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Yongqiang Lyu, Christopher James Vincent, Yu Chen,
Yuanchun Shi, Yida Tang, Wenyao Wang, Wei Liu,
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Designing and Optimizing a Healthcare Kiosk for the Community

First Author (Corresponding Author)
Yongqiang Lyu[1]

[1]Research Institute of Information Technology, Tsinghua University, Beijing, China.
luyq@tsinghua.edu.cn, +86-10-62793738 (office), +86-18910363606 (mobile).

Second Author
Christopher James Vincent[2]
[2]UCLIC, University College London, Malet Place Engineering Building 8th floor, Malet Place, London, WC1E 7JE

Third Author
Yu Chen[1]

Fourth Author
Yuanchun Shi[1]

Fifth Author
Yida Tang[3]
[3] Fuwai Hospital, Chinese Academy of Medical Science, Beijing, China

Sixth Author
Wenyao Wang[3]

Seventh Author
Wei Liu[1],

Eighth Author
Shuangshuang Zhang[1]

Ninth Author
Ke Fang[1]

Tenth Author
Ji Ding[1]

ABSTRACT
Investigating new ways to deliver care, such as the use of self-service kiosks to collect and monitor signs of wellness, supports healthcare efficiency and inclusivity. Self-service kiosks offer this potential, but there is a need for solutions to meet acceptable standards, e.g., provision of accurate measurements. This study investigates the design and optimization of a prototype healthcare kiosk to collect vital signs measures. The design problem was decomposed, formalized, focused and used to generate multiple solutions. Systematic implementation and evaluation allowed for the optimization of measurement accuracy, first for individuals and then for a population. The optimized solution was tested independently to check the suitability of the methods, and quality of the solution. The process resulted in a reduction of measurement noise and an optimal fit, in terms of the positioning of measurement devices. This guaranteed the accuracy of the solution and provides a general methodology for similar design problems.

Practitioner Summary
We developed an interactive self-service kiosk for healthcare. The aim was to apply a formal design methodology, to optimize positioning of vital signs monitors, and facilitate measurement accuracy. The contribution is two-fold in outlining a generalizable and rigorous approach to design, and showing how it guarantees optimality for certain properties.

Keywords: *human-machine interface; self-service healthcare kiosk; measurement accuracy; design methodology; parameter identification*

1 INTRODUCTION

Worldwide, there are both immediate and far-reaching challenges to the provision of healthcare. For many countries, changes in demographic, growth in Long Term Conditions (LTCs) and changes in the ratio of caregivers to cared for is forcing a rethink in the way that healthcare is provided. Recently, a new kind of healthcare technology has emerged, based upon the use of self-service kiosks (PK, 2013; SoloHealth, 2013). These systems can be used to take physiological measures such as blood pressure, in order to provide healthcare advice.

When it comes to the design of such technology, the Human Factors and Ergonomics literature provides many classic and applicable design rules, relating to the physical characteristics of technology. Designers can also apply data relating to the statistical characteristics of the target population in order to fit a proposed solution to the characteristics of the user population. There are also guidelines relating to design methods (AAMI, 2009; Maguire, 2001; Salvendy, 1997; Vincent et al., 2012), and user interfaces (Borchers et al., 1995; Johnson et al., 2005; Maguire, 1999). All of the above can help match the design of healthcare kiosks with the properties of both users and environments, but doesn't necessarily guarantee accuracy of measurement.

1.1 The need for measurement accuracy

Given the potential use of physiological measures in healthcare diagnosis, monitoring, and clinical decision-making, there is a need for accuracy. Measures need to be in compliance with clinical standards. This imposes challenges upon the design of the kiosk, because there is rarely a one size fits all solution. In addressing these challenges, it helps to break down the problem, consider the factors that impact

on measurement accuracy, and control them. The kiosk measurement process can be considered as an interaction between human and machine, of which there are multiple components (e.g. physical, sensorimotor and psychological). They include traditional physical capabilities, as characterized by anthropometry and biomechanics. These factors contribute to the measurement accuracy and include aspects such as body posture, measuring device height, spatial arrangement of the equipment, etc. For instance, different postures can cause a variation of more than 20% in the measured systolic/diastolic blood pressure (MacWilliam, 1933). Another component relates to the psychological or mental state of the individual. This can result in a variation of more than 20% on cardiovascular measurements (Madden and Savard, 1995).

