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DATA-DRIVEN ASSESSMENT OF SHORT-TERM HEALTH RISK USING CLINICAL AND BEHAVIORAL INDICATORS IN TELEHEALTH MONITORING

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ABSTRACT-

Telehealth monitoring is a chance to use routinely collected clinical and behavioral data to identify patients at higher risk for short-term health outcomes. This study assessed the association of demographic, physiological, behavioral, and healthcare-utilization indicators with 30-day high-risk status in a telehealth monitoring dataset. The secondary analytical observational design comprised 1,800 patient records of adult patients with complete data on age, sex, BMI, blood pressure, resting heart rate, daily steps, medication adherence, sleep duration, prior hospital admissions and risk status within 30 days. Descriptive statistics, Mann–Whitney U test, Fisher's exact test, Spearman correlation and binary logistic regression were used. There was significant class imbalance as only 14 patients were identified as high risk within 30 days. The high-risk individuals had an older age profile, higher diastolic blood pressure, higher resting heart rate, lower daily step count and poorer medication adherence. Logistic regression also found positive age, DBP, and RHR association with short-term risk, while daily steps and medication adherence had inverse associations with short-term risk. Correlations between most predictors were low, indicating that predictors were complementary aspects of the health status. These findings suggest that combining clinical and behavioral measures could enhance short term risk assessment for telehealth monitoring. However, the high-risk group is small, which limits the stability of estimates. Longitudinal data sets are needed to be larger, and external validation is required prior to clinical implementation.

Keywords: Telehealth monitoring; Short-term health risk; Clinical indicators; Behavioral indicators; Logistic regression

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1. Introduction

Digital health technologies have grown in significance in modern-day health care due to their ability to capture, analyse, and utilize health information outside of traditional in-person clinical environments. Continuous monitoring of patients with telehealth, remote patient monitoring, wearable devices and connected healthcare systems can help health care providers keep a better track of patients and detect changes that may need timely interventions. AI and data analysis have also been integrated into telehealth, enhancing opportunities for supporting clinical decision-making, improving attainability and boosting continuity of care (Amjad et al., 2023). Routine patient data can be leveraged to identify trends and patterns, alert medical staff to potential risks, and aid in more effective patient care management, thereby promoting long-term health outcomes (Alam et al., 2022).

Physiological data is now being used in conjunction with data on patients' daily activities in remote healthcare. Blood pressure, body mass index, resting heart rate and past health care use are examples of clinical indicators that may contain valuable information about an individual's health status. Simultaneously, behavioral factors such as physical activity, sleep and medication adherence can be an expression of lifestyle and self-management that can impact near term health outcomes. AI-powered telemedicine can enhance patient engagement beyond the confines of the healthcare facility and boost the link between patients and healthcare services (Chaturvedi et al., 2025). Evidence-based telehealth technologies can thus help facilitate more systematic interpretation of multidimensional patient information and the more responsive models of care (Christopoulou, 2024).

Digital health's potential is especially relevant when it comes to prevention and surveillance of the health of people who could develop a health issue within a relatively short timeframe. More and more, digital interventions are being studied for their potential to assist in health promotion and disease prevention, and to more actively manage modifiable risks (Faizan et al., 2025). Wearable and digital bioelectronic technologies have also been able to increase the capacity of capturing physiological signals and other health-related information in our daily lives continuously (Huang et al., 2025). Likewise, using wearable sensor data to integrate with intelligent analytical methods for remote monitoring and management of chronic conditions, demonstrating the value of continuous data in augmenting traditional clinical evaluations, has been explored (Kaliappan et al., 2023). Such advancements align with the general shift towards episodic care to continuous and predictive care.

The integration of Internet of Things (IoT) technology in healthcare has also enhanced the capability of healthcare devices for continuous monitoring by enabling the collection and transmission of patient-level data across interconnected systems (Meharkure et al., 2025). But health-risk assessment is more than simply physiological measures. A patient's lifestyle and

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behavioural information can offer further context about a patient's health and potentially help to identify those who need preventive support before they deteriorate significantly. Early lifestyle assessment has therefore been seen as useful in bridging the gap between everyday data about behaviours and decisions for preventive health care (Mønsted, 2022). In terms of service delivery, the effective application of health-related indicators and performance information could also enhance the quality of care provided in telehealth and enhance digital health outcomes (Morelli et al., 2024).

