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A smartphone-based solution to monitor daily physical activity in a care home

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Abstract

Introduction: In an ageing population, increasing chronic disease prevalence puts a high economic burden on society. Physical activity plays an important role in disease prevention and should therefore be promoted in the elderly.

Methods: In this study, a mobile health (mHealth) system was implemented in a care home setting to monitor and promote elderly peoples' daily activity. The physical activity of 20 elderly people (8 female and 12 male, aged 81 ± 9 years old) was monitored over 10 weeks using the mHealth system, consisting of a smartphone and heart rate belt. Feedback on physical activity was provided weekly. A reference performance test battery derived from the Senior Fitness Test determined the participants' physical fitness.

Results: Activity levels increased from week 1 onwards, peaking at week 5, and decreasing slightly until week 10. This illustrates that the use of mHealth and feedback on physical activity can motivate the elderly to become more active, but that the effect is transient without other incentives. Bio-data from the mHealth system were translated into a fitness score explaining 65% of the test battery's variance. After separating the elderly into three groups depending on physical fitness determined from the test battery, classification based on the fitness score resulted in a correct classification rate of 67.3%.

Discussion: This study demonstrates that an mHealth system can be implemented in a care home setting to motivate activity of the elderly, and that the bio-data can be translated in a fitness score predicting the outcome of labour-intensive tests.

Keywords

Smartphone, mHealth, physical activity, elderly

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Introduction

The ageing society is one of the major societal challenges of the 21st century. The worldwide proportion of people aged over 60 years will nearly double from 12 to 22% between 2015 and 2050.[1] This puts a high burden on society in terms of medical care needs because the prevalence of chronic diseases such as cancer, dementia and cardiovascular diseases is high at old age.[2] Daily physical activity (PA) is put forward as a non-pharmacological intervention and lifestyle habit that can play an important role in disease prevention, and that supports good mental and functional health.[3] In addition, an increased level of PA is related to improved bone mineral densities and reduced fall risks, both resulting in a lower risk of fractures.[4] It is important to know PA levels to develop programmes that can help the elderly to maintain sufficiently high PA levels that can contribute to their health.

PA levels can be estimated using different techniques. Self-reported questionnaires on PA levels are used very frequently, but consensus about format and content is lacking.[5] Additionally, self-reported questionnaires are subject to recall bias.[6] Quantitative measurements such as indirect calorimetry, the double-labelled water method or direct observations are very accurate, but not feasible for continuous use in a practical setting.[7]

Mobile health (mHealth) has been suggested to address the issue of continuous PA monitoring. mHealth is an area of telehealth that uses mobile devices (smartphones, tablets or wireless patient-monitoring sensors) for data collection, data processing and communication of the results back to the individual.[8] mHealth applications for use in chronic conditions have been developed.[9] Related to applications for the elderly, mHealth has been applied for fall detection,[10] wandering detection,[11] medication

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management[12] and PA monitoring.[13] Furthermore, mHealth has also been said to have a short-term, motivating effect on PA levels.[14]

Pedometers are probably the most used devices for PA monitoring.[14] However, pedometers tend to underestimate step counts during low walking intensities, which are common in elderly.[15] Accelerometers are considered more reliable for PA measurements at low intensities.[16] Furthermore, by using smartphone-embedded accelerometers, no additional accelerometers must be worn. However, implementation of smartphone measurements in daily life is limited because of the short battery life of the smartphones.[17] Other common issues of smartphones are varying localization[17] and the difficulties that the elderly may experience with new technologies.[18]

The field of wearable devices and mHealth applications is booming. However, very few scientific studies have been performed in a semi-controlled environment to investigate the quality and reliability of the data, especially with the elderly. In addition, the translation of the data into features that are relevant for estimating physical fitness and changes in physical fitness has not been performed in a systematic way. In this study, a smartphone-based mHealth system was implemented in the daily life setting of a care home centre to investigate to what extent daily PA levels of the elderly can be monitored during a 10-week period. The first goal was to evaluate if the use of mHealth changed the PA behaviour of the elderly during this period. The second objective consisted of investigating whether the mHealth data correlated with validated fitness tests from a well-established senior fitness test.

Methods

Participants and study design

The study was conducted at the care home *'t Gravenkasteel* (Lippelo, Belgium) from 29 March 2013 until 19 June 2013. The ethics board of University Hospital Antwerp (Antwerp, Belgium) approved the study. The care home management received detailed information about the study's objectives and practical implications. The physiotherapists at the care home pre-selected elderly participants that could be enrolled in the study, taking into account their physical fitness, independence and cognitive capacities. This was done using the Katz Index of Independence in Activities of Daily Living (Katz ADL), a widely used instrument to assess the individual's ability to perform activities of daily living independently.[19,20] The Katz ADL is used in Belgium to assess the functional capabilities of older people in care homes, and to detect problems in performing activities of daily living and plan care accordingly.[21] Test results are recorded by a healthcare professional through direct observation or indirectly by asking the patient subjective questions. The index ranks adequacy of performance in the six functions of bathing, dressing, toileting, transferring, continence and feeding. For each domain, there are four scores from independent to full support needed. This study enrolled only individuals that were completely independent and individuals that needed some support for bathing and/or dressing. Additionally, only elderly people that were in good health were pre-selected to participate in the study. All pre-selected elderly people received detailed information about the study and 20 of them agreed to participate. Written informed consent was obtained before the start of the measurements.

During a 10-week intervention period, the study participants were equipped with smartphones and heart rate monitors to collect data. Daily participation was supervised and guided by the physiotherapists. Measurements were obtained during weekdays. Weekends and public holidays were excluded a priori because of logistical reasons and limited staff availability on those days. The physiotherapists supported the elderly to mount the sensors every morning before breakfast (8–9 a.m.) and to remove them every evening around 5 p.m. The smartphone was used every day of the experimental period and was carried in a pouch, positioned on the middle of the waist in a horizontal position. A chest strap was used to collect heart rate data that were sent wirelessly to the smartphone. Heart rate data were collected in alternate weeks (due to the limited availability of chest straps) over five consecutive days. Wear time of the sensors was recorded at the end of every day. Every evening, raw data were uploaded to a secure server for data processing. Bi-weekly printed summary reports for each participant were presented to the physiotherapists who handed out the individual reports. The reports were provided in Dutch. An objective explanation about the report was given, but the physiotherapist gave no feedback or advice regarding the individual results. It was then up to the participants to decide whether or not to perform more PA and participate in more entertainment activities in the care home. No specific or additional programmes were set up to stimulate this.