Getting an accurate measure is important, as almost two-thirds of hypertensive individuals would be denied morbidity preventing treatment if the diastolic blood pressure is underestimated by 5 mmHg. Conversely, the number of people diagnosed with hypertension would more than double if systolic pressure is overestimated by 5 mmHg (Campbell and McKay, 1999). Therefore, the design of an interactive self-service kiosk for the reading of vital signs needs careful consideration, including theoretical modelling of measurement accuracy and optimization across a number of factors.

1.2 Optimizing device interactivity

When it comes to the user interface, although researchers have frequently studied the efficiency of using different interactive components to control equipment; comparatively few have investigated how to optimize the properties of equipment, to support the accuracy of measurement. Studies have contrasted the efficiency of various input modalities, for example the use of touch screens versus manual controls and tangible elements (Rogers et al., 2005; Zuckerman and Gal-Oz, 2013). There are also studies focusing on the use of formal methods to improve interactivity, such as the use of model checking to verify safety properties (Bolton et al., 2012); nonlinear programming to calibrate and tune the properties of the design prior to implementation (Eslambolchilar and Murray-Smith, 2008), and optimization though the use of parametric design problem solving (Motta and Zdrahal, 1996) (examples from outside of healthcare).

This paper focuses on the design of the physiological kiosk from the perspective of optimizing HMI and improving measurement accuracy. The proposed kiosk integrates several medical devices and sensors for reading the physiological characteristics of participants, including the blood pressure (BP), blood oxygen (SpO_2), pulse rate (PR), electrocardiograph (ECG), blood glucose (BG), height and weight. These vital signs are useful for both ubiquitous (general) and clinical (specialist) applications. Furthermore, amongst the educated population, the origins and meanings of these terms are well known. The main contributions of this paper are:

- Structuring the design problem formally, stating the factors that might impact on the formulation and choosing an appropriate design methodology.
- Stating the design method and linking it to a proposed implementation.
- Implementation of a design to realise the methodology.
- Conducting user trials to check the accuracy of the solution.

To do this, we formulated and analysed the design problem (section 2); generated and applied a design methodology (section 3); tested and analysed the implementation (section 0) and made conclusions about the success of the overall process (section 0).

2 FORMALIZING THE PROBLEM

In formulating the HMI design problem, we proposed a series of factors that could feasibly impact on physiological measurement. We then narrowed these down to create an approximate expression of the factors that could be considered and controlled during the design.

2.1 Design goal

The value of a vital sign (y), as read from a sensor could be formulated as a combination of factors emanating from human (X_{human}) and machine ($X_{machine}$) as defined by the function Γ (Equation (1)).

$$y = \Gamma(X_{human}, X_{machine}) \qquad (1)$$

An example of a factor relating to the human would be the position of their arm, relative to a blood pressure monitor. An example of a factor relating to a machine would be the ability for an ECG monitor to determine the rate of the heartbeat from analysis of the input signal. One of the aims of designing the kiosk was to integrate multiple standard sensors, to obtain physiological measures. We therefore focused on the human factors (X_{human}) that had the potential to affect measurement accuracy, as the equipment we were using had already been assessed in terms of quality and performance (e.g. the affects from the machine, $X_{machine}$, were discarded).

So, given the vital sign set V = {BP, SpO_2, PR, BG, ECG, Height, Weight}, the design goal was to minimize the total measurement error of each vital sign i, as a result of human factors, as described in the following optimization Equation (2):

$$\min. \quad \Phi = \sum_{i \in V} | \Gamma_i(X_{human}) - v_i | \qquad (2)$$

For Equation (2), $\Gamma_i(X_{human})$ is the measured value of vital sign i, as determined by the range of human factors (signal + noise). v_i is the reference value, believed to be the real value of the vital sign i when artifacts and noise are eliminated.

