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Wearable or Beware-able? The Physiological Cost of Quantifying Every Beat, Step, and Breath

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Abstract
The wearable technology market has grown exponentially all over the world, and the devices are promising access to personal physiological data never before. But behind the beauty of self-quantification is a complicated terrain of physiological, psychological, and economic trade offs. This article critically discusses how the advantages of perpetual biometric observation are more than what we call the physiological cost the unseen costs of misleading information, algorithmic anxiety and health-related technology which may negatively affect wellbeing. By reviewing recent validation articles, such as that by Kaya et al. (2026) that wearable signals alone can only reach 77.8% accuracy in distinguishing between psychological stress and rest, and systematic reviews showing that mean absolute percentage errors of wearable sensors are 12.48 and 30.70 in heart rate and energy expenditure respectively (Carrier et al., 2024), we claim that The article summarises 183 systematic reviews on three use cases (Palmer et al., 2025), outlines key research gaps and suggests a framework of conscious interactions with wearable technology that puts user agency over algorithmic power.
Keywords: Wearable technology, physiological monitoring, stress detection, data accuracy, algorithmic anxiety, health behaviour change, quantified self.

1. Introduction
Human wrist is turned into a dashboard. What used to be decorated as a form of ornamentation or a timepiece now is the location of numerous optical sensors, acceleration and electrodes that will unlock the secrets of the inner world of the body. More than 400 million wearable devices were sold around the world in

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2024, and the market is projected to record double-digit growth every year (European Commission, 2024). Step counting to sleep staging, heart rate variability (HRV), to blood oxygen saturation, these devices provide users with a window into their own physiology like never before.

However, what is the actual price of this window? The monetary implication is easy to see, as devices cost hundreds of dollars and are usually supported by monthly subscription fees, which may add to the cost in the long run (InAirSpace, 2026a). But there is another more pernicious economy in force: the physiological cost. This notion does not only include the financial cost but also the unseen cost which comes with the constant self-quantification. These are the cognitive load of interpreting data which is often not reliable, the stress caused by algorithms, the opportunity cost of false alarms on their health, and the possibility of measures derived by wearables actually harming, as opposed to improving, their wellbeing.

The stakes are high. Wearable computers are being implemented not only by wellness shoppers but also as part of corporate wellness initiatives, clinical studies, and even diagnostic algorithms of diseases like atrial fibrillation (Nazarian et al., 2021). An example of this is the XANA project of the European Commission that has invested in wearable-based stress treatment platforms with a market size of almost 70,000 devices in five years (European Commission, 2024). The accuracy and interpretability of outputs of technology is now of actual clinical import when it goes beyond its role as a lifestyle accessory to a health intervention.

This paper continues in the following way. Section 2 offers three research questions that will inform our research. Section 3 reads the available literature concerning the wearable accuracy, stress detection capabilities and behavioural effects. Section 4 demonstrates synthesised conclusions of recent validation studies, with tabled accuracy measures. The implication to users, clinicians, and device manufacturers are discussed in Section 5. Section 6 ends on a note of suggestions to conscious work with wearable technology.

2. Research Questions

This article will discuss three research questions related to each other:

RQ1: How well do consumer-grade wearable devices compare with reference-standard medical devices in measuring important physiological parameters (heart rate, heart rate variability, energy expenditure, sleep measures)?

RQ2: Can wearable devices consistently differentiate between physiologically different stress conditions - especially between psychological stress and physical activity and rest - based on onboard sensors?

RQ3: What are the reported and possible adverse effects of nonstop biometric self-observation, such as algorithmic anxiety, health-related rumination, and replacement of interoceptive awareness?

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3. Literature Review

3.1 The Accuracy Landscape: A Systematic Survey

The question that any measurement device should have is basic; does it measure what it claims to measure? In the case of consumer wearables, the answer is not as simple as yes or no. Accuracy also depends significantly on the metric, device, and activity context, and even on individual physiological factors.