In addition, all participants performed a subset of tests from the senior fitness test to characterize their physical performance. The test battery consisted of the 10-minute walk test (10MWT), the 8-foot up-and-go test (UGT) and the two-minute walk test (2MWT). The 10MWT has been shown to be a valid and reliable assessment of walking speed, whereas the UGT can be used for fall risk screening in the elderly.[22] The 2MWT is suggested to be a quicker, but valid, alternative of the six-minute walk test.[23,24] These tests were performed at the start (pre-test), after 1, 3, 5, 7 and 9 weeks, and immediately after (post-test) the 10-week intervention. During these tests, the participants used both the smartphone and chest strap. The results for the fitness tests were interpolated linearly to obtain weekly values.

mHealth equipment

The equipment consisted of a smartphone (Sony Xperia tipo, ST21i Sony, Sweden) and a wireless heart rate monitor (HxM BT, Zephyr Technology, USA). Heart rate data were measured at 1 Hz (range 30–240 BPM) and stored on the smartphone after transmission over Bluetooth 2.0. Accelerometery data was collected at 50 Hz using the three-dimensional (3D) accelerometer imbedded in the smartphone (range $\pm$ 2 g).

An online end-user mobile monitoring application developed by BioRICS NV (Heverlee, Belgium) allowed the collection, transmission and processing of the accelerometer and heart rate data that were stored in separate .csv files. The files were uploaded from the smartphones to the BioRICS server (hypertext preprocessor (PHP)-code for representational state transfer application program interface (REST API)) by means of an hyper text transfer protocol (HTTP) Post request by using the Wi-Fi connection of the care home. Subject identifiers (IDs) and smartphone ID linked every file to the corresponding individual. BioRICS algorithms designed in MATLAB (Mathworks Inc., Natick, Massachusetts) transferred data into relevant activity and heart rate parameters (further referred to as bio-data features). These parameters were compiled into the bi-weekly report and were used to obtain the fitness scores.

Bio-data features

Four types of bio-data features were obtained from the heart rate and acceleration data: activity features, stride features, heart rate features and features describing the influence of activity on heart rate. The calculation of these features is explained in more detail in this paragraph.

Activity features. Activity features include the steps per hour, the percentage of time walking, daily walking distance and the percentage of time active. A step detection algorithm calculates the hourly and daily number of steps from the raw acceleration signal. As illustrated in Figure 1, steps lead to distinctive peaks in the accelerometer data, which means that the starting points of steps can be identified using a simple peak detection algorithm. Steps per day are obtained by summing the number of steps that are taken in one day. Steps per hour are then calculated by dividing the total number of steps by the total duration of the measurement in hours.

Where steps are detected in the signal, the participants are considered to be walking. The percentage of time walking is then calculated by dividing the cumulative duration of walking periods by the total duration of the measurement. Daily walking distance is calculated as the number of steps multiplied by step length. Step length was calculated prior to the measurements for each participant individually by performing a 200 m walk reference test. Total steps during the test were visually counted and step length was calculated as 200 m divided by the number of steps taken.

To calculate the percentage of time active, first the activity counts per second had to be calculated from the raw 3D acceleration data. This is done by (a) detrending the acceleration in each axis in windows of 1 second, (b) taking the absolute value of this detrended signal, (c) summing the values in the 1-second window and (d) averaging this sum over the three axes. Second, an individual

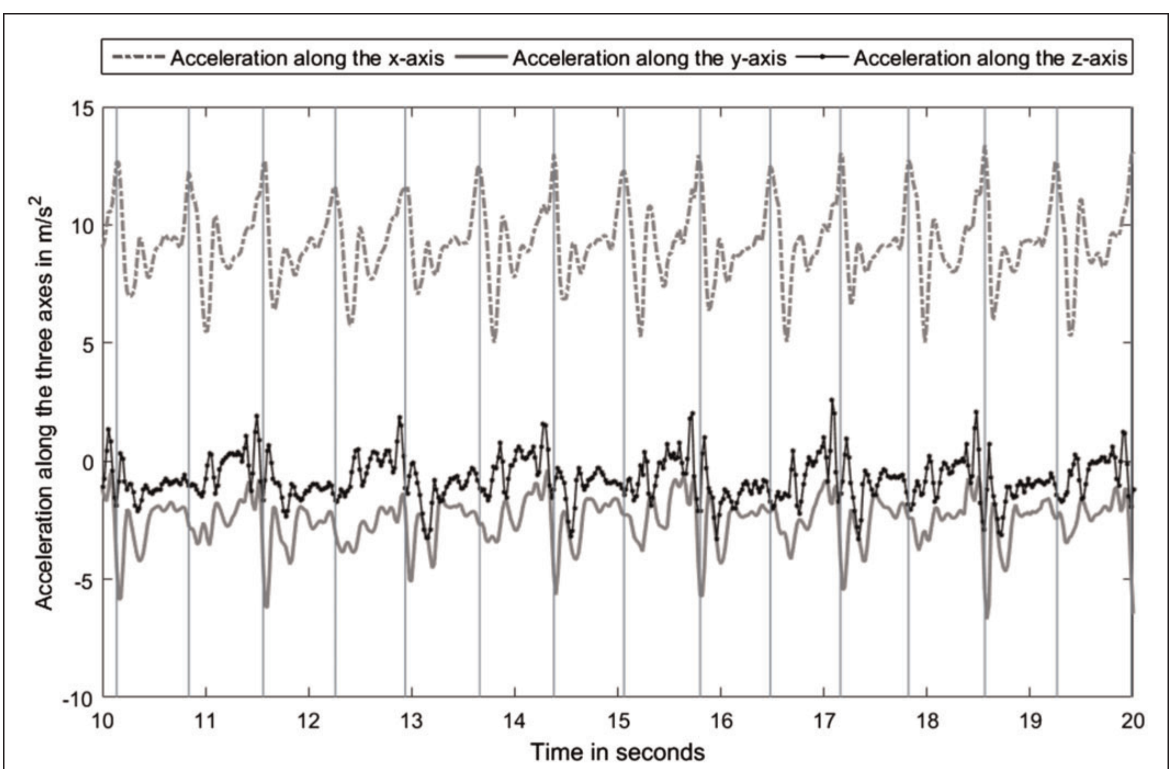

Figure 1. Raw acceleration signal and step detection (vertical lines).