In order to decompose the range of human factors (X_{human}), we considered the range of possible influences that might impact on the vital signs. The kiosk was designed to measure vital signs, as derived from intrinsic factors (changes that occur within the body, such as cardiovascular disease), as a result of the overall health of the user. We also needed to consider non-intrinsic inputs from either outside of the body (e.g. postural changes or environmental changes) as well as those from inside the body, but not relating to the general health of the user e.g. mood / emotions etc (Cacioppo et al., 2007; MacWilliam, 1933). The intrinsic inputs reflected the health status of the person using the kiosk. They determined the values of the vital sign*s*, as denoted by reference value v_i. The non-intrinsic inputs determined the noise to the vital signs; they were the ones that we needed to control and optimize when designing and implementing the kiosk. We therefore defined the value of the vital sign y_i as:

$$y_i = \Gamma_i(X_i) = v_i + \delta_i(X_i) \qquad (3)$$

which means that the measured value of the vital sign y_i, is composed of the intrinsic value v_i and the noise $\delta_i(X_i)$ relating to human factors X_i (the X_{human} in Equation (2)). This means that Equation (2) can be rewritten as:

$$\min. \quad \Phi = \sum_{i \in V} | v_i + \delta_i(X_i) - v_i | = \sum_{i \in V} | \delta_i(X_i) | \tag{4}$$

2.2 Considering the range of human factors

Table 1 shows a summary on the factors that could affect the vital signs, which are collected from the known physiological measurement guidelines (AAMI, 2009; Campbell and McKay, 1999; MacWilliam, 1933; Madden and Savard, 1995; Myrtek et al., 2000, Pickering et al., 2005).

Table 1: Human factors that could affect the vital signs.

Factor	**Possible effects**
Posture	Postures may affect the signal quality or the vital signs, e.g. sitting or standing,
Position	Positioning of the user may affect the signal quality or the vital signs arm position, etc.
Senses	Inputs from eyes, ears or touch may affect the vital signs.
Psychological activities	Moods, mental states and other mental activities may affect the vital signs.
Environment	Temperature, humidity, noise, lighting, etc. may affect the vital signs.
Exercise	Exercise affects some vital signs (e.g. blood pressure, heart rate, etc.).
Food	Food (e.g. salt content) may affect the vital signs.
Drink	Drink (e.g. coffee) may affect the vital signs (e.g. heart rate).
Time	Time (e.g. time of the day) may affect the vital signs.
Space	The location of the kiosk (e.g. private / public) may affect the vital signs.

Based on this summary, we developed a basic model of the range of factors that could impact on the vital sign measurements. This allowed us to decompose the optimization problem (Figure 1). Factors relating to exercise and food intake were difficult to control and optimize through the kiosk design and thus ignored in this model, although it is possible that they could be addressed though training and user instructions. From the perspective of the kiosk design, they were considered as background factors.

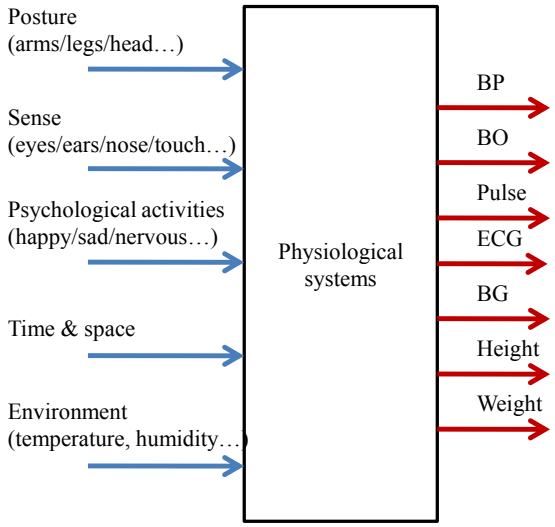


Figure 1: A black-box view of the human body with respect to the factors that impact on physiological measurement.

Regarding the black-box model, we needed to consider what was and wasn't likely to impact on the vital sign set (the output side). We formalized this in the following way:

- Let affecting factor set E = {Body posture, Sensory inputs, Psychological activities, Time, Space, Environment}.
- For any vital sign $i \square V$, the measurement error $\delta_i(X_i)$ in Equation (4) can be formulated as shown in Equation (5), according to the black-box model (Figure 1).
- This provided the total error caused by all of the affecting factors (e.g. Figure 1, left-hand side).
- The subscript i of each affecting factor is ignored.

$$\begin{aligned} \min.\ \Phi_i &= \left|\delta_i(X_i)\right| \\ &= \left|f_B(X_B)\right| + \left|f_S(X_S)\right| + |f_P(X_P)| \\ &\quad + |f_T(X_T)| + |f_A(X_A)| + \left|f_E(X_E)\right| \end{aligned} \qquad (5)$$

In Equation (5), $X_B, X_S, \ldots, X_E$ denote the variables of body posture, sensory input, psychological activities, time, space, and environment. These variables are listed in the affecting factor set E. The X_i is therefore equivalent to a set:

$$X_i = \bigcup_{j \in E} X_j = \cup(X_B, X_S, X_P, X_T, X_A, X_E)$$

The $f_B(X_B)$, $f_S(X_S)$, …, $f_E(X_E)$ denote the measurement errors of the vital signs which are affected by these variables. For convenience, let:

$$X_{Aff} = \bigcup_{j \in E} X_j = \cup(X_B, X_S, X_P, X_T, X_A, X_E)$$

which is referred to as the affecting variable set.

