

Review

Using wearable technology to predict health outcomes: a literature review

Jason P. Burnham,¹ Chenyang Lu,² Lauren H. Yaeger,³ Thomas C. Bailey,¹ and Marin H. Kollef⁴

¹Department of Internal Medicine, Division of Infectious Diseases Washington University School of Medicine, St. Louis, Missouri, USA, ²Department of Computer Science & Engineering, Washington University in St. Louis, Missouri, USA, ³Bernard Becker Medical Library, Washington University in St. Louis, Missouri, USA and ⁴Department of Internal Medicine, Division of Pulmonary and Critical Care Medicine, Washington University School of Medicine, St. Louis, Missouri, USA

Corresponding Author: Jason P. Burnham, MD, Division of Infectious Diseases, Washington University School of Medicine, 4523 Clayton Avenue, Campus Box 8051, St. Louis, MO 63110, USA (burnham@wustl.edu)

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ABSTRACT

Objective: To review and analyze the literature to determine whether wearable technologies can predict health outcomes.

Materials and methods: We queried Ovid Medline 1946 –, Embase 1947 –, Scopus 1823 –, the Cochrane Library, clinicaltrials.gov 1997 – April 17, 2018, and IEEE Xplore Digital Library and Engineering Village through April 18, 2018, for studies utilizing wearable technology in clinical outcome prediction. Studies were deemed relevant to the research question if they involved human subjects, used wearable technology that tracked a health-related parameter, and incorporated data from wearable technology into a predictive model of mortality, readmission, and/or emergency department (ED) visits.

Results: Eight unique studies were directly related to the research question, and all were of at least moderate quality. Six studies developed models for readmission and two for mortality. In each of the eight studies, data obtained from wearable technology were predictive of or significantly associated with the tracked outcome.

Discussion: Only eight unique studies incorporated wearable technology data into predictive models. The eight studies were of moderate quality or higher and thereby provide proof of concept for the use of wearable technology in developing models that predict clinical outcomes.

Conclusion: Wearable technology has significant potential to assist in predicting clinical outcomes, but needs further study. Well-designed clinical trials that incorporate data from wearable technology into clinical outcome prediction models are required to realize the opportunities of this advancing technology.

Key words: predictive modeling, mortality, readmission, wearable technology, emergency department

INTRODUCTION

Predicting clinical outcomes after hospital discharge remains a significant challenge. Strategies to predict and prevent post-discharge mortality, readmissions, and emergency department (ED) visits have had limited success.¹ If improvements in predictive models were possible, morbidity, mortality, readmissions, and ED visits might be

prevented by early interventions on modifiable risk factors. Potentially modifiable risk factors for these clinical outcomes include activity levels, sleep patterns, and tachy- or bradyarrhythmias, parameters that can be tracked with wearable technology.^{2–6}

Wearable technology that tracks health-related parameters is increasing in popularity in the lay market for fitness monitoring. These technologies have been used for healthcare insurance incentives and

discounts, but the extent to which the data they collect can be used in predictive models for healthcare outcomes is not well studied. Our goal was to review and analyze the currently available literature to determine whether wearable technologies can predict health outcomes and which outcomes have been tracked. We defined our primary outcome — models using wearable technology data to predict clinical outcomes — as any study that derived a model predicting mortality, readmissions, and/or ED visits that incorporated data from any wearable technology.

METHODS

Data sources and searches

The published literature was searched using strategies created by a medical librarian (L.H.Y.) for the concepts of activity trackers and hospital readmission, emergency room visits, emergency departments, and mortality. The search strategies were established using a combination of standardized terms and key words and implemented in Ovid Medline 1946 -, Embase 1947 -, Scopus 1823 -, the Cochrane Library, and clinicaltrials.gov 1997 — all through October 10, 2017, then updated on April 17, 2018. IEEE Xplore Digital Library and Engineering Village were searched and included as updated on April 18, 2018. Duplicate records were identified using Endnote's automatic duplication finder and manual review. For the eight papers (six unique studies) initially included in our analysis, we reviewed all references to identify additional studies that might have been missed by our initial search criteria. Two additional studies were identified and incorporated into the final analysis.