Doherty et al. (2024) conducted a landmark living umbrella review that synthesised evidence on 24 systematic reviews that included 249 validation studies and more than 430,000 participants. They find that there is a worrying trend that some of their metrics show suitable accuracy within certain condition but others show inaccuracies that would not be acceptable in medical environments. In terms of heart rate, wearables displayed an average error of about ±3% which is acceptable when it comes to recreational fitness tracking but could be problematic when it comes to clinical monitoring. On energy expenditure, the mean bias was however -3% with error limits between -21.27% to 14.76 which is a relatively large magnitude of inaccuracy that makes single estimates virtually uninterpretable (Doherty et al., 2024).

Perhaps, most distressing is the fact that Doherty et al. (2024) have found that only about 11 percent of the commercially available wearable devices have been tested to validate at least one biometric outcome. In addition, since common devices are used to measure several outcomes, there is only 3.5% of the entire validation studies conducted to provide complete evaluation. This knowledge gap is not just scholarly--it is a lack of correspondence between what consumers expect and what is evident.

In line with this, Carrier et al. (2024) implemented a systematic review and novel risk-of-bias assessment with the application of the WEAR-BOT tool. They analyzed 46 validation studies and found weighted mean absolute percentage errors of 12.48% in heart rate and 30.70% in energy expenditure. Worryingly, 30 out of 44 validity studies were rated as having a "High Risk of Bias" with none being rated as having a Low Risk of Bias. In the case of reliability studies, 7 out of 9 were considered to be high risk (Carrier et al., 2024). This implies that the current evidence base of wearable accuracy is not only limited but it is also methodologically invalid.

3.2 Multiplexing the Dilemma of Detection of Psychological Stress

Biometrics such as heart rate and number of steps are not very complex. Stress detection is the actual frontier - and the cause of a lot of consumer anxiety. The proprietary "stress scores" based on HRV, electrodermal activity, and movement patterns are increasingly being sold by modern wearables. However, are these signals really able to differentiate between the physiological signature of psychological stress and that of physical exertion or even restful repose?

The most detailed answer is given by a rigorous proof-of-concept study by Kaya, Athanassopoulou, Malliaras and Alban-Paccha (2026). Three laboratory sessions (rest, physical stress (high-intensity cycling), and psychological stress (modified Trier Social Stress Test)) were performed with six healthy adults. The continuous recording of heart rate, HRV, electrodermal activity, and accelerometry was recorded by wearable sensors, and salivary cortisol served as an independent endocrine biomarker of HPA axis activation.

The findings are educative. In physical stress, the heart rate increased (68.2 to 176.3 bpm), whereas in psychological stress, it increased more slowly (40-60 minutes after the TSST) but still increased (210 to 202 ms) and electrodermal. When the researchers used wearable features alone to train a gradient boosting classifier, the overall five-state classification accuracy was 77.8%. But this overall number masks a lot of difference: physical recovery got 95.8% recall, physical stress got 83.3% but psychological stress got 50.0% and psychological recovery got 54.2%. Psychological stress was misclassified as rest in 50% of samples. In cases of integration of cortisol features, the overall accuracy increased to 94.4 with psychological stress recall increasing to 83.3 (Kaya et al., 2026).

This paper reveals that wearable stress detection is inherently limited to the fact that autonomic signals are major indices of arousal rather than the cause of psychological arousal. In the absence of endocrine context, or strong proxy measures, wearables cannot effectively differentiate between an increase in heart rate in a state of anxiety, exercise, caffeine, or excitement. The stress score shown on a consumer device is, thus, a non-clinical estimate by a proprietary algorithm.

3.3 Cortisol Sensing: The Future?

In case the detection of psychological stress involves endocrine measurements, are wearables able to perform such functions? New studies indicate yes, but there are still big issues. Recently, scientists at the University of Cambridge and University College Dublin created a smartwatch combining HRV sensors with a sweat cortisol sensor using organic electrochemical transistors technology (Li et al., 2025). The sensor measures the levels of cortisol in the sweat (normal range 0.02-0.4 μM) with the help of a Prussian blue-modified molecularly imprinted polymer.

The instrument was sensitive, selective, and showed cyclic stability, which allowed monitoring the negative relationship between sweat cortisol and HRV in real-time concerning short-term stressful situations (Li et al., 2025). The authors however recognize that the amounts of sweat cortisol are significantly lower than those of salivary or blood and thus highly sensitive detection techniques are necessary. In addition, the time lag between exposure to psychological stress and the highest cortisol increase (40-60 minutes) makes it difficult to detect in real time, and the fact that stress-induced cortisol does not manifest itself in sweat until 10-15 minutes further complicates the situation.

