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Telehealth Monitoring of Patients in the Community

Abstract: This article outlines a decision support system that seeks to help community nurses monitor the well-being of their chronically ill patients. It is designed for nurses to stay in contact with their patients without spending unnecessary time on less productive aspects of community nursing, such as avoidable driving to and from patients’ houses and taking measurements of vital signs to assess their health condition. It therefore allows the nurse to spend more time on managing the factors that could lead to a healthier patient. The decision support system is developed for two levels of mathematical capability. Nurses with a statistical background are provided with in-depth information allowing them to detect changes in mean, mean square error (and hence variation), and correlations using a variation on dynamic principle components. Less mathematically inclined nurses are offered information about trends, change points, and a simpler multivariate view of a patient’s well-being involving parallel coordinate plots.

Keywords: surveillance, early detection, false discovery rate, well-being.

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1 Introduction

Chronic diseases such as heart disease, lung disease, diabetes, and arthritis cause 7 in 10 deaths each year in the United States, and about 133 million Americans – nearly 1 in 2 adults – live with at least one chronic illness. More than 75% of health-care costs are due to chronic conditions [2, 8].

Heart failure (HF) and chronic obstructive pulmonary disease (COPD), in particular, place considerable burdens on patients and health-care systems through repeated unscheduled emergency department visits and lengthy hospital admissions [11, 24]. The incidence of HF and COPD is increasing [3, 17, 24, 26], and in 2012, the combined total annual direct cost of HF and COPD in the United States was estimated to be more than $50 billion [5, 12].

As the population ages, the burden of chronic disease increases. Around 80% of general practitioner (GP) consultations relate to chronic disease [25]. Patients with a chronic disease or complications use >60% of hospital bed days, and two-third of patients admitted as medical emergencies have exacerbation of chronic disease or have a chronic disease [25]. For patients with more than one condition, the costs are six times higher than those with only one [25]. Some patients are highly intensive users of services (10% of inpatients account for 55% of inpatient days) or very intensive users (5% of inpatients account for 40% of bed days) [25].

In the United States, the Veterans Health Administration (VHA) introduced in 2003–2007 a national home telehealth program – Care Coordination/Home Telehealth (CCHT) [9]. Its purpose was to coordinate the care of veteran patients with chronic conditions and avoid their unnecessary admission to long-term institutional care. Between 2003 and 2007, the census figure (point prevalence) for VHA CCHT patients increased from...
2000 to 31,570 (1500% growth). The CCHT is now a routine non-institutional care service provided by the VHA to support veteran patients with chronic conditions as they age. Routine analysis of data obtained for quality and performance purposes from a cohort of 17,025 CCHT patients shows the benefits of a 25% reduction in numbers of bed days of care, 19% reduction in numbers of hospital admissions, and mean satisfaction score rating of 86% after enrolment into the program [9].

As at-home telemonitoring for the management of chronic disease becomes increasingly widespread, national and international attention is increasingly being focussed on utilising the advances in information and communication technologies (ICT), to design and develop new platforms for chronic care that include automated risk stratification and decision support. This includes strategies for supporting self-management of chronic conditions and remote monitoring of patients’ health [19]. ICT has the potential to address the great need for monitoring at-risk patients at home and flag when more nurse attention is required to keep chronically ill patients out of hospital.

The aim of this article is to develop a “real-time” risk stratification of telemonitored patients that healthcare providers can use to support them in managing chronic disease patients in the community. The objective is to improve the electronic methods for remotely identifying at-risk patients through daily monitoring of their vital signs. The article starts by outlining the data available from each patient being monitored in a current home-monitoring clinical trial. Before the appropriate method for telehealth monitoring can be discussed, the nature of the variation in data needs to be reviewed and understood. The method is then based on the understanding that was developed during this review process. Thereafter, two decision support systems are designed – one version for statistically trained clinicians and a second for those without much statistical training. The article concludes with several examples.

2 Patient Vital Signs

Data included in our research were obtained from a multisite “Home Monitoring of Chronic Disease for Aged Care” trial, an initiative funded by the Australian government and led by the Commonwealth Scientific and Industrial Research Organisation. One hundred test patients and 200 matched control patients with a range of chronic conditions that would lead to frequent unscheduled visits to the hospital were recruited from five different states along the eastern coast of Australia. Test or intervention patients were able to record their vital signs and to respond to clinical questionnaires at home using the Telemedcare monitor (http://www.telemedcare.com/). This article will only deal with the data of the 100 intervention patients. Eligible candidates were identified either by site staff familiar with their medical history, or by searching the hospital patient administration database system. Candidates were eligible to participate in the study if they have had either two hospitalisations in the past year or four hospitalisations in the past 5 years.