Study selection

After removal of all duplicate results, all titles and abstracts were reviewed independently for relevance to the research question by J.P.B. See Figure 1 for a schema of the phases of application of inclusion/exclusion criteria. An additional *post hoc* review of all titles and abstracts was performed by M.H.K., which resulted in one additional study being included in the final quantitative synthesis. For the first line of review, articles were considered relevant to the research question if they involved human subjects, made use of wearable technology that tracked a health-related parameter, and tracked some outcome (ie not a feasibility study). The list of wearable technology search terms can be found in the appendix. Health-related parameters could include anything related to a patient's health including vital signs, surrogates for physical activity such as movements or step counts, sleep quality, or electrocardiogram tracings. After determining that an article was relevant to the research question, articles were reviewed to determine what outcomes were tracked.

Studies that tracked mortality, readmission, and ED visits were reviewed independently in depth by J.P.B. and M.H.K. Only studies that used data from wearable technology in a predictive model for these outcomes were considered to be directly related to the research question.

Data extraction and quality and bias assessment

Full-text articles were independently reviewed by J.P.B. and M.H.K. for studies directly related to the research question. Methods and results were reviewed in depth to determine which studies incorporated data from wearable technology. Data were extracted independently by J.P.B. and M.H.K. in a standardized format and included predictive model type, patient population, enrollment, attrition

rates, outcome predictor characteristics, differences in groups with and without the tracked outcome, data capture rates for wearable technology, and wearable technology type. Discrepancies were resolved by a third party (T.C.B.).

Studies were considered of high quality if model development was fully described and the full breadth of data collected by wearable technology was incorporated into a predictive model. Moderate quality studies fully described model development, but data from wearable technology were simplified or dichotomized. There were no low-quality studies (studies that did not fully describe model development and simplified or dichotomized wearable technology data). All studies were reviewed for the following biases using established guidelines⁷: selection, performance, detection, attrition, reporting, and publication bias.

Data synthesis and analysis

Results are descriptive in nature and categorized by the outcome that was tracked (ED visits, readmissions, and/or mortality).

RESULTS

A total of 736 results were found using our initial search strategy completed on October 10, 2017. Three-hundred-sixty-three duplicate records were identified using Endnote's automatic duplication finder, and an additional 55 duplicate records were discovered and removed, leaving 456 unique citations in the project library. We updated our search on April 17, 2018, and added the IEEE Xplore Digital Library and Engineering Village databases on April 18, 2018. With these updates and additions, we identified an additional 153 results, 18 of which were duplicates, leaving an additional 135 records to be added to the project library. Fully reportable searches can be found in Appendix 1.

After review of the remaining titles and abstracts, 168 search results were deemed relevant to the search question. Of these 168 search results, nine included mortality as an outcome, 13 included readmission as an outcome, seven included ED visits as an outcome, and 137 included other outcomes (see Appendix 2 for studies that looked at other clinical outcomes). Of the studies including mortality as an outcome, two included both readmissions and ED visits as outcomes. Of the other 11 articles including readmission as an outcome, an additional five included ED visits as an outcome. No articles looked only at ED visits. The 20 articles including one or more of mortality, readmissions, and ED visits as an outcome were included in the initial qualitative synthesis and are discussed below under the sections "Mortality" and "Readmissions."

In full-text review of the 20 articles, a total of eight papers were identified that incorporated data from wearable technology into a predictive model of a target clinical outcome: four for mortality,^{8–11} and four for readmissions.^{12–15} Of the four papers predicting mortality, two were analyses of the same trial.^{9,10} Two papers analyzing readmissions were preliminary and final analyses of the same cohort.^{12,13} An additional two unique studies that included readmissions as an outcome were discovered during review of references from these six papers,^{16,17} bringing the number of unique studies included in the final analysis to the eight in Table 1.

The included populations in these eight studies were patients with cardiovascular disease risk factors, congestive heart failure (CHF), post-operative metastatic peritoneal cancer, elderly patients admitted to medicine services, cardiac surgery patients, and elderly patients admitted to a trauma service. The studies were published