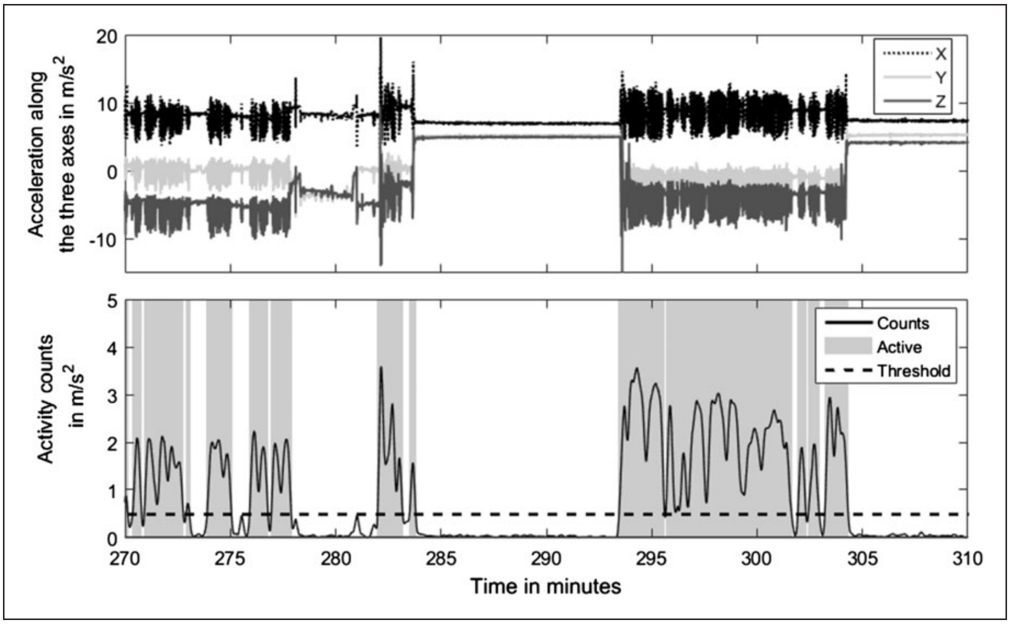

Figure 2. Computation of the activity features. Top: raw acceleration data in the three axes. Bottom: activity counts and active periods.

threshold is defined as 10% of the maximal daily activity count. If this calculated threshold is lower than $0.5\,m/s^2$, the threshold is set to equal this value instead. The percentage of time active is then defined as the cumulative time the activity counts exceed the threshold (active periods), divided by the total duration of the measurement. Figure 2 provides an overview of the computation of the activity features.

Stride features. Stride features include the stride duration, stride acceleration, stride speed and stride displacement. Given that strides are defined as one step of both feet combined, the step detection algorithm can also be used to detect strides. More specifically, every other detected step in the acceleration data indicates the starting point of a stride. Stride duration is then determined by the time between the start of two consecutive strides. The average acceleration magnitude during a stride represents the stride acceleration. By integrating the acceleration magnitude of the three axes and taking the mean value, mean stride speed is calculated. Stride displacement can be obtained by integrating and averaging the stride speed of the three axes (Figure 3).

Heart rate features. The heart rate features comprise the median, maximal and minimal daily heartrate. These features are calculated from the bi-weekly measured heart rate and are linearly interpolated to obtain weekly values.

Influence of activity on heart rate features. The features describing the influence of activity on heart rate consist of the model gain and the model time constant. Their calculation is illustrated in Figure 4.

Firstly, a first-order transfer model is computed using measured heart rate (1 Hz) as output and calculated activity counts (1 Hz) as input, using eqn (1):

$$y(k) = \frac{b_0}{1 + a_1 z^{-1}}\, u(k-1), \qquad (1)$$

where y is the output (heart rate), u is the input (activity counts), b_0 and a_1 are the model parameters, z^{-1} is the backward shift operator, and k is the sample number (equal to seconds in this case). Secondly, the model gain can be calculated by eqn (2):

$$b_0/(1 + a_1) \qquad (2)$$

The model gain represents the increase in heart rate for a unit increase in activity counts. Thirdly, the model time constant is obtained using eqn (3):

$$-1/\log(-a_1) \qquad (3)$$

The model time constant represents the time needed for the heart rate to increase to 63% of the total heart rate change as a response to a unit increase in activity counts.

Weekly report

The weekly report contained the total daily active time, the daily number of steps, the daily walking distance and the daily minimal, median and maximal heart rates.

Fitness score

Canonical correlation analysis (CCA) is used to investigate whether bio-data can be translated to a fitness score.[25,26] For this study, the test scores from the 10MWT, UGT and 2MWT (dependent variables), and