2.3 Considering the measurement sequence

In solving the optimization problem in Equation (4), we came across several challenges. Firstly, not all of the vital sign functions were explicitly defined.

Secondly, it may be that some of the factors influencing the vital signs, X_i (Figure 1), overlapped with each other. For example, both the blood pressure and pulse rate could have been correlated with posture (X_B). There were common variables, within the affecting factor set X_i. This made the problem in Equation (4) difficult to solve. To address this we conducted further decomposition and simplification.

One way to do this was to consider the sequencing of the measurements; that is, the X_i for each vital sign could be distinguished by the time at which the measurement was taken. This made it possible to separate the factors, for example, the postural factor X_B in X_i was configured for blood pressure, and then configured separately for the ECG. As long as the optimal solution is achieved for each vital sign, the total measurement error will be optimal (see Annex 1 for the proof).

2.4 Identifying independent variables

Furthermore, we could also determine which of the variables listed in Equation (5) could be regarded as independent. For example, if we change body posture from sitting to standing, other variables (e.g. environment - temperature) are unlikely to change. At the same time, some variables were sufficiently related that they could impact on the measurement error either directly and/or indirectly. For example, disagreeable sights or sounds may affect measurements indirectly, by causing a change in mood as a result of a corresponding sensation; they may also impact directly, for example a loud noise causing a change in a measurement purely as a result of the sensation.

We needed to differentiate between dependent and independent sets (see Annex 2 for detailed definitions and the proof). The formal design optimization then became possible and could be solved using standard optimization techniques (see Annex 3 for the detailed analysis using nonlinear optimization methods).

3 METHODS

3.1 Kiosk design

3.1.1 Designing for a population

As the kiosk was designed for public use, we needed to generalize a solution (i.e. design for a population), based on our formulation (section 2). Applying the optimization process for an entire population was not practical, but applying it for an individual and then generalizing to a population was. Validation was achieved using an inferential approach, whereby we checked that our generalized solution, met the needs of individuals, within a predefined "error tolerance" (Figure 2):

Firstly, our population sample (the potential users of the kiosk) was divided into two groups; the training group and the testing group. For everyone in the training group, the optimized HMI design was achieved using the problem formulation (section 2), e.g. in the "individual optimization" stage in Figure 2.

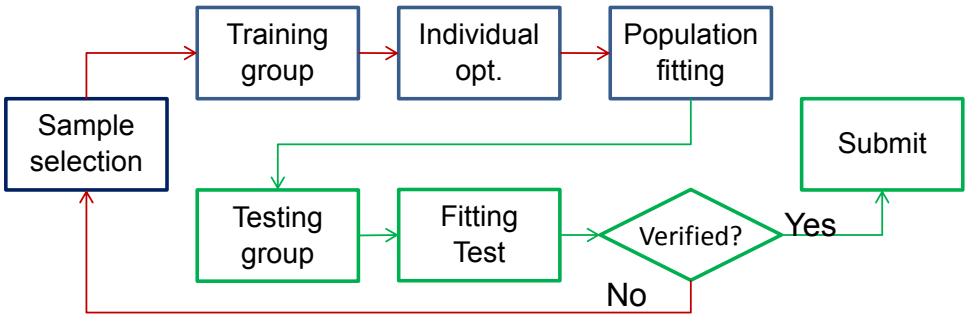


Figure 2: Validating the design methodology for the population.

We then took the sets of optimization parameters and balanced them for use across the population (population fitting). The process of population fitting needed to keep the individual measurement errors within a given significance. This was measured during the "testing group phase" that occurred after the population fitting had occurred. It provided an independent check of the fitting results. Each individual in the "testing group" was asked to try the design and measurement errors were recorded. We either accepted (submitted) the design solution, or repeated the overall process, (based on a 5% significance test) (Figure 2).