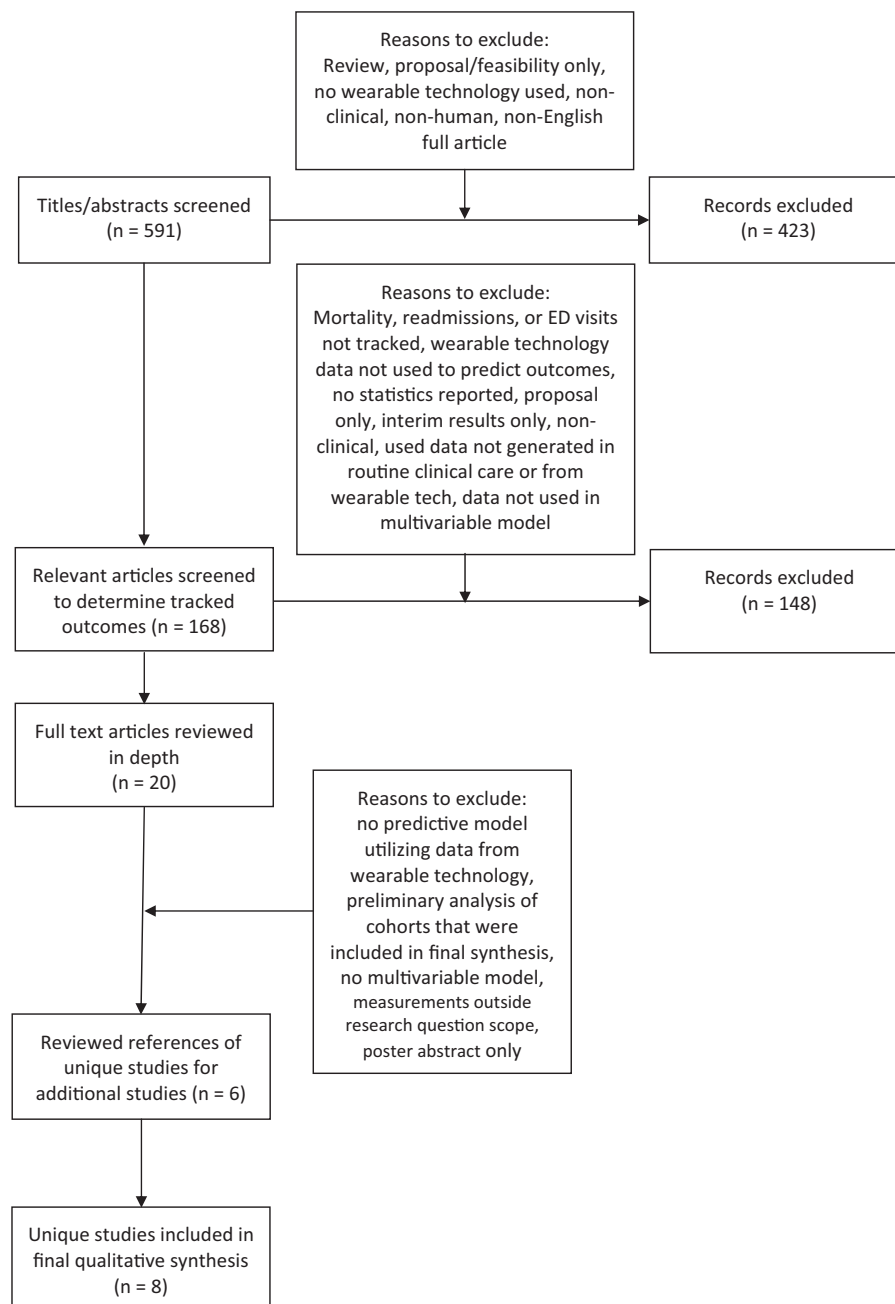


Figure 1. Phases of application of exclusion/inclusion criteria as used by J.P.B. and M.H.K.

between 1997 and 2018. The eight unique studies included 17 285 patients, which is skewed by the NAVIGATOR trial of patients with cardiovascular disease risk factors, which had 9306 patients, and the Pyrkov et al study with 7454 patients. The model quality of the eight unique studies was at least moderate (Table 1).

In all eight unique studies, every participant used wearable technology, minimizing selection and performance bias. In the Yates et al study,⁹ patients with complete pedometer data were more likely to be smokers and less likely to have congestive heart failure. However, these two particular differences would likely have biased toward the null for mortality. As our inclusion criteria required mortality, readmissions, or ED visits to be tracked, all of which are objective measures, no detection bias was found in the studies. In

addition, no reporting bias was found in any of the eight unique studies. Significant associations between wearable technology data and the tracked outcomes were reported for all eight unique studies, which makes it possible that publication bias is an issue for this review. With only eight unique published studies, it is also possible that no negative studies have yet been completed. Finally, only the Yates et al study lost patients to follow-up (3.1%), which minimizes the likelihood of attrition bias.