These intervention patients were provided with a Telehealth monitoring device that helped them collect daily measures of routinely measured vital signs from themselves:
- Systolic blood pressure (SBP),
- Diastolic blood pressure (DBP),
- Heart rate (HR),
- Body temperature (BT),
- Body weight (BW),
- Oxygen concentration in blood, denoted as SpO₂, and
- Blood glucose measures for diabetics (BGL).

Spirometry included
- Measure of the forced expired volume in 1 s (FEV1),
- Peak expiratory flow (PEF), and
- The amount of air that can be forcibly exhaled from the lungs after taking the deepest breath possible (FVC).
These measures were electronically sent daily to a centralised database where the decision support reports are produced and placed on a portal for the nurses to view. This process is fully automated.

The decision support system was designed for clinicians and carers to provide the following information daily:
1. Data identifying when a patient’s single measure is trending away from historical benchmarks using a univariate monitoring tool.
2. Estimated change points when a significant change in trend is flagged. This change point system assumes a step change in the well-being measures.
3. An overview plot for all patients under the responsibility of one clinical care coordinator (CCC).
4. A simple multivariate view of how patients are tracking overall relative to their own historical benchmarks.

The decision support could also be used for patients who are not too afflicted by their condition, with the aim of helping them self-manage their well-being by providing a web-based reporting system. For privacy reasons, the patients are not provided with information from other patients – they only receive their own measurements.

3 Review of the Data

Twelve months into the home-monitoring trial, the available data for the intervention patients were retrieved and reviewed to perform initial exploratory data analysis. Patient vital sign measures are typically taken daily within the first 40 min of waking up in the morning. The measures are uploaded to the database every day using the telemonitoring device.

When monitoring vital signs over time, one of the first steps is to define in-control behaviour. This is sometimes referred to as phase I monitoring [14, 15]. We are not going to document the full phase I monitoring process; however, we will cover the main issues of autocorrelation and the nature of variation.

Generally, nearly all measured values experienced no autocorrelation when measurements were in-control. In other words, in >50% of all cases, patient measures were uncorrelated. The exception was BW. This was the only measure that demonstrated persistent autocorrelation across most patients in the trial; therefore, for this measure, we assumed in-control data were autocorrelated following a Box-Jenkins AR1 model [4]. The exponentially weighted moving average (EWMA) approach of Montgomery and Mastrangelo [18] is used for BW. These decisions influenced the monitoring technology that we used to flag “out-of-control” situations.

Most measures were approximately normally distributed except for patients with SpO2 readings close to 100% most of the time. In nearly half of the patients, this was not a problem. For those patients with SpO2 values close to 100%, it is unlikely that they will flag a problem unless the variation in the SpO2 measures is near zero. Rather than having a separate method for this measure, we kept the assumption of normality. We used EWMA charts based on normality [21], and these are robust to such assumption in most cases. However, there are several non-parametric EWMA alternatives that are available in the literature (e.g., Reference [27]). These were not included in the decision support mix provided to nurses because we did not want to provide the nurses with too many different options at the start and therefore confuse them. These could be introduced at a later stage when the nurses have become more familiar with the new technology.

The autocorrelation plots for a range of patients from one of the trial sites with a long enough history of measurements are presented in Figure 1. We can see that in all these cases, most of the autocorrelations are insignificant. The only case that is a little deceptive is BW, which is usually significantly autocorrelated; however, later we will see why this is deceptive when we explore the qq-plot (measured quantiles vs. normally distributed quantiles) of this patient’s measures.

Figure 2 investigates the qq-normal probability plot for the same measurement patient combination in Figure 1. First, we explore the BW of patient 8 in Figure 2; we can see that the BW of patient 8 does not vary for a long time and then changes from about 90 to 108 kg – much more than expected in one day. BW is the
measure that relies on the patient’s manual entry. We therefore suspect that patient 8 only measured BW at the start and then recorded this value for the next several weeks without formally re-measuring weight and then later started actually measuring it. For this reason, the autocorrelation for the BW of patient 8 is to be ignored. This fact indicates the need to have the appropriate data quality assessment before monitoring the data. We have set up monitoring processes that flag unrealistic measures and automatically exclude these from the monitoring data. One of these is to detect when measures do not vary from one day to the next for too many days in a row.

4 Monitoring Method

The ideal patient monitoring tool for a nurse involves assessing a patient’s well-being by looking at several dimensions of patient concern, and making a judgement on whether that patient needs more or less care. Community nurses often do this by taking several measurements during the visit to the patient’s home, or by observing how well a patient functions in their home. Time can be saved if many of these measurements are available electronically before nurses travel to the patient’s home, as they can determine whether a visit is indeed necessary. Nurses can engage with the patients using video-conferencing facilities and discuss the vital signs with the patient, and thus assess their well-being without the need to visit the patients.