3.1.2 Optimizing for individuals

The process of generalizing for the population was dependent upon the results of an individuals' optimization process (Figure 3). This started by setting design parameters, to evaluate the functions in Equation (8) (Annex 3). This step required a model of the target design, including properties relating to the placement of devices.

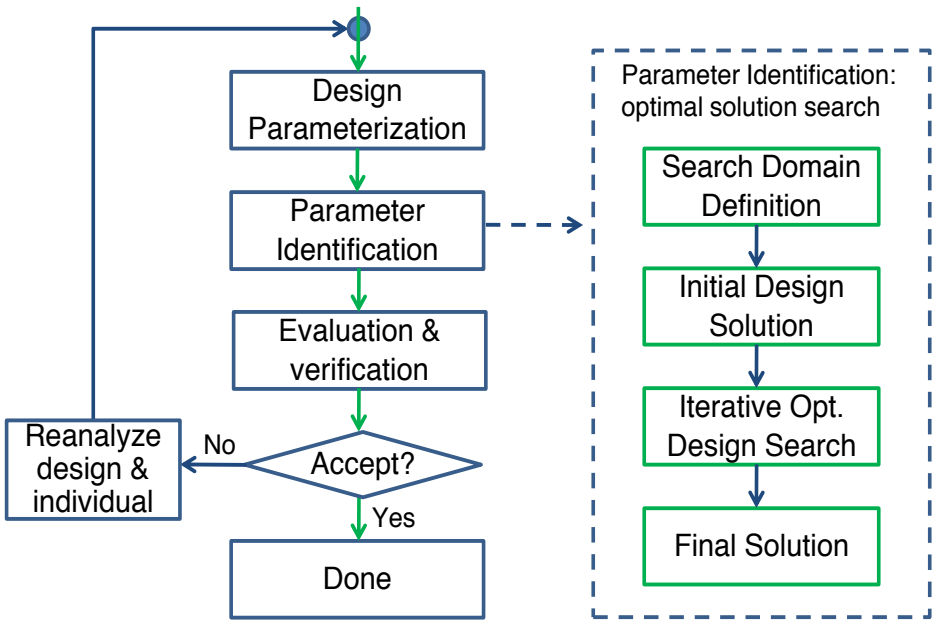


Figure 3: The optimization process.

The parameter identification process was not only used to specify the design, but also provided the basis for the optimization process. In solving this process, we got a design solution; although it was not always possible to do this explicitly (even if independent variables were established). In this case an iterative measurement process / analytical solver was used, which found the local optima in the KTT condition (as described in Annex 3).

A search domain was defined, (i.e. a sub-domain of the variables), because the theoretical domain could have been infinite but the experimental measures were finite. The initial solution was assigned (for the iterative search routine), and the relationship between the variables / measurement accuracy derived by defining the turning (stationary) points. This process was robust to noise.

After the search routine was completed, the relationship between the variables and the measurement error was fitted. The formulation was solved based on the fit, e.g. through solving Equation (8) (Annex 3). In this way, the final design solution was achieved for the individual in question.

Although the solution should have been optimal, when the search was finished, an additional evaluation and verification process was used to check that the design was acceptable. If the solution was not reasonable, the design parameterization for the given individual was reanalysed, or the individual was excluded from the process.

3.1.3 Population fitting and testing

We proceeded to the population-fitting stage when the (individual) solutions were accepted for the training group. In this step, the dominant characteristics of the individuals, relating to the optimal solutions were found, using correlation analysis. For example, the optimal solution of the blood pressure monitor was highly correlated with the shoulder-width and the height of the individuals, so the population-fitting curve of the optimal position could be based upon the should-width and height. We could provide a general solution, as long as such a relationship could be determined. If this wasn't the case, it meant that there was too much noise in the measurement data and we needed to review, collect more or restart the optimization process. The fitted curve for the population was then verified during the "testing group phase" that occurred after the population fitting. It provided an independent check of the fitting results (as per section 3.1.1).

3.1.4 Controlling for noise

In order to minimize noise during the measurement process, we also:

1) *Used clinical standards*. e.g. (Pickering et al., 2005).
2) *Used statistical analysis* e.g. use of confidence levels.