While there are significant implementation hurdles, opportunities for monitoring, personalized care, and timely healthcare management exist with connected healthcare systems, interoperability and data integration challenges remain, and the clinical value needs to be assessed (Shafik, 2024). As more large-scale data is available through remote patient monitoring, there are more opportunities to integrate clinical and behavioral data to support risk assessment and decision-making (Shorna et al., 2024). However, additional studies are needed that use clinically interpretable data to investigate how common clinical and behavioral measures are associated with short-term health-risk status. Evaluating these relationships could be helpful for risk stratification, follow-up and monitoring of patients via telehealth.

Objectives

- To describe the demographic, clinical, and behavioral characteristics of individuals represented in the telehealth monitoring dataset.
- To compare clinical and behavioral indicators between individuals with and without short-term 30-day high-risk status.
- To assess the association of selected clinical and behavioral indicators with short-term health risk in a telehealth monitoring context.

2. Materials and Methods

2.1 Study Design

The design of this study was analytical observational with a secondary data approach to evaluate short term health risk using readily available clinical and behavioural indicators in a telehealth monitoring (THM) scenario. This analysis examined the differences in patient characteristics based on 30-day health-risk status and the association of selected clinical and behavioral characteristics with short-term risk. This design was suitable because the data available contained characteristics of patients at the individual level (e.g., demographic, physiological, behavioral, and healthcare utilization characteristics) and a short-term risk outcome that was predetermined.

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2.2 Data Source and Study Population

The existing telehealth risk-monitoring dataset consisted of 1,800 patient records and 12 variables (West, 2026). These records were all from individual patients and contained demographic information, clinical measurements, behavioral indicators, prior health care utilization, and a 30-day risk status. The population consisted of adults ages 25-89 years with enough information to answer all the variables needed for the analysis. No sampling of available records was done, and all records that fit the criteria were retained.

2.3 Study Variables

Variables were categorized based on their relation to a demographic characteristic, clinical status, behavioral characteristic, health care utilization and short-term health risk. Demographic variables used were age and sex. Clinical parameters were body mass index, SBP, DBP and RR. The behavioral parameters were number of steps taken daily, percentage of adherence to the medication and average sleep duration. An indicator of recent health burden and health-care use was added to reflect previous hospital admissions in the 12 months prior. The primary outcome variable was high risk status at 30 days. This variable was coded as 0 if they were not identified as high risk and 1 if they were identified as high risk within 30 days. For comparison and association analysis, the outcome was coded an ordinal variable.

2.4 Data Preparation and Quality Assessment

Data were reviewed prior to statistical analysis to evaluate completeness, duplicates, consistency, and ranges of the variables. There were no missing values in any of the 12 variables and no duplicate patient identifiers were found nor were any duplicate records. Numeric variables were scanned for appropriate representation of values and to ensure that values were within ranges available in the source data. Where appropriate, sex, 30-day risk status was treated as categorical, while age, BMI, blood pressure readings, resting HR, steps, medication adherence, sleep time and previous admissions were kept as quantitative variables. The patient identifier was only used to identify individual records and has not been used for inferential statistical analysis. No alterations of the original clinical and behavioral measures were made except for statistical coding for analysis.

2.5 Descriptive Statistical Analysis

Descriptive statistics were performed to describe the entire study population. Frequencies and percentages were used to summarize categorical variables. For continuous variables, approximately normally distributed variables were summarized by mean and standard deviation, whereas those with a significant non-normality or skewness were summarized by median and interquartile range. Group comparisons were not conducted until demographic and clinical, behavioral, and healthcare utilization characteristics were first explored. The number of people

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with 30-day high-risk status were also described. Due to the small proportion of the study population that was identified as being high risk, this was taken into account when choosing subsequent inferential statistical methods and interpreting the results.