Figure 1. Autocorrelation Functions for a Range of Measures and Patients from Tasmania for Assessing Correlations between Consecutive Daily Patient Measurements.
few patients that do need a visit could then be followed in person. This could save an enormous amount of resource and time by not needing to drive to the patients’ place of residence to monitor their well-being. In addition, there is no need to take the measurement manually. A longitudinal record of patients’ vital signs and other measures can permit the early diagnosis of an exacerbation of a patient’s condition, and thus the early coordination of care, to ensure that the patient is not hospitalised. Such a longitudinal record is not usually available in traditional models of care based on episodic interventions, which may not identify the exacerbation of disease in time to avoid hospitalisation.

However, it is important to have a statistically robust and well-designed decision support system to automate the detection of early trends in a patient’s health status. The type of tool that is useful may differ depending on the mathematical capability of the nurse. Most nurses have only limited training in statistics or computer science. The statistically trained nurse may want a multivariate monitoring tool that describes significant changes in well-being using a single chart. Here, we use the dynamic biplot to visualise the changes and a group of moving average vectors and Hotelling’s $T^2$ test [13] to assess the significance of changes in mean vector. These are linked to the traditional univariate tests to diagnose the nature of the multivariate change (see Reference [22] for more detail).

There is a small amount of measurement error in each of the measurements examined [7], and these are expected to be housed in the lower dimension of the principal components used in constructing the biplot.
Therefore, there is an advantage in examining the measures in a reduced dimensional space because it generally means that nurses avoid responding to measurement errors.

However, we will first start from the univariate approaches to flagging unusual trends in the individual charts.

5 Trend Plot

The EWMA smoothing of measurements is a well-known monitoring tool [21]. This smoothing helps reduce noise (measurement error and random variation) in the data and therefore is efficient at revealing trends. The EWMA-smoothed measure $y_t$ recorded at time $t$, denoted $S_t$, is given by

$$S_t = \alpha y_t + (1 - \alpha) S_{t-1},$$

(1)

where $\alpha$ takes on values between 0 and 1. Smaller values of $\alpha$ smooth more, and values close to 1 have nearly no smoothing.

Baseline data are used to estimate the in-control mean and variance of $y_t$. Let these be denoted by $\mu$ and $\sigma^2$. Let $S_0 = \mu$. The asymptotic variance of $S_t$ is given by $\frac{\alpha^2 \sigma^2}{2 - \alpha}$ under the assumption that these measures are uncorrelated. The change in the mean of $y_t$ from the mean of the baseline distribution is flagged if either

$$S_t > \mu + k \sqrt{\frac{\alpha}{2 - \alpha} \sigma}$$

or

$$S_t < \mu - k \sqrt{\frac{\alpha}{2 - \alpha} \sigma}.$$

The values of $k$ are determined using Knoth’s spc package [16], assuming normality to deliver a particular in-control average run length (ARL). In this article, the in-control ARL is taken as 100 days, i.e., we can expect, on average, one false alarm for $y_t$ every 100 days. As one CCC is looking at about 200 (a maximum of 225) measurements per day, they expect roughly two false alarms per day. Therefore, we propose that if the CCC is not convinced by the trend plot, then the following two run rules, with low probabilities of occurring when in-control, should be used:

1. “Nine consecutive points fall on the same side of the baseline mean value.”
2. “Six (or more) points in a row are continually increasing (or decreasing).”

To check whether signalled trends holds up to one or both of these rules.

For the autocorrelated BW measures, we used the Akaike Information Criterion (AIC) criteria [1] to establish that the Box-Jenkins AR1 model [4] fitted the data the best. We assume the model for BW is of the form

$$y_t = \phi_0 + \phi_1 y_{t-1} + e_t,$$

where $e_t$ is the random error with mean zero and variance given by $\sigma^2$. Note that this has mean and variance given by $\phi_0/(1 - \phi_1)$ and $\sigma^2/(1 - \phi_1)$. The EWMA-smoothed BW measures use the same process as described before in equation (1). Therefore, the control limit used for the autoregressive process is given by

$$E(S_t) \pm k \sqrt{\frac{\alpha}{2 - \alpha} \frac{\sigma^2}{1 - \phi_1^2}},$$

where $E(S_t) = \alpha(\hat{\phi}_0 + \hat{\phi}_1 y_{t-1}) + (1 - \alpha) E(S_{t-1})$; $\hat{\phi}_0$ and $\hat{\phi}_1$ are the estimates of the AR1 model parameters $\phi_0$ and $\phi_1$, respectively. The estimates of the model parameters are updated daily. The constant $k$ is chosen to deliver a false discovery rate of 1 in 100 days. A signal is given whenever $S_t$ falls outside of this interval.
Once a trend is detected, we are interested in the assignable cause of such change. It is helpful to identify the change point for assessing potential causal links. For this, we use the phase I distribution-free analysis in Capizzi and Masarotto [6] by applying their rsp package in R (http://cran.r-project.org/web/packages/). This distribution free test is a deliberate alternative to the normality assumption made in testing for a significant trend using \( S \).