3.1.5 Selection of sub-problems

The formulae in Equations (7) and (8) provided the theoretical basis for the design of the kiosk. We went about a process of selecting independent sub-problems based upon the categories of factors that could potentially influence the vital signs (Figure 1). We split these into insensitive factors (those where variation should be minimized), shielding factors (needing to be kept constant) and dominant factors (the focus of the optimization). For more information about how these sources of noise were defined and controlled see Annex 4 and Table 2. The paper focuses on the dominant factors (postural factors), which were those that had a major effect on the measures taken by the self-service kiosk. We assumed them to be measurable and controllable.

Table 2: Methods of controlling noise.

Factor	Control
Insensitive Factor	The sessions were finished within 30 minutes.
Insensitive Factor	The sessions maintained the same spatial position and geographical location.
Insensitive Factor	The temperature, humidity, lighting, air quality, and noise level of the environment were maintained at similar levels for each session. Abnormal days in terms of rainy/heavily cloudy/heavily windy weather were skipped.
Shielding Factor	The measurements were taken in a silent room with suitable lighting, 18ºC - 20 ºC, 40% - 60% humidity, and air conditioning.
Shielding Factor	The participants were asked to refrain from physical exercise and maintain a state of rest at least one hour before the testing.
Shielding Factor	The participants were asked to wear headphones and listen to piano music.
Shielding Factor	The participants were well trained. We conducted a familiarization session prior to the experiment in order to ensure the smooth running of the later sessions.
Shielding Factor	The experimenters would talk to participants and gently respond to their questions, but not do anything that might change their affective state or mood.

3.2 Kiosk implementation

3.2.1 Design Plan

Participants

There were 32 volunteers (12 female) recruited to participate during the design process; the training group consisted of 16 volunteers (6 female), the testing group consisted of 16 volunteers (6 female). There were two physicians who evaluated the participants, assigned the candidates to groups and then supervised the measurement process. Table 3 lists descriptive statistics for the training group. It should be noted that the characteristics of the training and testing group impacts on the generalizability of the solution (e.g. the output of the optimization process). This means the properties of the final design relate to the population selected. Regardless, the theory and methods in this paper can be employed for any other population.

Table 3: Statistics for the training group: Age (years), height (cm), weight (kg), Body Mass Index (BMI) (kg/m^2), shoulder width (ssh_w, cm) and length of arm to shoulder (Arm_s, cm) were measured. The BMI was calculated as follows: $weight/height^2$ (kg/m^2).

	Age	Height	Weight	BMI	Sh_w	Arm_s
Mean	27.2	1.75	62.3	20.8	40.8	95.1
SD	2.6	0.08	12.5	3.1	4.4	6.9

Measurement sessions

The design optimization needed a series of measurements, for different vital signs, to be taken from both the training and testing groups. The series of measurements

were organized into sessions. A session was defined as the period during which one participant carried out sequenced measurements *of the same vital sign*, across a given time duration. The use and organization of sessions was designed to provide for Theorem 1 (Annex 1).

Measurements relating to 4 vital signs were chosen for optimization through the kiosk design, i.e. V_E={BP, SpO_2, PR, ECG}. They were measured using clinically standard, commercially available equipment (Table 4). The four vital signs needed at least three sessions for each participant. We optimized the position for all devices, but only report results relating to the blood pressure monitor.

Reference values

In order to calculate the error component of the vital sign, we needed to calculate reference values. The reference value for each vital sign was measured and recorded by a physician, according to clinical best practice (Pickering et al., 2005). Multiple readings were taken. Reference values were measured every day before the participants started their sessions; average values were then adopted and applied as described in Equation (3).

3.2.2 Design flow

Design Parameterization

The kiosk consisted of three medical devices, used to read vital signs (Table 4), selected for a "self-service" scenario.

Table 4: The devices integrated in the kiosk.

Device	Description
BP monitor	An automatic blood pressure monitor without the cord-cuff.
Oximeter	A fingertip oximeter for SpO_2 and pulse rate (PR).
ECG monitor	A single-lead ECG monitor with three ECG limb-clamps.

We applied the design method to determine where best to place them in the kiosk "target model" or prototype. We were setting the final coordinates of the devices in the 3D Cartesian coordinate system to optimize the measurement accuracy. The user of the kiosk was defined as being seated, with upright posture. The origin (x_o, y_o, z_o) of the target model was set to the centre of the ground projection of the user. The following variables were extracted in order to formulate the relationship between user position and measurement device position (Figure 4).