2.6 Comparison According to 30-Day Risk Status

Clinical and behavioural features were compared between those who were classified as high risk and not classified as high risk within 30 days. When the assumptions for the independent-samples t-test of continuous variables were met, an independent-samples t-test was evaluated. If these assumptions were not fulfilled, a non-parametric alternative (Mann Whitney U) was used. Where cell frequencies were adequate, categorical variables were compared with the chi-square test. Fisher's exact test was used when the expected value of a cell was small, especially in the High-risk group where there were relatively few observations. Using these analyses, it was determined whether there were differences in demographic, clinical, behavioral or health-care utilization characteristics based on short term health-risk status.

2.7 Association Analysis

Pearson correlation coefficients were calculated for approximately normally distributed continuous clinical and behavioral variables and Spearman rank correlation coefficients for non-normal and/or non-linearly related continuous variables. The relationships between correlated health indicators and between potential explanatory variables were largely assessed using correlation analysis. Association between selected predictors and 30-day high risk was analysed by binary logistic regression. First, each individual predictor was assessed separately to give an estimate of the unadjusted association with the binary outcome. The number of predictors simultaneously entered into any multiple models was kept to the minimum to minimize the risk of overfitting the models or producing unstable estimates because only 14 of the 1,800 participants were considered as high risk. Preliminary comparison of variables was done to select those included in the adjusted analysis, based on clinical relevance. Results of regression were reported as odds ratios and the corresponding 95% confidence interval. Importance of statistical significance was determined at a two-sided threshold of $p<0.05$, but also emphasis was placed on the direction, magnitude and precision of observed associations.

2.8 Ethical Considerations

The study was conducted using only secondary data, which was de-identified, and there was no patient interaction. Available file was a coded patient identifier but not personally identifying information that directly identified an individual. Only the information contained in the data set was used and for research purposes only. Since no new data are collected and the intervention is not provided, problems of informed consent and institutional ethical approval should be presented

based on the circumstances of the release of the original data set and the requirements of the target journal.

3. Results

3.1 Characteristics of the Study Population

In total, 1,800 patient records were analysed, and full data were obtained for all demographic, clinical, behavioural and healthcare-utilization variables. The study population spanned a wide range of ages and there was wide variation with respect to BMI, BP, RHR, DBP, physical activity, medication adherence, sleep duration, and previous hospital use. Table 1 shows the overall distribution of continuous study variables.

Table 1. Descriptive characteristics of the study population

Variable	Mean ± SD	Median (IQR)	Range
Age (years)	56.93 ± 18.76	57.0 (41.0–73.0)	25.0–89.0
BMI (kg/m²)	28.93 ± 5.85	29.0 (25.0–32.7)	16.0–48.0
Systolic BP (mmHg)	129.39 ± 19.13	129.0 (116.0–143.0)	90.0–189.0
Diastolic BP (mmHg)	79.14 ± 10.49	79.0 (72.0–86.0)	55.0–116.0
Resting HR (bpm)	73.49 ± 11.80	73.0 (65.8–81.0)	45.0–109.0
Daily steps	6011.85 ± 1795.75	6013.0 (4778.2–7276.2)	300–11877
Medication adherence (%)	81.32 ± 11.40	81.7 (73.4–90.0)	42.7–100.0
Sleep duration (hours)	6.93 ± 1.08	6.9 (6.2–7.6)	3.5–9.5
Prior admissions in 12 months	0.67 ± 0.83	0.0 (0.0–1.0)	0–4

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The categorical characteristics and distribution of short-term risk status are shown in Table 2. Male and female participants were both well represented. However, the outcome variable was strongly imbalanced, with only a small proportion of patients classified as being at high risk within 30 days.

Table 2. Sex distribution and 30-day health-risk status

Characteristic	**n**	**%**
Female	845	46.9
Male	955	53.1
Not high risk within 30 days	1786	99.2
High risk within 30 days	14	0.8

The marked imbalance in the short-term outcome is visually demonstrated in Figure 1, with many observations belonging to the non-high-risk category.