### 6 Decision Support System

The CCCs do not have the time to look at all 200 charts every day, and therefore need support on where to focus their attention in their efforts to provide the best care for their patients. One way of achieving this aim is to use a multivariate chart that is designed to have an overall false alarm rate of 0.5 in 100 days or 1 in 200 days. For this, we used the dynamic biplot [22]. An example of this chart is provided in Figure 7.

Although these charts are informative, we speculate that these might be too complex for nurses to interpret in a short time. It was therefore decided to keep the decision support system simple by providing intuitive charts that would assist the nurse to consider all the dimensions of a patient’s well-being, for example, assessing the total well-being of a patient rather than looking at the patient measures individually.

The decision support system involved the following plots:

**Overview plot:** This plot provides the CCC with a snapshot of what the measure-patient combinations are indicating. The nurse’s attention should focus on out-of-control measurements, i.e., only consider those measurements that signal significant a departure from the baseline distribution. This plot provides a summary of the significant trends for all the patients under their care. Simple “traffic” lights indicate which measures have changed significantly. Each CCC in our trial has a maximum of 25 test patients to care for, and there are nine measures that patients can take daily. (In practice, we believe that using this technology, the CCC should be able to manage 80 patients simultaneously.) This, in total, amounts to a potential 225 (25 \( \times \) 9) measure-patient combinations. An overview plot that helps the nurse gain a broad overview of significant trends is a useful start to the daily monitoring routine. This is meant to help identify patients who are doing significantly better than their baseline average scores so that the nurse can provide them with positive feedback for their efforts or treatment compliance. It also identifies patients who are getting significantly worse than their baseline, and these patients potentially warrant extra attention or assistance. The overview plot also importantly identifies patients who are not taking their measurements regularly, and measurements that are unreliable.

**Trend plot:** This plot is meant to help the CCC follow those patients who were identified with significant trends in the overview plot. These plots help identify the nature of the trends and flags when the measures have departed significantly from the baseline average measure. The baseline measurements in this article are taken as the measures for the first 30 days during the study period; however, the CCCs have the option of selecting whatever baseline they feel is appropriate. The baseline measurement must either be (i) the last period of “good” health as identified by the nurse/patient or (ii) the baseline derived from health measures of 1 month earlier. The trend plot indicates the raw measurement (as circular points in the plot); the EWMA of these measures is shown either as a black line when they do not differ significantly from the baseline average or a red line when they do. Questions the CCCs may ask themselves are as follows: Has this patient’s measurement value been here before? If the answer is yes, then how well were they doing on previous occasions? If patient is not well or the current patient state is unique, then closer monitoring of the patient may be required as well as responding appropriately to get the patient back to a stable and less risky health status.

**Change point plot for level:** The CCC needs to know the estimated change point to establish the assignable cause to the deterioration in well-being. The change point plot indicates the estimated time when the level of the measure changed significantly. It also provides an estimate of the magnitude of this change under the assumption that the change is a step change [1]. The process only considers step changes, while gradual changes are indicated by the trend plot. The change point test is purposefully non-parametric to differ from...
the parametric test in the trend plot. The CCC is looking for rapid, significantly large changes in the measures. If the change point line is horizontal without a change, then this indicates that there has not been a change in the level of the measure throughout the study period. The patient is stable and does not need attention for this measurement. The CCC only looks at these change points if a significant trend is identified. This helps the CCC identify the event that may have triggered such a change. If the event has a positive outcome, then similar future events should be encouraged. If the event is found to have a significant adverse effect on the patient, then such events should be discouraged in the future.

**Change point plot for scale:** This indicates whether the time point at which the estimated uncertainty (scale) of the measure has changed and estimates the magnitude of this change [1]. This plot only considers step changes. Changes in uncertainty could have two causes. First, they could be caused by greater or lesser measurement error. If, for example, the measures do not vary because of a long period of consecutive identical values (such as BW in Figure 2), then this will flag a change to zero variation in the measures, indicating a problem with this patient’s measurement entries. Alternatively, they could be due to the patient entering into a period of unstable health status.