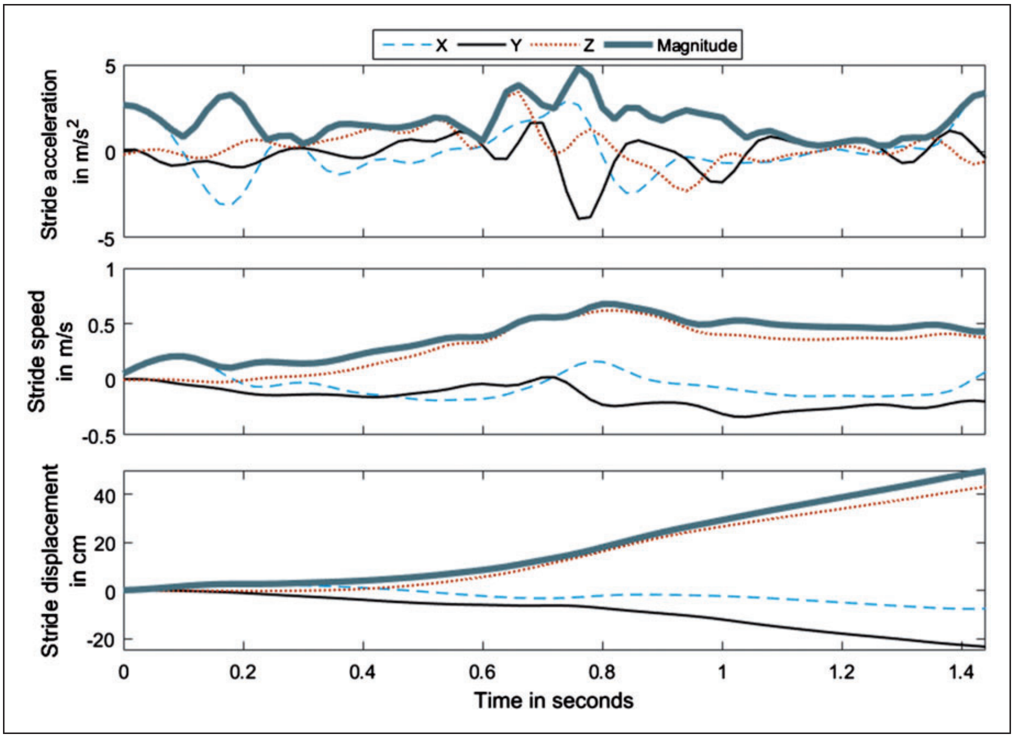

Figure 3. Calculation of stride features. Top: stride acceleration, middle: stride speed and bottom: stride displacement.

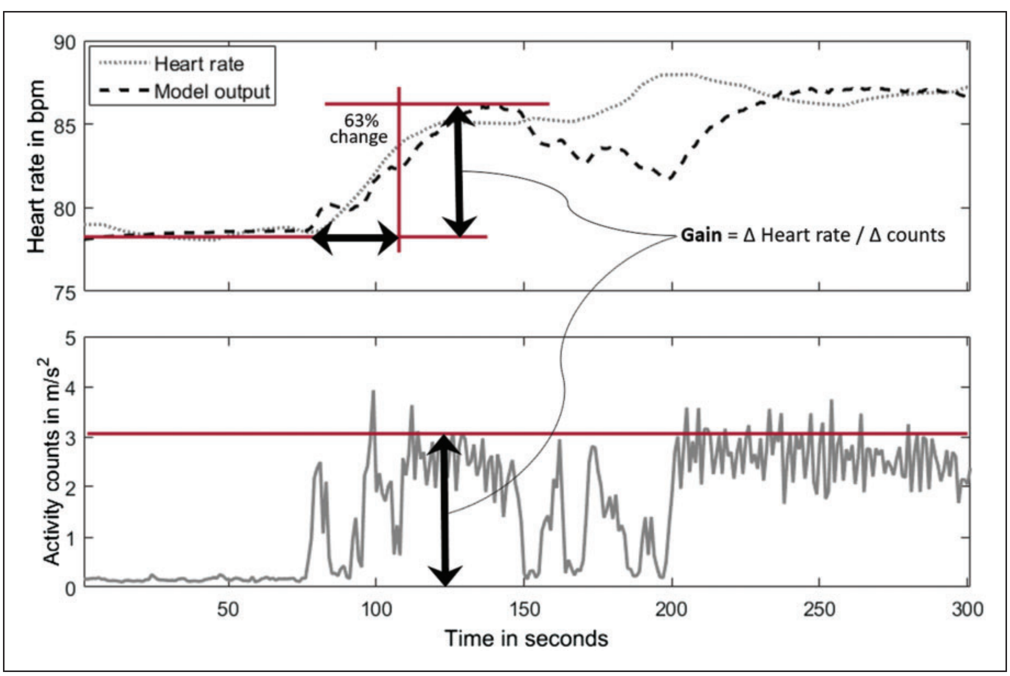

Figure 4. Illustration of model gain and model time constant calculation. Top: measured heart rate and first order model. Bottom: activity counts.

the following bio-data features obtained from the smartphone and heart rate sensors (independent variables), are used: percentage of time active, steps per hour, percentage of time walking, stride duration, stride acceleration, stride speed, stride displacement, model gain and model time constant. Before performing the CCA, missing data are linearly interpolated to obtain weekly samples for all variables. Next, multiple linear combinations or canonical variates are computed for both the dependent and independent variables.

Performance measures from CCA that are important for the interpretation of the results are the correlation coefficient, the canonical loadings and the canonical cross-loadings. The correlation coefficient is a measure of the linear relationship between two canonical variates. The canonical loading of a variable is the linear correlation between this variable and its own canonical variate. The canonical cross-loading of a variable is calculated as the linear relationship between this variable and the canonical variate of the other set of variables. Before the CCA can be interpreted, its significance must be tested by calculating the level of significance, the magnitude of the canonical relationships (R^2) and the redundancy index.

The first purpose of applying CCA in this study is to find a linear combination of the bio-data features that can be used as a fitness score to evaluate the physical condition of an individual. The second goal is to obtain a linear combination of the performance test scores that can be used as a gold standard for assessing an individual's physical condition. Subsequently, the fitness score (based on smartphone and heart rate sensor data) and gold standard (based on 10MWT, UGT and 2MWT) are used to perform classification of physical condition. Before comparing both scores using linear regression, both parameters are rescaled between 0 and 100. The linear relationship can then be used to estimate the gold standard based on the fitness score that is determined with mHealth sensors. Finally, these results are compared with each other for validation of the classification and the confusion matrix is composed.

Statistics

The study followed a pre–post-randomized group design. Repeated measures analysis of variance (ANOVA) was applied to the data sets to compare the physical performance and bio-data features pre-testing, in weeks 1, 3, 5, 7 and 9, and post-testing. In case the repeated measures ANOVA revealed significant differences, Tukey's least significant difference procedure was performed. The analyses were done in Matlab (Mathworks Inc., Natick, Massachusetts).

Enquiry

To assess participants' perceptions of the activity monitoring system, participants were asked to complete a questionnaire containing questions corresponding to a four-point Likert scale with categories 'not at all', 'slightly', 'somewhat' and 'a lot'.

Results

Participants and study design

The study included 12 male and 8 female participants with an average age (±SD) of 81 ± 9 years (range 59–94). A total of 943 smartphone data sets were collected over the 10-week intervention period, of which 141 were rejected for data analysis due to missing data as a result of technical failure or cancelled measurement due to illness of the subject. The remaining data sets had a mean duration (±SD) of 6.4 ± 1.8 hours. The majority (±70%) of activity monitoring sessions were longer than 6 hours long.