Mortality

The four studies that incorporated data from wearable technology into a model predicting death^{8–11} used pedometers or

Table 1. Key aspects and limitations of studies included in the final analysis

Study (year), # of patients	Patient population and technology used	Key findings and study quality	Limitations
Pyrkov et al. (2018), n = 7454 ¹¹	<ul style="list-style-type: none"> Participants in the NHANES cohort ActiGraph AM-7164 single-axis piezoelectric accelerometer 	<ul style="list-style-type: none"> Machine learning algorithms are able to predict biological age from activity counts as recorded by wearable technology Derived biological age is a significant predictor of all-cause mortality High quality 	<ul style="list-style-type: none"> Limited number of deaths could make prediction models inaccurate Complex analysis that may not be widely generalizable Wearable technology data were not used prospectively to intervene and prevent clinical deterioration
Low et al (2018), n = 71 ¹⁵	<ul style="list-style-type: none"> Metastatic peritoneal cancer Fitbit Flex or Charge 	<ul style="list-style-type: none"> Mean steps/inpatient day was significantly associated with 30-day and 60-day readmissions (OR 0.83 and 0.82, respectively) Moderate quality 	<ul style="list-style-type: none"> Inpatient data only Very specific patient population/limited generalizability Did not incorporate pain severity in predictive models, which correlates with mobility Wearable technology data were not used prospectively to intervene and prevent clinical deterioration
Joseph et al (2017), n = 101 ¹⁴	<ul style="list-style-type: none"> Elderly patients admitted to a trauma service triaxial wearable gyroscope sensor 	<ul style="list-style-type: none"> Upper extremity function (derived from wearable sensor data) used as a surrogate for frailty was significantly associated with readmissions in multivariate model High quality 	<ul style="list-style-type: none"> Data collected by the wearable sensor were not passively collected and require protocolized instruction to patient Derived frailty index using wearable sensor requires additional steps of data analysis Not all patients may be able to perform required motions for data capture Data not used prospectively to prevent unfavorable clinical outcomes Questionable generalizability
Bae et al. (2016), n = 25 ^{12, 13}	<ul style="list-style-type: none"> Metastatic peritoneal cancer Fitbit Flex 	<ul style="list-style-type: none"> Extracted 89 features from Fitbit data for model building Readmitted patients had significantly longer sedentary bouts, fewer daily steps Using Fitbit step counts and behavioral data, model predicted readmission with 88.3% accuracy Using only Fitbit step counts predicted readmission 67.1% of the time High quality 	<ul style="list-style-type: none"> Inpatient data only Very specific patient population/limited generalizability Small sample size Did not incorporate pain severity in predictive models, which correlates with mobility Wearable technology data were not used prospectively to intervene and prevent clinical deterioration
Takahashi et al. (2015), n = 133 ¹⁷	<ul style="list-style-type: none"> Post cardiac surgery patients Active Style Pro HJA-350IT 	<ul style="list-style-type: none"> Mean number of steps walked during the last three inpatient days was significantly lower in patients who were re-hospitalized in the year after cardiac surgery Moderate quality 	<ul style="list-style-type: none"> Data capture rate was not reported Used only step counts Dropout rate of 17% Inpatient data only Wearable technology data were not used prospectively to intervene and prevent clinical deterioration
Yates et al. (2014), n = 9306 ^{9,10}	<ul style="list-style-type: none"> Cardiovascular disease or cardiovascular disease risk factors Pedometers 	<ul style="list-style-type: none"> For each 2000 step/day increase in baseline steps, risk of a cardiovascular event decreased 10% For each 2000 step/day increase in steps over time, risk of a cardiovascular event decreased by 8% Moderate quality 	<ul style="list-style-type: none"> Only used step counts Only tracked step counts for two 1-week periods at 0 and 12 months Primary goal of the original study was not to model clinical outcomes with wearable technology data Conducted in 2002-2004, since which time wearable technology has advanced Relied on patients to record step counts from the pedometer Dichotomized or categorized step counts rather than using full breadth of data for modeling (eg average number of steps/day, change in activity from baseline at 12 months) Cox proportional hazards rather than machine learning 25% of the cohort had missing pedometer data at baseline 45% of the cohort had missing pedometer data at 12 months

(continued)