**Parallel coordinate plot:** This last plot examines all the measurements for a single patient simultaneously. This plot calculates the 99% confidence interval around the baseline mean using a local estimate of the sample variance to establish the control limits (boundary of the grey region in Figure 6). The plot helps observe whether the current measures fall outside the 99% confidence interval (outside the grey region), and therefore provides slightly different information to the trend plot. It offers a more informative overview of a single patient than the overview plot. In addition, it is much easier to interpret than the dynamic biplot in Figure 7. If the local measures are persistently outside the respective confidence bounds, then the mean of their local measures are significantly different from the baseline mean [e.g., heart rate (HR_ecg) for patient 1 in Figure 6A].

The above-mentioned reports are supplied to the CCCs on a daily basis. They were found to be useful by the CCCs for monitoring the patients under their care.

### 7 Application of the Simple Decision Support System for Nurses and GPs

The decision support is illustrated for the Tasmania region because these patients have been monitored for the longest duration in the trial. Below, we review the most recent decision support reports sent to the Tasmania clinical care coordinating nurses.

#### 7.1 Overview Plot

The overview plot offers a view of all patient measures in a traffic light matrix form. The matrix has the number of rows equal to the number of patients, and the number of columns is the full number of measures. The green circle traffic lights indicate that a measure is taken that day and the local average measurement is not significantly different from the baseline average measurements, e.g., patient 52 and SBP in Figure 3. The red plus sign indicates that the local average measurement is statistically significantly higher than the baseline average value, e.g., patient 20 and measurement DBP in Figure 3. The red minus sign indicates that the local average measurement is statistically significantly lower than the baseline average value. If a specific measure is not taken for a patient on the latest day, then a black-filled circle appears for the patient-measure combination, e.g., patient 48 and measurement SBP. If the patient has never measured that variable, then a blank appears in the appropriate location. If a patient measurement is assessed as a measurement error by our quality assurance process, then an orange circle appears in the appropriate location. This allows the nurse to quickly observe what measures the patient is recording and what is unusual relative to the baseline average measure.
Patient 21 in Figure 3 never measured BGL but measured everything else on 26 July 2014, whereas patients 13, 14, and 15 failed to measure anything on this same date. For patient 21, blood pressure and HR have decreased, whereas FVC, FEV1, and PEF have increased. This patient’s scores are moving in the right direction, e.g., SBP changed from 140 mm Hg in the first 90 days of the study period to averaging 130 mm Hg; the HR went from about 100 beats per minute to just over 89 beats per minute; and FVC, FEV1, and PEF all increased significantly. This patient should be recognised and rewarded for managing his/her chronic condition so well.

Ideally, you would want to follow the trends in the traffic light signals from one day to the next to understand what trends are emerging in the suite of measurements.

The following information is included on the HR trend plot for patient 33 displayed in the left-hand-side plot of Figure 4. The green line on the plot indicates the average measure during the baseline period (baseline is taken as the first month in the report). The region between the red dashed lines indicates where trend plot lines should remain if it is not significantly different from the baseline distribution of measures.

Figure 3. An Example of an Overview Plot for a Subgroup of Tasmanian Patients Providing a Snapshot of All Patients under the Nurses’ Care for a Day.

Figure 4. An Example of the Trend Plot for Patient 33 from Tasmania that Indicates Temporal Drifts in Trends and Estimates the Change Points for Abrupt Significant Changes in the Level and Spread of Measures.
The trend in the average HR values is shown by the black line in Figure 4, which is the moving average of the measured values. The grey region indicates the confidence interval for the smoothed estimate of the local trend. If the black line trend remains within the grey-shaded region, then the trend is more believable. If the grey region lies outside the region spanned by the red dashed lines, then we are almost certain the patient condition from this measure differs from the baseline.

Figure 4 clearly indicates an increasing HR trend soon after the patient returned from vacation in early March 2014.

### 7.2 Change Point Plots

The remaining two plots in Figure 4 are change point identification plots (labelled change point and magnitude for level and change point and magnitude for scale plots). This change point is tested over the whole history of the patient measurement process. If a significant change point is detected, then the change points are estimated together with the magnitude of the change and then the change is plotted in a graph (e.g., in Figure 4, the HR went from about 56 beats per minute to 66 beats per minute). This change point has a significance value of $p < 0.0001$. Although this is a significant increase, a heart rate of 66 beats per minute is still very reasonable, and this increase may not be a concern if it does not correspond to any other negative measurement or well-being events. Such a rapid and sustained increase in heart rate, however, warrants further investigation and could suggest that the dose of a prescribed β-blocker may have been reduced.