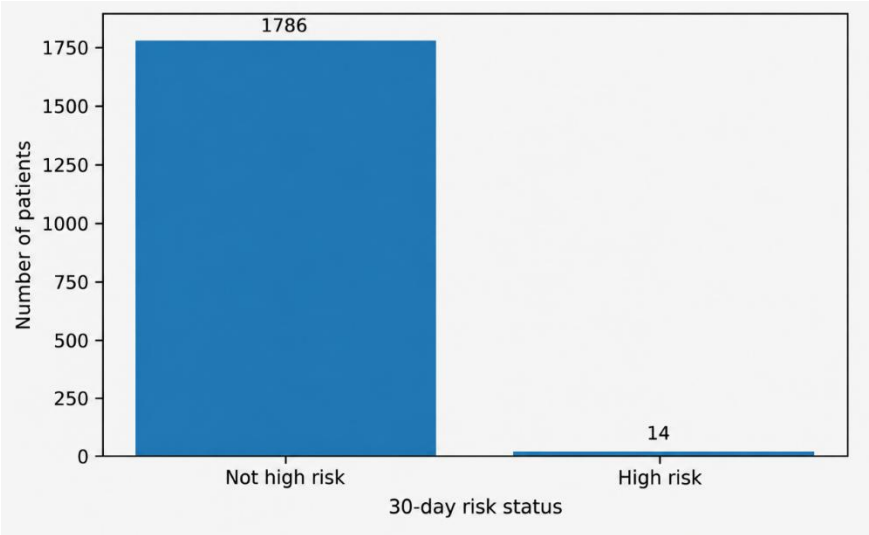


Figure 1. Distribution of 30-day high-risk status

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The figure demonstrates the substantial imbalance between patients classified as high risk and those not classified as high risk within 30 days.

3.2 Comparison of Clinical and Behavioral Indicators According to 30-Day Risk Status

The Mann–Whitney U test was used to compare clinical and behavioural observations between the high-risk group and non-high-risk group due to the extremely small number of high-risk observations and hence the imbalance between the two groups. Statistically significant group differences were identified for age, DBP, RHR, steps per day, and medication adherence as shown in Table 3. BMI, systolic blood pressure, sleep duration and previous hospital admissions did not differ significantly between the risk groups.

Table 3. Comparison of clinical and behavioral indicators according to 30-day risk status

Variable	**Not high risk (n=1786), Median (IQR)**	**High risk (n=14), Median (IQR)**	**p-value**
Age (years)	57.0 (41.0–73.0)	74.0 (57.5–81.2)	0.028
BMI (kg/m²)	29.0 (25.0–32.7)	30.4 (26.8–37.0)	0.162
Systolic BP (mmHg)	129.0 (116.0–143.0)	136.5 (120.0–153.8)	0.209
Diastolic BP (mmHg)	79.0 (72.0–86.0)	88.0 (79.2–94.8)	0.011
Resting HR (bpm)	73.0 (65.0–81.0)	82.0 (72.5–91.8)	0.007
Daily steps	6019.0 (4789.0–7277.0)	4720.5 (3177.5–6739.5)	0.043
Medication adherence (%)	81.8 (73.4–90.0)	74.8 (64.9–81.9)	0.011
Sleep duration (hours)	6.9 (6.2–7.6)	7.2 (6.7–7.8)	0.250

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Prior admissions in 12 months	0.0 (0.0–1.0)	0.5 (0.0–1.0)	0.957

The sex distribution did not differ significantly according to 30-day risk status on Fisher's exact testing (p = 0.189), indicating that short-term risk classification was not clearly associated with sex in this dataset.

Medication adherence showed a visibly lower distribution among individuals classified as high risk, consistent with the group-comparison analysis. This relationship is illustrated in Figure 2.

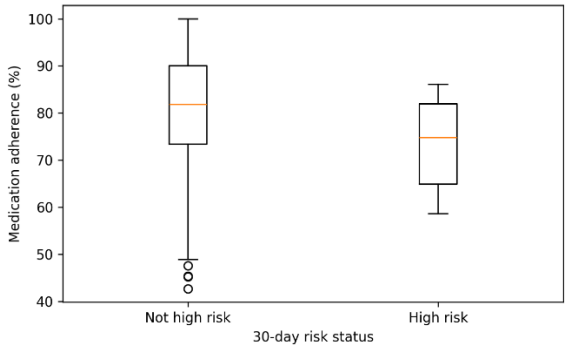


Figure 2. Medication adherence according to 30-day risk status

Patients classified as high risk demonstrated a lower distribution of medication adherence compared with those not classified as high risk.