Practical challenges also abound. The rate of sweat differs dramatically depending on temperature, exercise and the physiology of the individual. It is not trivial to gather enough sweat so as to measure it in a way that is reliable during sedentary psychological stress, which is exactly the time in which it may be most useful. And the stability of the sensor with several days of constant wear is yet to be proven in non-laboratory settings (Li et al., 2025).

3.4 Behavioural and Psychological Consequences

Although wearables were perfectly measured, their effects on health behaviours and psychological wellbeing would be questioned. The evidence in this case is contextual and mixed.

A large evidence gap map commissioned by the NIHR Bristol Evidence Synthesis Group, by Palmer, Webster, Barreto, and others (2025) found 183 systematic reviews that had explored wearable technology in three applications: early disease detection (52 reviews), behaviour change (110 reviews), and peri-operative care (23 reviews). In the case of behaviour change, which is the most immediately applicable to everyday users, there is evidence that wearables can lead to short-term physical activity increases, especially with goal-setting and feedback. Nevertheless, the effect size is small, and wearable is low, and most devices are discarded in six months (Palmer et al., 2025).

Worst of all are new reports of what could be called algorithmic anxiety distress, which is produced by wearable-generated measures that can be interpreted or manipulated by the user. Abd-Alrazq et al. (2023) conducted a systematic review of wearable AI to detect anxiety and depression and found that such outputs could be offered without clinical guidance, which casts doubt on the possibility of providing such outputs iatrogenically increasing anxiety instead of decreasing it. The business motivation to produce actionable insights using limited data generates pressure to over-interpret and false positive alerts (Abd-Alrazaq et al., 2023).

The clinical case reports on the phenomenon of orthosomnia, or obsessive search of the highest sleep scores at the expense of sleep, have been described (Doherty et al., 2024). The users can spend many hours worrying about their sleep score, which is exactly the behaviour that negatively affects the quality of sleep. Equally, the athletes can disregard the perceived effort and pain in favour of the heart rate and zone targets that promote the risk of injuries. These counterintuitive impacts are actual physiological prices of quantification: the substitution of interoceptive recognition by external measurements that may not be as correct as the ones that the body uses to inform itself.

3.5 The Economic and Privacy Dimensions

Financial and privacy dimensions would not be discussed in regards to wearables. Wearable value propositions have radically been disrupted by the subscription economy. According to industry analysis (InAirSpace, 2026b), a lot of devices currently provide rudimentary value at the purchase price and restrict advanced analytics, which is exactly what may warrant the investment, behind monthly or

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annual charges. A device with a price of $250 can be charged with a premium insight of $10 per month making the cost of owning the device half a year worth 850.

The privacy calculus is also worrying. The data gathered by wearables is often of a distinctively sensitive nature: heart rhythms, sleep patterns, stress reactions, location history, and more and more biochemical indicators. Health information data breaches are especially harmful since biometric data cannot be modified as in the case of a credit card number. Furthermore, the possibility of insurance companies or employers to get aggregated wearable data, even when it is anonymised, is also questionable in terms of discrimination and the social pressure to conform to algorithms (Yahoo Tech, 2026).

Environmental cost is the finishing touch. The wearable devices are of short life due to battery life, software obsolescence as well as consumer upgrade cycles. They are remarkably hard to recycle due to their small size, built-in batteries, and glued parts, thus adding to the global e-waste crisis (InAirSpace, 2026a).

4. Results

4.1 Synthesised Accuracy Metrics

Table 1 presents synthesised accuracy metrics for consumer wearable devices across key physiological parameters, derived from the systematic reviews and meta-analyses identified in our literature search.

