. Manufacturer-derived metrics such as training load, recovery, and readiness are based partly on proprietary algorithms and estimates. Their interpretation may therefore be limited when the broader individual and contextual factors affecting training response are not considered. In particular, changes in HR or HRV should not be interpreted in isolation as direct evidence of overreaching or overtraining.

The analysis of YouTube, Instagram, and TikTok content revealed that wearable-derived metrics are frequently presented as practical indicators of fatigue, recovery, or excessive training load. Popular online content often places considerable emphasis on HRV, resting HR, sleep, and perceived fatigue. However, the interpretation presented in such content may be more definitive than is supported by the scientific literature. This highlights an important discrepancy between the accessibility and simplicity of consumer-oriented information and the more cautious interpretation required when physiological measures are evaluated in scientific research.

The findings also emphasize the importance of combining objective and subjective information. Wearable-derived data may provide useful longitudinal information about changes in physiological responses and training exposure, but these measurements cannot independently determine the cause of a change. For example, an increase in resting HR or a decrease in HRV may be associated with training stress, but may also reflect insufficient sleep, psychological stress, illness, changes in daily activity, or other individual factors. Consequently, training decisions should not be based solely on a single device-generated alert or isolated physiological measurement.

The potential role of wearable technology in injury prevention should therefore also be interpreted cautiously. Although these devices can facilitate monitoring of training exposure and may help identify changes in training patterns, the available evidence does not support the assumption that wearable-derived metrics can independently predict running-related injuries or overtraining. Their practical value is more appropriately considered as part of a broader monitoring strategy that includes training history, recovery, sleep, perceived exertion, symptoms, and individual circumstances.

Overall, the findings of this review support the use of commercial wearable biosensors as complementary tools for monitoring training load, physiological responses, and recovery in runners. Their usefulness depends not only on the accuracy of individual measurements but also on the appropriate interpretation of derived metrics and recognition of their limitations. The comparison of scientific evidence, manufacturers' specifications, and popular online content indicates that wearable-derived information may be presented with different levels of certainty depending on the source. Therefore, a critical approach that integrates wearable-derived data with training history, subjective assessment, recovery, sleep, and individual circumstances may provide a more appropriate basis for training decisions and injury-prevention strategies.

8. Conclusions

Commercial wearable biosensors can provide useful information for monitoring training load, physiological responses, and recovery in runners. However, the reliability of individual measurements and derived metrics varies according to the device, parameter assessed, measurement method, and conditions of use.

Wearable-derived data should not be interpreted as independent evidence of overreaching, overtraining, or injury risk. Changes in HR, HRV, resting HR, sleep, or training-load metrics may provide valuable information, but they should be considered in relation to training history, recovery, subjective symptoms, sleep, and other individual factors.

The comparison of scientific evidence with manufacturers' specifications and popular online content indicates that wearable-derived metrics may be presented with different levels of certainty and may sometimes be interpreted more definitively than supported by the available evidence. Therefore, commercial wearable technology should be used to supplement, rather than replace, established methods of training monitoring and subjective assessment. A comprehensive and critical approach combining wearable-derived data with individual context may support more informed training and recovery decisions and contribute to safer athletic development.

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