Similarly, Figure 3 shows a higher distribution of resting heart rate among high-risk patients, supporting the significant between-group difference observed in the comparative analysis.

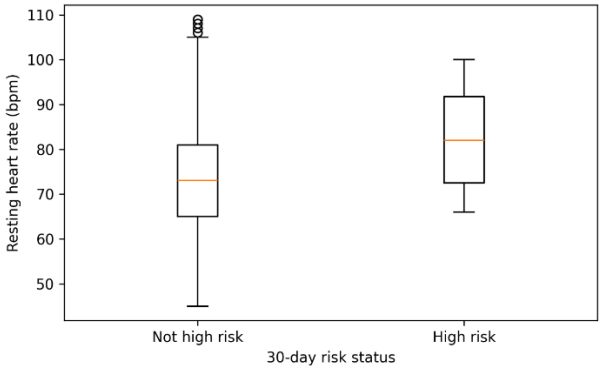


Figure 3. Resting heart rate according to 30-day risk status

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Resting heart rate was generally higher among patients classified as high risk within 30 days.

3.3 Relationships Among Clinical and Behavioral Indicators

Relationships between continuous clinical and behavioral indicators were explored using the Spearman correlation analysis. Most of the correlations were weak, with little overlap among the various measures. Age, blood pressure and physical activity had the most obvious associations. Age was positively associated with both systolic and diastolic blood pressure and negatively associated with daily steps as presented in Table 4.

Table 4. Selected Spearman correlations among clinical and behavioral indicators

Indicator 1	Indicator 2	Spearman ρ	p-value
Age	Systolic BP	0.315	<0.001
Age	Diastolic BP	0.239	<0.001
Age	Daily steps	-0.216	<0.001

These findings indicate that increasing age was associated with higher blood pressure measurements and lower habitual physical activity. The generally modest strength of the correlations suggested that the indicators represented relatively distinct dimensions of clinical and behavioral health rather than strongly redundant measurements.

3.4 Association of Individual Indicators With 30-Day High-Risk Status

Binary logistic regression was then performed to examine the relationship of each indicator with short-term high-risk status. Due to the limited number of high-risk events in the outcome, a first exploratory analysis of the predictors was conducted separately. All odds ratios in Table 5 are standardized odds ratios and thus indicate the change in odds for each one standard deviation increase in the continuous predictor. There were positive associations between age, diastolic blood pressure and resting heart rate and 30-day high-risk status. In contrast, an inverse association was found between daily step count and adherence to medication. There were no statistically significant individual associations with BMI, SBP, sleep duration or previous hospital admissions.

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Table 5. Unadjusted logistic regression for 30-day high-risk status

Predictor, per 1 SD increase	OR	95% CI	p-value
Age	1.89	1.05–3.40	0.035
BMI	1.58	0.94–2.67	0.085
Systolic BP	1.41	0.84–2.36	0.196
Diastolic BP	2.12	1.27–3.54	0.004
Resting HR	2.15	1.26–3.64	0.005
Daily steps	0.54	0.32–0.90	0.019
Medication adherence	0.52	0.31–0.86	0.011
Sleep duration	1.32	0.78–2.25	0.304
Prior admissions in 12 months	0.97	0.57–1.66	0.916

3.5 Parsimonious Adjusted Association Model

Due to the small number of high-risk events, only a limited adjusted model was used instead of including all the candidate predictors at once. Two behaviourally relevant indicators of step count and medication adherence were retained that demonstrated evidence of association in the preliminary analysis. The adjusted estimates are shown in Table 6.

Table 6. Parsimonious adjusted logistic regression for 30-day high-risk status

Predictor, per 1 SD increase	Adjusted OR	95% CI	p-value

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Medication adherence	0.53	0.32–0.88	0.014
Daily steps	0.55	0.32–0.93	0.025

When both medication adherence and daily physical activity were added simultaneously, both factors showed inverse relationships with short-term high-risk status as seen in Table 6. As indicated by the direction of the associations, the more adhered and the more active, the less likely to be in the short-term high-risk group. The adjusted estimates should, however, be used with caution since there were only 14 high-risk events and limited information for multivariable modelling.