A scale change point indicates that the volatility in HR level has significantly increased around the same time the HR changed, and thereafter it has been more volatile. This increase in volatility may indicate that the patient is entering an unstable well-being period. This patient also indicated a significant deterioration in PEF and FEV1 measurements. Therefore, this patient should be monitored closely over the next few months.

Figure 5 gives an example of BW that was assessed to be autocorrelated when the measures are behaving normally (in-control), and plots the BW for a patient in Australian Capital Territory (ACT) (Canberra and surrounding areas). This was the only patient to flag an out-of-control BW for 26 July 2014. Notice now that

![Figure 5](image-url)
the expected BW is allowed to vary a little; however, e.g., whilst we may expect BW to usually vary a little day by day, for patient 35 in Figure 5, the increase is flagged for three consecutive days. Such a rapid increase in BW would be considered highly clinically significant if the patient was experiencing, e.g., congestive HF. Note that this increase is not large (a little over 3.5 kg); however, it is flagged as unusual because this patient’s weight has been so stable. The assumptions of zero autocorrelation for the change point analysis are no longer valid.

There is a need for a simple plot that looks at temporal trends in all measurements for a single patient. Here, we used an adaptation of the parallel coordinate plot. Figure 6A and B give two examples of parallel coordinate plots for patients 1 and 65, respectively. Figure 6A indicates a significant increase in FVC and FEV1 values (albeit low in mathematical magnitude), and HR (HR.SpO₂ and HR.ecg) indicates an occasional significant increase within the past week; however, this was not significant on 26 July 2014. Figure 6B, on the other hand, indicates significant increases in SBP (to 145 mm Hg), DBP, HR_bp (HR as measured from blood pressure), and SpO₂, and a significant lowering of FVC, FEV1, PEF, and BT values, most of which is a concern. Therefore, this patient warrants closer care, and a nurse visit to the patient’s home is potentially required.

Figure 6. Parallel Coordinate Plots Providing a Patient Overview: Information on Trends in All Measurement Dimensions.
8 The Dynamic Biplot for Clinicians with Training in Principle Component Analysis

All measurements were assumed to be normally distributed (a necessary assumption for applying the dynamic biplot) other than SpO₂, where the Box-Cox t transform was used Rigby and Stasinopoulos (2005) [20]. The BW measures were assumed to be uncorrelated because the autocorrelations were not significant during the training period (first 60 days of the study period) for the three patients considered. An alternative for BW is to monitor the patient’s standardised one-day-ahead forecast errors. The dynamic biplot may suit a CCC with a strong statistical background, as it is a rich source of information packed into one plot. However, it is likely to be too complicated for nurses with limited or no statistical training. The dynamic biplot assesses

– Multivariate trends in the observation plot,
– Correlations in and below the variable plot, and
– The direction of changes, by observing the position of points in the observation plot ellipses in relation to the direction and length of the vectors in the variable plot.

However, we acknowledge that simpler approaches are needed that provide the information in this biplot in an intuitively easy way to interpret.

The main advantage of the dynamic biplot is that it provides all the information (about changes in mean, variance, and correlations) in a single plot, thus making it easier to assess the overall well-being of a patient relative to the baseline. The multivariate test of whether the average vector of measurements for the most recent 1, 7, 12, 20, or 30 days differs from the baseline average is carried out using the Hotelling’s $T^2$ test [13]. This test, applied to groups of moving averages of different sizes (1, 7, 12, 20, and 30 observations), has robust detection advantages, as demonstrated [22] for the univariate case. The approach holds several levels of temporal memory, and, therefore, is robust at detecting a range of mean shifts of different sizes efficiently. The details of the other tests used in the dynamic biplot can be found in Sparks et al. [23]. In this study, the first 60 observations are used as the baseline, and the last 30 days going back from 15 July 2014 are taken as the test data that are compared to the baseline. This assessment process is a pseudo “before and after” test to evaluate whether the trial is adding value to the patients using this telehealth technology, because for most of the initial period (60 days), the nurses were familiarising themselves with the system and they were probably not making the best use of the monitoring data.

Simple rules for interpreting the biplot are as follows:

1. If a sequence of recent observations cluster away from the origin in the observation plot, then the local sample means (for the past 7, 12, 20, or 30 observations) of some variables have shifted away from the baseline or training sample mean value. In these instances, an ellipse is drawn around these points to indicate the statistical significance of the shift in mean in the observation plot. The variables that contribute to this shift are diagnosed from the variable plot as follows:
   a. The vectors with a coloured thickened line in the centre of the vector flag a change in mean value for the associated variable. The direction of the change is diagnosed from the vectors orientated in the plot relative to the cluster location in the observation plot. Vectors in the same direction as the quadrant (or half) as the recent points clustered away from the origin in the observation plot flag a significant increase in their mean value, while those in the opposite quadrant (or half) flag a significant decrease in their mean value.
   b. The vectors that are perpendicular to the direction of the observations clustered away from the origin in the observation plot have generally not contributed to this change in mean, i.e., they generally have not shifted in mean value.