Table 1. continued

Study (year), # of patients	Patient population and technology used	Key findings and study quality	Limitations
Fisher et al. (2013) n = 111 ¹⁶	–Elderly medicine patients –waterproof dual-axis accelerometer	–in unadjusted models, mean daily step count was associated with 30-day readmission –in multivariate logistic regression, mean daily step count was retained in the final model, but not a statistically significant predictor of 30-day readmission –Moderate quality	–Wearable technology data were not used prospectively to intervene and prevent clinical deterioration –Included only mean daily step count in multivariable model –Wearable technology data was not used prospectively to intervene and prevent clinical deterioration
Walsh et al. (1997), n = 84 ⁸	–Heart failure –Pedometers	–Patients who took >25,000 steps/week had relative risk of death of 0.2236 –Moderate quality	–Published in 1997, since which time wearable technology has advanced –Only used step counts –Small sample size –Step counts were dichotomized –Primary goal of the original study was not to model clinical outcomes with wearable technology data –Wearable technology data were not used prospectively to intervene and prevent clinical deterioration –Data capture rate was not reported

accelerometers, and step or activity counts were the measures incorporated into predictive models of mortality. The Walsh et al study of 84 chronic heart failure patients found that fewer steps per week were significantly associated with mortality during the 710-day follow-up period.⁸ Other variables in the model that were predictive of mortality were related to cardiac disease severity. Two papers were analyses of the NAVIGATOR trial.^{9,10} In the study by Yates et al of 9306 participants with baseline cardiovascular disease or cardiovascular risk factors, baseline step counts and change in step counts from baseline both correlated with mortality during the average six years of follow-up.⁹ The other paper was a preliminary analysis of the NAVIGATOR trial.¹⁰ In the paper by Pyrkov et al, accelerometer data from participants in the National Health and Nutrition Examination Survey (NHANES) were used in various models to predict mortality.¹¹ Their model found that activity levels predicted biological age, which in turn was a predictor of mortality.¹¹ After incorporating biological age into their models (as calculated from activity records), activity level was a significant predictor of mortality only as the derived value of biological age. A summary of the key findings of these studies is shown in Table 1.

Of the other five studies that discussed mortality (not included in Table 1), patient populations included healthy patients, those with CHF, chronic obstructive pulmonary disease (COPD), or those on hemodialysis. These studies did not always use multivariable models, potentially falsely increasing the association of mortality with activity levels.¹⁸ Wearable technology was used in two studies to track adherence to activity programs, with adherence treated as a binary variable.^{19,20} Activity levels were found to be associated with reduced mortality, but data directly from wearable technology were not incorporated into the predictive models.^{19,20} In a study of 453 hemodialysis patients, step counts as tracked by a pedometer were

not associated with mortality.²¹ The study by Nes et al developed an algorithm to help predict mortality that incorporated data from wearable technology.²² However, the algorithm also required the intensive step of laboratory-based VO₂max measurements, which is outside the scope of our research question.

Readmissions

There were five unique studies (see Table 1) that incorporated wearable technology data into predictive models for readmissions.^{13–17} In a well-done study of 25 postsurgical oncology patients by Bae et al, Fitbit data were used to predict readmissions.¹³ They found that duration of sedentary bouts and the total number of steps were associated with readmissions.¹³ Their multifactorial model of Fitbit collected step counts and other patient activity was able to predict readmission in 88.3% of cases.¹³ The model that used only Fitbit collected step counts predicted readmission accurately only 67.1% of the time.¹³ In a follow-up study, the authors found that in 71 patients with metastatic peritoneal cancer, higher mean daily step counts were predictive of 30- and 60-day readmissions even after adjusting for other risk factors.¹⁵

In the Joseph et al study of 101 elderly trauma patients, a wearable sensor was used to collect data about upper extremity function.¹⁴ The derived upper extremity function score was used as a proxy for frailty, and patients with scores indicative of lesser functioning upper extremities had higher rates of readmission as assessed in a multivariable model.