Physical performance tests

Bi-weekly performance in the 10MWT, UGT and 2MWT was compared to pre-test performance. First, subjects with an incomplete data set (one or more missing weeks) were rejected for further analysis. This resulted in a data set of 20, 17 and 20 subjects for the 10MWT, UGT and 2MWT, respectively. Second, repeated measures ANOVA was applied to these data sets to compare physical performance between the pre-test, weeks 1, 3, 5, 7 and 9, and the post-test results. In case the repeated measures ANOVA revealed significant differences, Tukey's least significant difference procedure was applied as a post hoc test. The results at group level for the three performance tests are shown in Figures 5 to 7.

Figure 5 shows the box plots and bi-weekly changes with SD at group level for the 10MWT. From the box plot, a slight but gradual decrease in time needed to walk 10 m can be noted from the pre-test to week 5, followed by a small increase from week 5 to the post-test. A significant difference in time needed for the 10MWT compared to the pre-test is observed in weeks 3–9.

In Figure 6, the results of the UGT at group level are shown. Although there is no apparent trend in the box plots, a significant difference in time to complete the UGT compared to the pre-test is found in weeks 1–7. The results for the 2MWT are given in Figure 7. No clear pattern can be observed in the box plots, and no significant differences can be observed when comparing weeks 1–9 and the post-test to the pre-test.

Bio-data features

The weekly percentage active time for the entire monitoring period is shown in Figure 8. The percentage of active time from week 2 to week 10 was compared to week 1 in order to evaluate change over time. Analogously to the comparison of the physical performance tests, a repeated measures ANOVA and post hoc Tukey's least significant difference procedure were applied. A modest, but statistically significant, increase in activity was observed for weeks 3 to 9 when comparing activity to week 1. The absolute increase peaked at week 5 and gradually decreased towards week 9.

Fitness score

CCA between the set of performance tests (dependent set) and set of bio-data features (independent set) has a

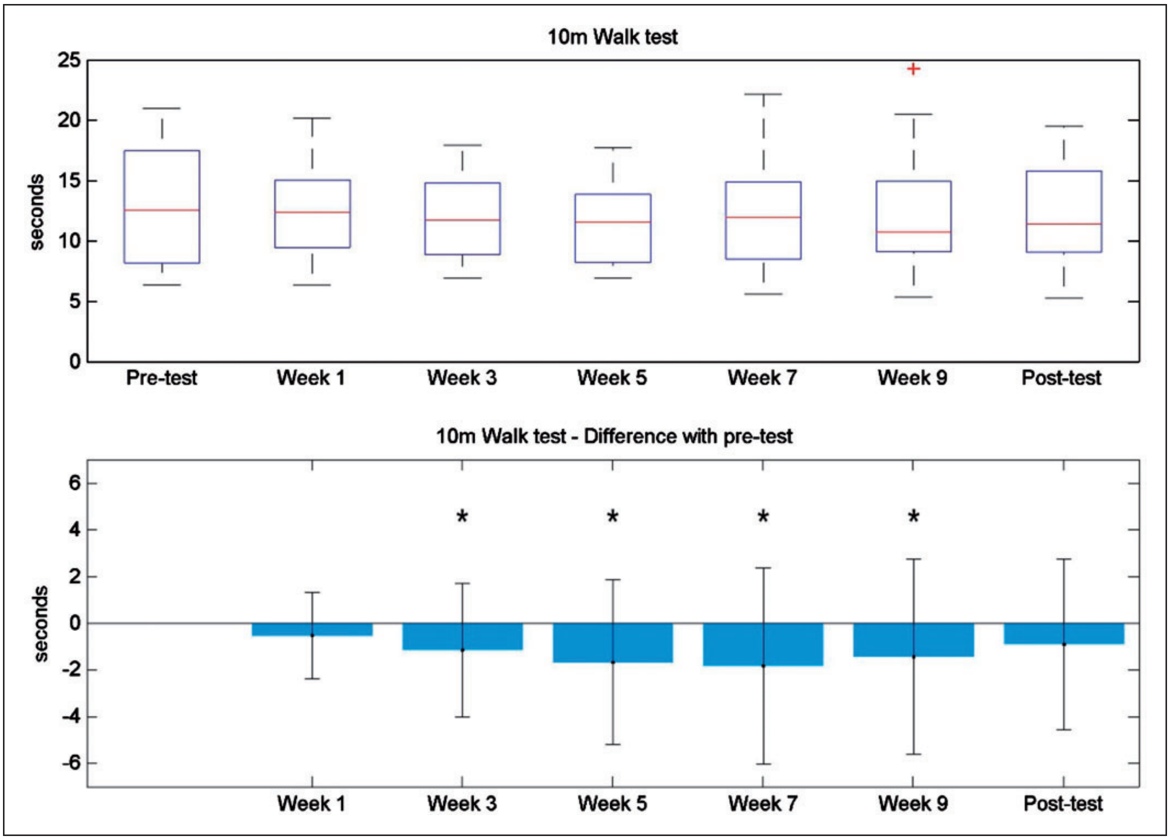

Figure 5. Top: box plots of 10-minute walk test. Bottom: bi-weekly changes ($\pm$SD) of the 10-minute walk test. $^*p < 0.1$ significantly different to pre-test.