4. Discussion

The current study evaluated clinical, behavioral, and healthcare-utilization indicators to assess the health risk, specifically in a telehealth monitoring setting. Within 30 days, those defined as "high risk" were more likely to have higher levels of diastolic blood pressure and resting heart rate, and lowered physical activity and adherence to medication, in addition to being of an older age. These results indicate that a combination of physiological and behavioral measures is better suited to understand the short-term risk, than the use of individual clinical measures. The overall low correlations between most of the predictors also suggest that these variables might be useful in giving complementary information to remote risk assessment (Liza & Akter, 2025).

The results align with the increase of data-driven methods of early identification of health deterioration. The routine monitoring data has been proven to assist in the prediction of adverse health states and clinically significant changes before big events take place (Bijlani et al., 2022). Intelligent remote monitoring systems are also increasingly integrating with automated analytics to facilitate timely clinical decision-making, based on physiological data (Garg & Tiwari, 2025). The correlations highlighted between BP and RHR and short-term risk, further support the relevance of cardiovascular indicators in digital health assessment, and cardiovascular and metabolic biomarkers have proven valuable in previous research using data-driven methods (Jorquera et al., 2025).

Behavioral indicators also were significant. The low self-management behaviours of decreased daily stepping and decreased medication adherence were correlated with increased short-term risk, suggesting that every day self-management behaviours can provide valuable information in addition to physiological measurements. This aligns with the overall evolution of the field of wearable and connected health systems, which evolve towards continuous monitoring of patient behaviour and enable personalised monitoring (Konstantinou et al., 2025). Digital health

technologies are also being used in cardiovascular diseases to integrate remote sensing with personalized management approaches (Li et al., 2025). There is thus a potential for more comprehensive risk assessments of patients with data-driven decision-support systems, incorporating both behavioral and healthcare data.

These are useful conclusions for telehealth care providers. Together with clinical measurements, activity and adherence information would be helpful to identify patients that may require closer follow up and/or prevention. In other clinical care scenarios, predictive analytics have already proven to help inform patient care and data-driven healthcare decision making (Meystre et al., 2022). Similarly, the use of multimodal digital assessment platforms and wireless sensing technologies show promise in the ability to combine various patient data in a structured monitoring system (Pang et al., 2025; Toruner et al., 2025). The concept of digitally supported risk monitoring (Sundaram, 2024; Zhang et al., 2024) has further been explored in other areas, such as mental healthcare and gerontology, underscoring its broader potential.

There were a few limitations in this study. A high-risk group was extremely small, and the predicted value of the multi-variable estimates was not stable. The secondary data set also lacked a limited number of variables and included only limited diagnoses, lab results, type of medications and socioeconomic factors. Furthermore, the design of the study is one of observation, which cannot determine cause and effect. Variability in measurement from the devices can also impact data collected remotely (Vizitiu et al., 2024) and factors such as implementation and cost considerations can impact the scalability of data-driven healthcare systems (Okunuga, 2025). Future research should involve larger high-risk samples and repeated longitudinal assessments and external validation among other populations in telehealth.

5. Conclusion

This study provides evidence that routine clinical and behavioral measures can be used together to meaningfully assess short-term health risk in telehealth monitoring. The high-risk patients within 30 days exhibited a distinctive profile, with a higher age, higher DBP, higher resting HR, lower daily physical activity, and poor medication adherence. Of these, cardiovascular measures and behavioral indicators were especially salient to short-term risk and most correlations between predictors were low. There is a possibility that the variables represent different facets of patient health and could complement each other when taken together. The results demonstrated the potential for use of physiological monitoring in telehealth systems in combination with behavioral data. Obviously, daily step count and medication adherence were particularly significant as these are behaviours that can be tracked remotely, monitored, and could help identify patients who need closer monitoring. Such indicators could enhance the capabilities of preventive care, prompt more timely clinical care, and enhance prioritization of patients for remote monitoring when incorporated in telehealth-based risk assessment. However, these results need to be carefully

interpreted due to the small number of patients in the high-risk group and because the data was analysed from a secondary source with limited number of variables. These associations need to be further confirmed with larger longitudinal studies that have more high-risk events, more comprehensive clinical data, repeated measurements, and external validation to increase the reliability of future models for risk assessment via telehealth.

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