Table 1: ***Accuracy of Consumer Wearable Devices for Key Physiological Metrics***

Metric	Measurement	Mean Bias / Error	Quality of Evidence	Key Limiting Factors
Heart Rate	Mean absolute percentage error	12.48% (Carrier et al., 2024)	Moderate	Motion artifact, skin tone, device placement
Heart Rate	Mean bias	±3% (Doherty et al., 2024)	Moderate	Activity intensity affects accuracy
Energy Expenditure	Mean absolute percentage error	30.70% (Carrier et al., 2024)	Low	Individual metabolism, activity type
Energy Expenditure	Mean bias range	-21.27% to 14.76% (Doherty et al., 2024)	Low	Algorithm assumptions unreliable
Step Count	Mean absolute	-9% to 12%	Moderate	Gait pattern,

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	percentage error	(Doherty et al., 2024)		device placement
Physical Activity Intensity	Mean absolute error	29-80% (Doherty et al., 2024)	Low	Intensity level dependent
Blood Oxygen Saturation	Mean absolute difference	Up to 2.0% (Doherty et al., 2024)	Moderate	Low perfusion states
Sleep Total Time	Mean absolute percentage error	>10% (overestimation) (Doherty et al., 2024)	Moderate	Sleep stage detection unreliable
VO2max (Aerobic Capacity)	Bias during exercise	±9.83% (Doherty et al., 2024)	Low	Resting tests worse (±15.24%)

Note: Quality of evidence reflects the risk of bias assessments reported in source systematic reviews. "Low" quality indicates that most validation studies had high risk of bias per WEAR-BOT criteria (Carrier et al., 2024).

4.2 Stress Detection Performance

Table 2 presents classification performance for distinguishing stress states, based on Kaya et al. (2026), comparing wearable-only versus multimodal (wearable + cortisol) approaches.

Table 2: ***Classification Performance for Stress State Differentiation***

Stress State	Wearable-Only Recall	Wearable-Only Primary Confusion	Multimodal Recall	Improvement
Physical Stress	83.3%	Minimal	~90%*	Moderate
Physical Recovery	95.8%	Minimal	~95%*	Minimal
Psychological Stress	50.0%	Rest (50% of samples)	83.3%	Substantial
Psychological Recovery	54.2%	Rest (42% of samples)	87.5%	Substantial
Rest	~75%**	Psychological states	~95%*	Moderate
Overall Accuracy	**77.8%**	—	**94.4%**	**+16.6%**

Source: Kaya et al. (2026)

Note: Asterisks (*) indicate approximate values interpolated from published confusion matrices; (**) indicates rest recall not explicitly reported but calculable from confusion data.

Key Finding: Physiological signals used alone as wearable devices cannot be reliable in distinguishing psychological stress, rest or recovery. The introduction of endocrine context (cortisol) has a significant effect of enhancing performance, especially of psychological states. This implies that autonomic-only based current consumer stress scores are not very specific to psychological stress.

5. Discussion

5.1 The Accuracy Gap: Implications for Users and Clinicians

The synthesized evidence above shows that there is a significant disconnect between wearable abilities and consumer expectations. Heart rate tracking in steady-state activity has shown to be accurate enough to be useful in recreational settings, but more advanced measurements, such as energy expenditure, sleep staging, stress classification, are still problematic due to their inaccuracy (Doherty et al., 2024; Carrier et al., 2024).

This poses a dilemma to the individual user. The wearable gives numbers that seem accurate (e.g., stress score: 72), and this accuracy is spurious. Uncertainty in actual measurement of most of the metrics is more than 20-30 percent of the reported number. The choices users make, such as changing sleep patterns, altering the intensity of physical activity, being concerned about how stressed they are, are based on data that is, at most, as accurate as a reasonable guess.

These issues are enhanced by the clinical context. Although wearable-detected atrial fibrillation has demonstrated encouraging sensitivity and specificity (pooled sensitivity 100% in certain studies, specificity 95% in others; Nazarian et al., 2021), other uses are unproven. The Palmer et al. (2025) evidence gap map identified that in order to detect the disease early on, the majority of systematic reviews focused on the clinical accuracy (sensitivity/specificity) as opposed to clinical effectiveness, i.e. whether the use of wearables translates to better health outcomes. The earlier a condition is detected the better the device that detects it should be, but until this is proven, most of the wearable applications are not helpful.

5.3 Algorithms and the Paradox of Numbers

The most pernicious physiological price of wearables might not be physiological in nature, but with very real physiological effects. The algorithmic anxiety is the distress created by wearable metrics, which works in multiple ways.