2. If a sequence of observations is significantly more variable about the origin, then this could flag a change in the covariance matrix. The significance of this is reported below the observation plot. The contribution of variables to this significant increase/decrease in variance(s) can be diagnosed from the variable plot by
   a. The vectors increasing in length sufficiently to change to a red line without a thickening in the middle of the vector. The red vectors indicate a significant increase in mean square error, and if there are no
thickened lines in the middle of the vector, representing a significant change in mean, then there is also a significant increase in variance.

b. If the vectors decrease in length sufficiently to change to a light blue colour, this indicates a significant decrease in mean square error, i.e., a significant decrease in variance.

3. Significant changes in correlation without changes in mean value or variance are flagged by a change in the covariance matrix shown below the observation plot. This change can be noted either as changes in variances or changes in correlations. The changes in variance have already been covered; however, changes in correlations are diagnosed as follows:
   a. A change in the pairwise correlations is flagged by colouring the respective blue-outlined squares in the matrix of squares below the variable plot. The colour magenta flags a significant increase, while light blue flags a significant decrease. The other colours are warnings of near-significant changes.
   b. The angle of the vectors changing dramatically in the variable plot indicates changes in correlation when there are no changes in mean. Variables becoming more correlated have a significantly smaller angle between their respective vectors (vectors that coincide are nearly perfectly correlated), or vectors increasing their angle indicate reduced correlation (vectors with an angle of 180° are nearly perfectly negatively correlated). Vectors that are perpendicular correspond to variables that are nearly uncorrelated.

Figures 7–9 present the dynamic biplots as described in Sparks et al. [23]. In Figures 7–9, if the sample average vector of the past 7, 12, 20, or 30 days flags a significant departure from the mean vector, then an ellipse is constructed around the points. The ellipses are drawn only for the two largest moving averages that are significant. The significance of the other moving averages is reported below the observation plot. The variable plot in Figure 7 indicates a reduced mean square error for BW, FEV1, and FVC by their vectors being coloured magenta. The BT has increased significantly, as flagged by the green thickening of the line in the middle of its vector. This is true only for the last 30 observations (not the last 20) illustrated by the green thickening of the line (same colour as the ellipse for the last 30 observations). As there is no blue thickening that appears on the vector BT in the variable plot, the last 20 observations have not significantly shifted in mean.

**Figure 7.** Dynamic Biplot for Patient 12 Using the First 60 Days of Measurements as the Baseline and the Last 30 Days to Check for Trends Relative to the Baseline.
The non-significance of the last 20 observations is indicated by the absence of the blue thickening of the line on the graph. PEF and FEV1 also indicate a significant increase in their values compared with the baseline; however, this is only significant for the most recent 20 observations (it is not significant for the most recent 30 observations) by the thickening of the line in the middle of the vector being coloured blue (the same as the
ellipse for the most recent 20 observations). \(\text{SpO}_2\) and BT have flagged a significant increase in mean square error by the vectors being coloured red. \(\text{SpO}_2\) has trended below the baseline mean value, indicated by being in the opposite half of the circle to the ellipse; however, as no thickening of the line appears on its vector, its mean square error has increased but there is no evidence of a shift in mean. The colour changes in the matrix below the vector plot indicate significant changes in correlations after correcting for significant changes in mean. Red and green solid squares indicate significant changes at the 1% and at the 10% level of significance, respectively. Magenta and purple indicate increases in correlation.

Figure 8 indicates that FEV1, PEF, and FVC have all increased significantly from the baseline, and \(\text{SpO}_2\) has increased as well albeit insignificantly. BW has decreased significantly. The information relevant to this particular patient thus far indicates a good outcome, as this patient was overweight. The only bad news is that patient 13’s BT has increased significantly and should be followed closely over the next few days. The variables with their vectors red indicate a significant increase in mean square errors, i.e., BW, FVC, and FEV1 all have significantly increased mean square errors, whereas BT and PEF had significant mean shifts but these mean changes were insufficient to cause the mean square errors to have a significant increase.

Figure 9 indicates that a significant multivariate change in mean for the past 7, 12, 20, and 30 observations occurred, and this persistent significant multivariate change was only found to be due to the contribution of SBP and DBP, which have increased significantly from the baseline. However, the changes are not large enough to force the mean square error to be significant and are only univariately significant for the 20-day moving average and not the 30-day moving average. BW and HR (HR\(\times\)SpO\(^2\)) have decreased but not significantly. Many of the correlations have changed significantly.