Fisher et al tracked post-discharge daily step counts in 111 elderly medicine patients and found that in an unadjusted model, mean daily step count was associated with an increased risk of 30-day readmission.¹⁶ However, when incorporated into a multivar-

iable logistic regression model, daily step count was not a statistically significant predictor of readmission.¹⁶

In a study of 133 cardiac surgery patients, Takahashi et al found that low mean step counts prior to discharge was a strong predictor of cardiac re-hospitalization after cardiac surgery.¹⁷

The remainder of the studies that included readmissions as an outcome were not included in the final analysis (nor Table 1) for various reasons, discussed below. Though readmissions were a tracked outcome in the studies by Evangelista et al and Paneroni et al.,^{19,20} these data were not incorporated into a model to predict outcomes. In a poster abstract, Berry et al reported the results of a prospective interventional trial aimed at preventing readmissions and ED visits in patients with heart failure by using wearable technology.²³ However, only 24 patients were enrolled, and the study was not adequately powered to determine whether the wearable technology intervention led to a reduction in readmissions.²³ In a study of 26 patients with COPD using wearable technology to track activity, increased step counts from baseline did not correlate with reduction in days of hospitalization, although data were not used in a predictive model, nor was the study adequately powered to detect a difference.²⁴ In a randomized controlled trial of COPD patients, Katsaras et al report reductions in readmissions and ER visits with a wearable technology, but provide no statistical analysis to support this.²⁵ In a similar publication by the same authors, they again report that their wearable technology resulted in reductions in readmissions and ED visits without providing any statistical analyses.²⁶

In a study of 108 post bariatric surgery patients who were given an activity tracker, patients who had fewer initial steps were more likely to be readmitted or have ED visits with a *P* value of 0.06 (effect size not reported), though this study did not use steps to predict readmissions or ED visits.²⁷ Though not used to predict readmissions, Fitbit data from post-op neurosurgery patients demonstrated that readmitted patients took fewer steps and had a decline in steps over time after discharge.²⁸ In a case report, a patient wearing an activity tracker was found to have atrial fibrillation and was cardioverted, thereby averting a hospital admission.²⁹

ED visits

There were no studies mentioning ED visits that did not also look at mortality or readmissions. None of the studies mentioning ED visits as an outcome used wearable technology data to predict the occurrence of ED visits.^{19,20,23–27}

CONCLUSIONS

In this literature review, we identified only eight unique studies that directly incorporated data from wearable technology into models associating wearable technology data with clinical outcomes. Given the small number of studies, we can only speculate on the utility of wearable technology for predicting clinical outcomes. However, there are several promising findings from this review that suggest that further research on wearable technology for predicting clinical outcomes is needed. The studies by Yates et al of over 9306 patients and Pyrkov et al of 7454 patients demonstrate feasibility and biologic plausibility of tracking patient data with wearable technology. Yates et al were able to associate data collected by wearable technology with clinical outcomes, despite dichotomizing complex step count data.

Utilizing more features of complicated wearable technology data would likely improve predictive models, which was demonstrated

by Bae et al.¹³ With a sample size of only 25 patients, Bae et al used 89 features of Fitbit data and were able to predict readmission with 88.3% accuracy. Their model was significantly better at predicting readmission than previously reported models that use traditional retrospective clinical data.³⁰ The strategy of using the full breadth of wearable technology data in clinical outcome prediction is promising,¹³ as model accuracy was high despite a small sample size. This strategy warrants study in larger and more diverse populations to assure generalizability and minimize the likelihood of model overfitting.

In the future, we expect that enhancements in wearable technology will overcome many of the existing hurdles to its use in routine clinical care. Wearable technology is likely to support additional sensing modalities (eg, pulse oximetry, blood pressure, electrocardiography, glucose), last longer on battery power, adopt new form factors (eg hearing aid, contact lens, and generally smaller size), and achieve FDA approvals. Efforts on many of these advancements exist as prototypes or are under development. Clinical studies need to advance hand in hand with the evolution of hardware and software of wearable technology.

One potential source of bias in our study was the method of title and abstract review in which the second reviewer was not blinded to the determinations made by the first reviewer. However, strict inclusion criteria were utilized, as all studies had to use wearable technology and track mortality, readmission, or ED visits, which likely minimizes any possible bias introduced by a lack of blinding.

In conclusion, wearable technology has significant potential to assist in predicting clinical outcomes, but needs further study. Well-designed clinical trials that incorporate data from wearable technology into clinical outcome prediction models are required to realize the opportunities of this advancing technology.

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CONTRIBUTORS

JPB, CL, LHY, TCB, and MKH made substantial contributions to the conception or design of the work; or the acquisition, analysis, or interpretation of data for the work; drafted the work or revised it critically for important intellectual content; will provide final approval of the version to be published; and agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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