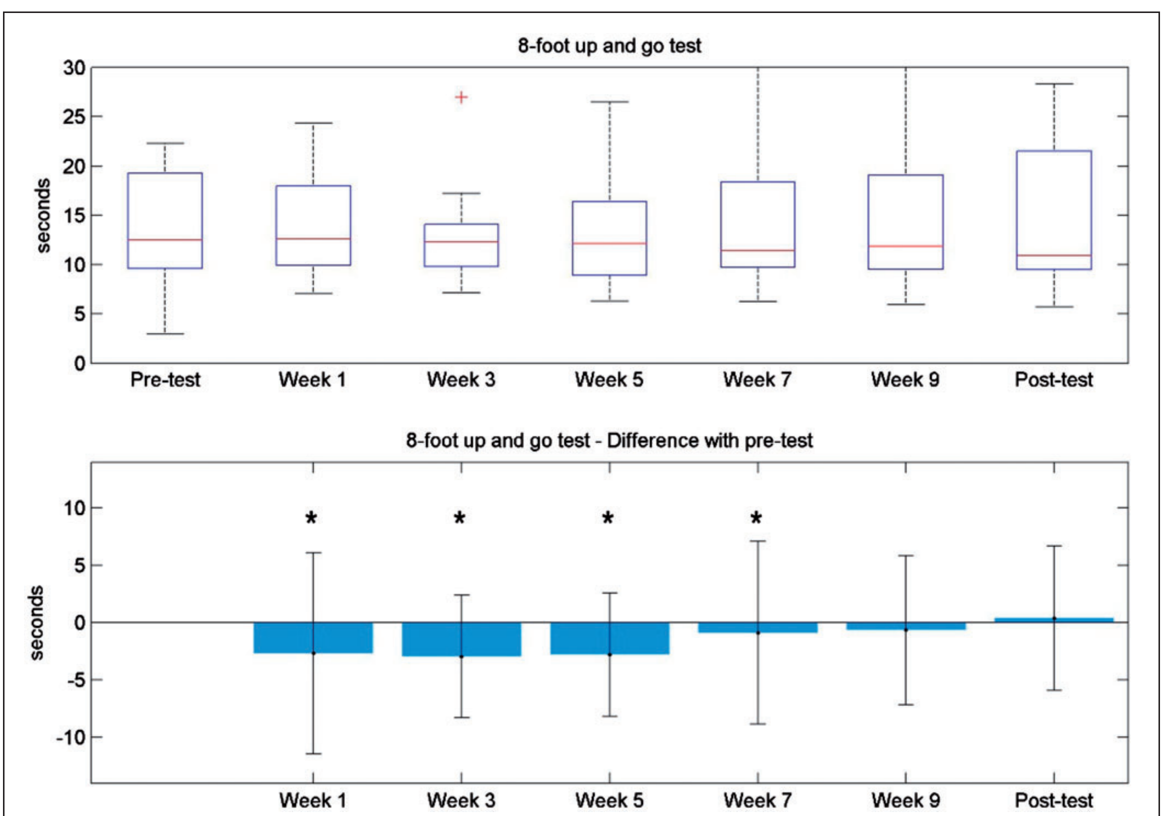

Figure 6. Top: box plots of the 8-foot up-and-go test . Bottom: bi-weekly changes ($\pm$SD) of the 8-foot up-and-go test. $^*p < 0.1$ significantly different to pre-test.

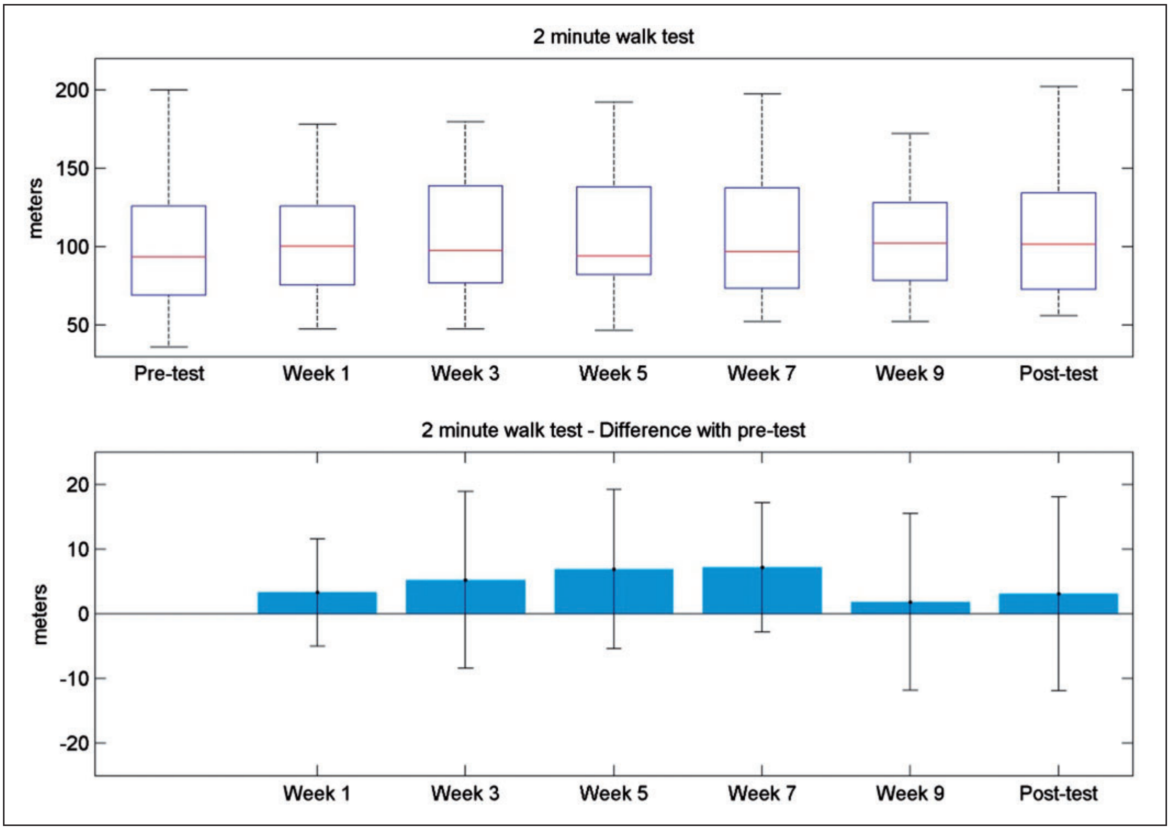

Figure 7. Top: box plots of 2-minute walk test. Bottom: bi-weekly changes (±SD) of the 2-minute walk test. *$p < 0.1$ significantly different to pre-test.