9 Nurse Feedback and the Need to Change the Way Things Are Done

Five nurse CCCs monitor trial patients in five different states and territories in Australia [Queensland, New South Wales (NSW), ACT, Victoria, and Tasmania]. We requested feedback from each, after they had received one training session of about 30 min on the overview plot, trend plots, change points, and parallel coordinate plots.

The feedback from two nurses was that they have some value but are not looked at because of time constraints. Another said, “Personally I would not use them as they are on a different portal – they need to be integrated into the portal we use for managing our patients.” In NSW and ACT, the CCC had not had enough experience with the decision support system to comment – most test patients had not been monitored that long, and they were not at the stage where they could effectively use the decision support and evaluate its value.

When chronically ill patients are under the care of a GP, they may visit the GP episodically as their symptoms and health concerns warrant. Unfortunately, this may be, in some cases, too late to avoid an acute exacerbation of disease. When patients are under the care of a community nurse, they may be visited as often as three times a week. At-home telemonitoring offers the opportunity to track the patients’ conditions on a daily basis and, should early evidence of an exacerbation be observed, to orchestrate the most appropriate and timely response to avoid an unscheduled hospitalisation.

In our study, one CCC monitors up to 25 patients, which is approximately one-third of a full-time patient monitoring load. The CCCs were all experienced nurses but have not received any significant additional training on how to interpret the longitudinal patients’ record, and typically use their own clinical experience and judgement to determine when and how to intervene. The question of whether this “close to the patient coal face” model is the best way to monitor patients’ health status is still unresolved.

An alternative model that is being considered is the establishment of specialised call centres staffed by highly trained clinicians who are very experienced at identifying early signs of an exacerbation of a patient’s health status and have the resources and the authority to communicate their concerns to the patient’s carers, whether they may be a GP or a community nurse. In an environment where a regional call centre may be monitoring tens of thousands of patients, our proposed decision support system could become an indispensable tool for more cost-effective and better management of a chronically ill population.
However, at this stage, funding models for providing at-home telemonitoring services are still not well defined, and GPs, in particular, see this as a major constraint on their direct involvement in the process of monitoring. GPs are not well placed to carry out this monitoring function, and, in the specialised call centre model discussed above, GP interactions with their patients, prompted by a call or e-mail from the monitoring centre, would be routinely reimbursed through the national Medicare system.

10 Concluding Remarks

Care systems have been relatively slow to adopt self-management programs and to integrate them into more comprehensive care for patients with chronic disease. Technology solutions have not been adopted as eagerly as might have been anticipated, and obstacles to uptake have been identified as lack of reimbursement for physicians offering remote medical treatment, regulatory and professional liability concerns, and accuracy of data [10].

Not all community nurses will find the transition to using telehealth easy, given some aspects of patient care are going to be lost with not having regular visits to their patients’ home. For example, although high-definition video conferencing will help read some of the patient’s body language and help collect information from visual cues on how the patient functions, this may not be as efficient as directly observing the patient. In addition, how the transition to using telehealth is going to influence the patients’ psychological and emotional well-being, particularly for those who are living alone, is an open question. However, the value of patients monitoring their own well-being in terms of informed self-care, plus the extra time clinicians can put into diagnosing patient problems by not needing to take measurement or travel to the patient, also needs to be included in the mix for designing the implementation of telehealth into public health settings. Therefore, future work should consider redesigning the nurse visiting process with the aim of providing a cost-effective community care program that involves telehealth capabilities.

On the more positive side, we have already noticed that a lack of compliance with the measurement regimen is an indicator of either poor well-being or that the patient is away from home, e.g., on vacation. Efficient ways of using this information should be devised in the future.

Two versions of the decision support systems are provided to clinicians. One version is for the statistically trained CCC and involves an overview plot and the dynamic biplot. This allows the nurse to go to the trend plots and change point plots if they need to confirm unusual trends or need a better estimate of change points. The second version helps the nurse trained through more graphs but builds up to the parallel coordinate plot for the few patients that may need a nurse visit or need to be encouraged for doing well.

The measuring and reporting process aims to reduce the travel time for nurses while still remaining in contact with patients that do not need a visit, through video-conferencing facilities. This reduces the time-consuming job of having to take patient measurements and facilitates an assessment of patient risk in a few minutes rather than wasting time travelling and taking measurements. More time, therefore, can be devoted to diagnosing factors influencing patient well-being, and hence the result is a healthier and satisfied patient.

Bibliography