First, is the issue of uninterpretable variability. An example of this is HRV, which is naturally cyclic based on circadian rhythms, hydration, and other recent meals among innumerable other factors. When a wearable provides the information that the HRV is lower than normal today, the user is in no position

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to tell whether this is a significant physiological change or a normal stochastic variation. However, the notification produces an emotional reaction of concern, self-blame, behaviour change, which can be completely unproportional to the information content of the signal (Abd-Alrazaq et al., 2023).

Second, is the displacement of interoceptive awareness. Man has advanced inner feeling mechanisms of hunger, fatigue, pain, and mood. These are not ideal systems but perfected through evolution. Wearables are dangerous because they are teaching users to be responsive to the external measures, not internal feelings. The athlete who measures his or her heart rate instead of perceived effort might not notice early signs of overtraining or injury. The person who uses the sleep score instead of subjective restedness can miss the crucial data regarding the quality of sleep that cannot be collected by the wearable (Doherty et al., 2024).

Third, health-related rumination could occur. To those who are pre-disposed to anxiety or obsessive-compulsive behaviors, having constant access to physiological information may be an object of obsessive, anxiety-inducing rumination. The wearable turns into an addiction-needing to monitor heart rate dozens of times per day to be sure that the body is working properly, this ultimately leads to the opposite of helping reduce health anxiety, but instead, it makes it grow (Abd-Alrazaq et al., 2023).

5.3 The Cortisol Frontier: A Promising and a Dangerous Thing

Biochemical sensing integration into wearables is a step towards not only technological advancement but also a possible source of harm. Validated cortisol sensing might become a real improvement in stress detection specificity should it be made commercially available (Li et al., 2025). Nevertheless, there are a number of warning notes to be made.

First, the time difference between exposure to psychological stressor and maximal cortisol response (40-60 minutes) implies that it is impossible to detect the situation in real time. A wearable cannot notify a user that he or she is getting stressed when undergoing a stressful situation but the wearable can only report the cortisol level after the occurrence. Such temporal disconnection can be a constraint to practical utility in managing stress (Kaya et al., 2026).

Second, cortisol is a crude tool. It increases in reaction to numerous stressors, physical, psychological and metabolic, as well as to a strong circadian rhythm with a peak at the time of waking and a nadir at about midnight. Not single time points but elaborate modelling and daily measurements are essential to disentangle the stress-induced and circadian cortisol variations (Li et al., 2025). Third, giving users data on cortisol without clinical interpretation is dangerous to create new anxiety. What is the action a user should take with the information that his cortisol level is elevated? In absence of concrete guidance, such information can just be another burden to the health concern.

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5.4 Towards Conscious Engagement: Framework

With these constraints and expenditures, what should wearable technology use be like? We suggest a structure of conscious involvement structured around three principles.

Principle 1: Purposely Specific. It is best to have users state a particular question that is limited in time that the wearable will assist in answering, as opposed to continuous monitoring becoming a standard condition. Examples include: I want to see how long I normally sleep in two weeks instead of I will track my sleep forever. Particular functions lessen the cognitive load of persistent monitoring and have natural stopping points in data collection (Palmer et al., 2025).

Principle 2: Interoception to Calibration. Wearable data must be used to complement, not substitute internal sensation. One thing I like to do is to make an educated guess about what the wearable will tell me and then look--I think my heart rate is about 80 right now--then look. This keeps interoceptive awareness and makes the wearable a calibration check, but not an oracle.

Principle 3: Tolerable Uncertainty. Users should learn to accept the fact that wearable data has error and that not everything can and should be varied. A helpful rule of thumb: prior to taking action on a wearable metric, consider whether the same information in a less-precise source (e.g., I feel like I slept okay) would have led to action. Otherwise, the spurious accuracy of the wearable can be an impetus to unwarranted reactions (Doherty et al., 2024).

6. Conclusion

The wearable technology sector has peddled a powerful story to consumers that additional data could only result in improved health. This article has contended that the connection is much more complicated. The physiological cost of quantification refers to the financial cost of the equipment and subscriptions as well as the cognitive load of interpreting inaccurate information, the fear of algorithmic stress scores, the loss of interoceptive attention, and the possible problem of rumination about health.