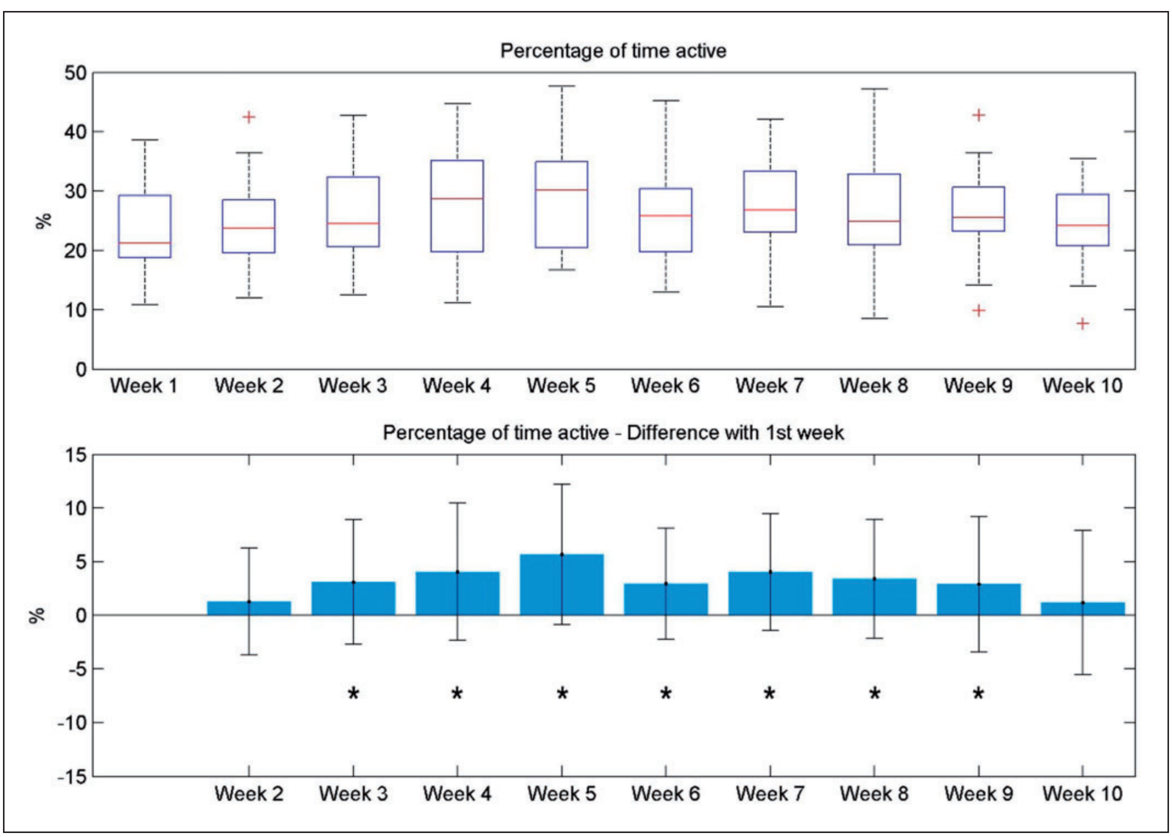

Figure 8. Top: box plots of percentage time active. Bottom: weekly changes (±SD) of the percentage time active. *$p < 0.05$ significantly different to week 1.

Table 1. Canonical loadings and cross-loadings.

Dependent variable	Canonical loading	Independent variable	Canonical cross-loading
10-m walk	–96.01 %	% time active	17.42 %
		% time walking	**40.64 %**
		Steps per hour	**42.28%**
2-minute walk	94.80 %	Stride duration	–21.08%
		Stride acceleration	**55.95%**
		Stride speed	–2.52%
8-foot up-and-go	–92.56 %	Stride displacement	–14.07%
		Model gain	**–63.33%**
		Model time constant	3.87%

Note: The independent variables that show the highest correlation with the dependent canonical variates are marked in bold.

Table 2. Division in three classes: bad, neutral and good.

Class	GS_norm/GS_est
Bad	>60
Neutral	40–60
Good	<40

GS_est: estimated gold standard; GS_norm: gold standard.

significant first canonical function (correlation = 81.02%, $F > 3.68$, $R^2 = 65.64\%$, redundancy index = 58.57%). The canonical loadings and cross-loadings, shown in Table 1, indicate the weights of the different performance tests and bio-data features. The independent variables that show the highest correlation with the dependent canonical variate are marked in bold in the table.

After calculating the gold standard for physical condition and the fitness score from the canonical variates, the gold standard and fitness score were normalized between 0 and 100, further referred to as GS_norm and FS_norm, respectively. Next, linear regression between GS_norm and FS_norm was performed to obtain the estimated gold standard or GS_est, using eqn (4):

$$\mathrm{GS\_est} = \mathrm{B} + \mathrm{A} * \mathrm{FS\_norm} \tag{4}$$

This linear regression resulted in an R^2 of 65%, meaning that 65% of the variability in GS_norm can be explained by FS_norm. For classification, the data were first divided in three classes according to GS_norm (Table 2). Secondly, the same division in three classes was performed according to GS_est (Table 2).

Thirdly, the classification according to GS_est was compared against the classification according to GS_norm. The resulting confusion matrix is given in Table 3. Condition classification using the fitness score results in 67.32 % of correctly classified data. Only 0.97% of all data is classified completely wrong (good as bad and vice versa) by the fitness score.

Table 3. Confusion matrix.

	GS_norm		
	Bad	Neutral	Good
GS_est			
Bad	18.36 %	6.76 %	0.97 %
Neutral	5.80 %	26.09 %	7.25 %
Good	0 %	11.60 %	23.19 %

GS_est: estimated gold standard; GS_norm: gold standard.

Enquiry

At the end of the 10-week measurement period, the participants were asked to fill in a questionnaire to evaluate their perception of the activity monitoring system. Of the subjects, 58% were motivated to be more active because they were wearing the activity monitor and 68% found the activity reports useful. Another interesting observation is that 74% of the subjects said that they would be more active in the future if they were encouraged to do so. Comparing this to the 58% mentioned earlier that were motivated to be more active because they were monitored, this indicates that motivation must also come from elsewhere, as was previously stated.

Discussion

In this study, a smartphone-based mHealth system was implemented in the daily life setting of a care home centre to investigate to what extent daily PA levels of elderly people can be monitored over a 10-week period. During the testing period, 20 care home residents (81 ± 9 years old) were equipped with the system, consisting of a smartphone and heart rate belt, which describes PA levels and physical fitness. Although 15% of the data sets were compromised because of technical failures or cancelled measurements, there was no drop-out of participants over the 10-week program and more than 70% of the data sets contained more than 6 hours of usable data. According to previous studies, an mHealth system should be comfortable, easy to use, non-intrusive and data should be available for caretakers to ensure successful implementation.[27,28] The mHealth system implemented in this study fulfilled these requirements and was therefore well perceived. This indicates that once technical failures are solved, the mHealth system can easily be implemented in a care home centre for PA monitoring of the elderly. An improvement towards ease of use and comfort of wear that can be made in the future is to use watches instead of belts to monitor heart rates of the subjects. These watches will be more practical for the physiotherapists to apply and will be more comfortable to wear all day long.

The first goal of this study was to investigate whether the use of mHealth could induce a change in the PA behaviour of the elderly. For this purpose, the participants received a weekly report of their measurements. This report contained information on daily active time, daily number of steps, daily walking distance and the daily minimal, maximal and median heart rates. The weekly feedback contained only activity and heart rate features, because the stride and modelling features would be less straightforward for the participants to interpret. These reports were handed out to the participants by the physiotherapists without additional feedback or advice regarding their results. It was up to them to decide how much they would participate in the standard available physical and entertainment activities at the care home.

Feedback has been shown to be a positive stimulus for mHealth system compliance,[29] as well as being able to increase PA levels.[30] This is confirmed in this study, as the median active time rose from a little over 20% to just under 30% between weeks 1 and 5 (Figure 8). However, the motivating effect wore off after five weeks and median active time gradually decreased again to 24% in week 10. Still, the increase in active time compared to week 1 remained significant until week 9. Results from the 10MWT are similar to the active time of the participants: an improvement was present from weeks 1 to 5, after which the improvement diminished. This resulted in a significant improvement of the 10MWT from week 3 until week 9 compared to the pre-test score, similar to the increase in active time. The UGT also showed a significant improvement from weeks 1 to 7 compared with the pre-test score. For 2MWT, however, no significant change was shown over the weeks. Note that the results from all tests were subject to large SDs due to the large individual differences between participants. Nevertheless, this study shows that the presented technology has a positive influence on the physical condition of participants, but that this technology is not sufficient to motivate the elderly in the long-term. These findings were confirmed by the questionnaire that was filled in by the participants after the measurement period. In this questionnaire, 58% of the participants indicated that just wearing the mHealth system made them more motivated to be physically active. On the other hand, 74% of the subjects said that they would be more active in the future if they were encouraged to do so. This confirms that the motivation must also come from elsewhere. Previous studies suggest that using apps,[31] setting activity goals[14] or providing actionable feedback[29] might lead to a maintained higher level of PA over a longer period of time, which could easily be implemented in the currently used mHealth system.

The second objective of this study was to evaluate whether bio-data features obtained from the mHealth system can be correlated with validated reference performance tests from the senior fitness test (i.e. 10MWT, UGT and 2MWT). To that end, bio-data features were translated into a meaningful fitness score based on CCA between the bio-data features (independent variables) and the performance tests (dependent variables). The bio-data features consisted of steps per hour, percentage of time walking, stride duration, stride acceleration, stride speed and stride displacement, which were obtained using a simple peak detection algorithm. Some additional calculations provided the percentage of time active. Finally, transfer function model features (model gain and model time constant) were calculated to take into account the dynamic response of HR to changes in PA. CCA between the bio-data features and the performance tests showed a significant first canonical function. Additionally, every performance test was strongly correlated with the dependent canonical variate. The 10MWT and UGT showed a negative correlation, meaning that a shorter duration of these tests corresponds to a better physical condition. Similarly, the 2MWT was positively correlated with the dependent canonical variate (a longer distance in this test corresponds to a better condition). This indicates that the dependent canonical variate, consisting of the three performance tests, is meaningful and reliable as a gold standard for physical condition.

The canonical cross-loadings also show logical relationships. The steps per hour and the percentages of time active and walking are positively correlated with the dependent canonical variate, meaning that they are related to a better physical condition. Regarding stride-based features, a better physical condition is associated with a shorter stride duration, speed and displacement. However, when considering the stride-based features, stride acceleration has the highest (positive) correlation with physical condition. Hence, an improved physical condition leads to swifter strides. The model gain, referring to a heart rate increase in response to PA increase, is negatively correlated with physical condition. This indicates that a better physical condition leads to smaller heart rate increases in response to PA increases. Lastly, the model time constant showed a very small positive correlation with physical condition.

Four bio-data features have been identified as the most valuable for physical condition monitoring: percentage of time walking, steps per hour, stride acceleration and the model gain of a first-order transfer function model. The former three can easily be computed, which indicates that a fitness score could already be calculated solely based on simple features. The latter is more complex, but also has the highest canonical cross-loading. This indicates that more complex features should be considered, as they are able to improve fitness score performance.

The canonical variates were then used to calculate the gold standard for physical condition from the reference performance tests, as well as the fitness score from the bio-data features. After normalising the gold standard and fitness score between 0 and 100 to obtain GS_norm and FS_norm, linear regression was performed between them. This resulted in the calculation of the estimated gold standard GS_est, with an R^2 of 65%. The data were then divided into three groups and the classification according to GS_est was compared against the classification according to GS_norm. It was found that 67.32% of the data could be correctly classified using GS_est and that only 0.97% of all data were classified completely wrongly (good as bad and vice versa). These results show that the measured bio-data features can be translated into one meaningful fitness score, and that this fitness score can be used to relatively accurately monitor the PA of elderly automatically in a care home setting.

A possible limitation of the current study is that a relatively small sample size was considered and that all subjects were recruited at the same care home. For this reason, the results of this study should be interpreted with care and generalizations of the results to the entire elderly population should be made with caution. Another limitation of the study is that heart rate data were only collected every two weeks due to the limited availability of chest straps. Weekly heart rate data might have provided an even more complete and accurate understanding of the participant's daily PA and motivation to be active. Finally, the applicability of the proposed mHealth system for widespread use in care home settings could be disputed. The current system requires staff to apply, remove and charge the mHealth system on a daily basis for all participants. The authors suggest that the possibility of monitoring the elderly using the proposed mHealth system should be investigated on an interval basis, while still capturing their PA in an accurate way, as well as keeping the elderly motivated to be more active.

In conclusion, a smartphone-based mHealth system was implemented in a care home setting to monitor the PA levels of elderly participants. The system was well perceived by caretakers and participants. This demonstrates the feasibility of implement mHealth technology in a care home setting to monitor the daily PA of participants. Feedback about PA levels was given on a weekly basis, with participants consistently increasing their PA levels from weeks 1 to 5, after which the motivating effects of feedback wore off. This indicates that additional incentives are necessary to permanently increase PA levels. Finally, this study has shown that the measured bio-data features retrieved by the mHealth system can be translated into one meaningful fitness score that correlates with reference performance tests for physical fitness.

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