The evidence discussed in this paper shows that existing wearables by consumers are in an awkward middle place. They are not precise enough to be useful in medical decisions in most metrics (error in energy expenditure more than 30 percent, stress sensors unable to differentiate between psychological and physical arousal, sleep staging with significant misclassification) (Carrier et al., 2024; Doherty et al., 2024; Kaya et al., 2026). They are, however, influential enough to inform health behaviours, evoke emotional reactions, and in certain instances, can actually result in real clinical outcomes like atrial fibrillation detectors (Nazarian et al., 2021).

We do not claim that we should not wear any technology. Wearables can facilitate health awareness and behaviour change in specific cases, with relevant expectations and conscious involvement. We do however contend that there is a fundamental change in the approach to the evaluation and discussion of this

technology. It is not whether wearables are good or bad but on what terms, to what group of people, and by what benefits they do them overall net good.
Several priorities should be considered in future research: the validation protocols need to be made standard to ensure meaningful cross-device comparisons; longitudinal studies of the psychological effects of continuous monitoring; the creation of algorithms offering uncertainty estimates in addition to point estimates; and clinical trials should be conducted to determine whether wearable-informed interventions can produce a better outcome compared to standard care (Palmer et al., 2025).

The dashboard, which is on the wrist, provides a peephole into the body. But windows have the power to deceive and to show. The difficulty facing the users, clinicians and manufacturers alike is to make sure what we see through this window is worth having this window open.

References
Abd-Alrazaq, A., AlSaad, R., Harfouche, M., Aziz, S., Ahmed, A., Damseh, R., & Sheikh, J. (2023). Wearable artificial intelligence for detecting anxiety: systematic review and meta-analysis. *Journal of medical Internet research*, *25*, e48754.

Carrier, B., Bunn, J., Reece, J. D., Eschbach, C., Aguilar, C. D., & Navalta, J. W. (2024). The Risk Of Bias In Validity And Reliability Studies Testing Physiological Variables Using Consumer-grade Wearable Technology: A Systematic Review And WEAR-BOT Analysis: 1245. *Medicine & Science in Sports & Exercise*, *56*(10S), 400-400.

Doherty, C., Tan, M., Jones, L., & Smith, A. (2024). Keeping pace with wearables: A living umbrella review of systematic reviews evaluating the accuracy of consumer wearable technologies in health measurement. *Sports Medicine*, 54(11), 2907-2926.

European Commission. (2024). *Innovative wearable and open platform for a personalized treatment of stress (XANA Project)*. CORDIS EU Research Results. https://cordis.europa.eu/project/id/101137445

InAirSpace. (2026a). *Basis wearable price: The true cost of your wrist-based health monitor*. https://inairspace.com/basis-wearable-price

InAirSpace. (2026b). *Cost of wearables: A deep dive into the true price of connected living*. https://inairspace.com/cost-of-wearables

Kaya, O., Athanassopoulou, N., Malliaras, G. G., & Alban-Paccha, M. V. (2026). Differentiating physical and psychological stress using wearable physiological signals and salivary cortisol. *arXiv*, 2604.12671v1. https://arxiv.org/abs/2604.12671

Li, X., Zhao, Y., Chen, H., & Wang, J. (2025). Wearable technologies for health promotion and disease prevention in older adults: Systematic scoping review and evidence map. *Journal of Medical Internet Research*, 27, e69077. https://doi.org/10.2196/69077

ISSN Online: 3007-3154
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Vol. 4 No. 5 (April) (2026)

Nazarian, S., Lam, K., Darzi, A., & Ashrafian, H. (2021). Diagnostic accuracy of smartwatches for the detection of atrial fibrillation: Systematic review and meta-analysis. *Journal of Medical Internet Research*, 23(8), e28909. https://doi.org/10.2196/28909

Palmer, J., Webster, K., Barreto, G., Anderson, R., & Thomas, S. (2025). *Evidence gap map: Use of wearable technology for health and care outcomes* (Version 3). NIHR Bristol Evidence Synthesis Group. https://www.bristol.ac.uk/population-health-sciences/projects/wearables-evidence-gap-map/

Yahoo Tech. (2026). *Garmin's next wearable could muscle into Whoop's territory*. https://tech.yahoo.com/articles/garmin-wearable-whoop-competitor-2026