- The position of the blood pressure monitor: (x_{bp}, y_{bp}, z_{bp}).
- The position of the oximeter: (x_{ox}, y_{ox}, z_{ox}).
- The position of the three ECG clamps: ($x^1_{ecg}, y^1_{ecg}, z^1_{ecg}$) for the right ankle, ($x^2_{ecg}, y^2_{ecg}, z^2_{ecg}$) for the left ankle and ($x^3_{ecg}, y^3_{ecg}, z^3_{ecg}$) for the right wrist. One of the three is shown in the Figure 4.

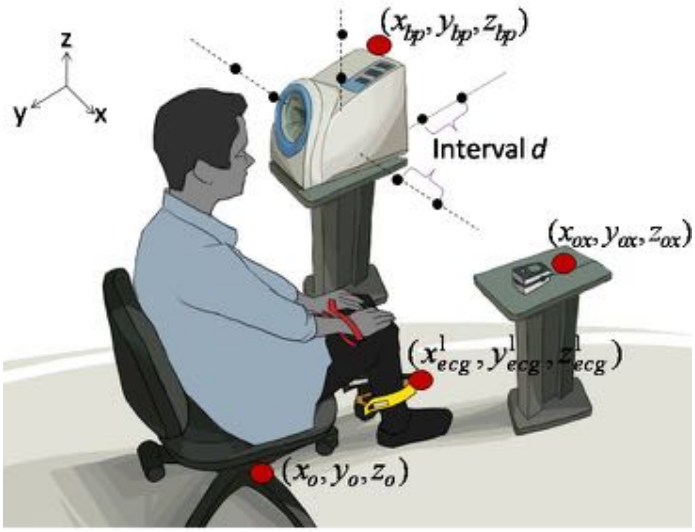


Figure 4: The parameters in the kiosk design. The figure shows the directions and the interval of the trials (5cm), for the blood pressure monitor at (x_{bp}, y_{bp}, z_{bp}).

The user position was regarded as fixed (at the origin), and the device positions, i.e. the BP, oximeter and ECG, variable. The aim was to optimize the design solution within this problem space. The device positions were moved along an interval of 5cm in each direction of X, Y and Z. The measurement error of a given vital sign on a given device was refined using Equation (10) (Annex 3). The following Equation shows the linear sum, similar to the independent sub-problems in Theorem 2 (Annex 2):

$$\begin{aligned}
&\min . \Psi = \Psi_x + \Psi_y + \Psi_z \\
&\Psi_x = f_x(x)^2 \\
&\Psi_y = f_y(y)^2 \\
&\Psi_z = f_z(z)^2
\end{aligned}$$

where x, y and z are the coordinates of the devices outlined in Table 4. The following lemma can be proved based on Theorem 2 (Annex 2), so independence among the errors caused by x, y and z can be assumed.

Lemma 1 (Equivalence Based on Cartesian Coordinates): $X^* = \left(x^*, y^*, z^*\right)$ is the optimal solution of $\Psi \Leftrightarrow x^*, y^*, z^*$ are the optimal solutions of the independent sub-problems Ψ_x , Ψ_y and Ψ_z respectively.

The proof is similar to that of Theorem 2 (Annex 2) and Theorem 1 (Annex 1) and omitted here.

Based on the Lemma 1, the parameter identification can be carried out as follows.

Parameter Identification

According to the Theorem 1 (Annex 1), the devices were arranged to be optimized separately, in sequenced sessions. This provided independence between the optimization processes conducted for each device.

For each device, the parameter identification process sought to address the optimization problem defined for the individual optimization in section 3.1.2 (the Equation (10) in Annex 3). Variables were set up, with the functional form relating to the measurement error, as yet to be determined. The problem was then solved

analytically using the pseudo code listed in Figure 5. The procedure takes any component of the device position (*x, y, z*) as the input, and records the measurement error accordingly. The interval *d* and the search directions are also shown in Figure 4.

Procedure 1: opt_pos_solve (x)

Input: the position component x, y or z
Output: record the measurement error

Begin
1. Given the search domains [*d1*, *d2*]
2. Given the interval *d*
3. *x = initial solution*
4. While (*x* <= *d2*) do
5. record the measurement error p
6. Iterate *x* using the iterval *d*
7. End while

End

Figure 5: The optimization procedure

Procedure 1 was used to perform the main steps of the parameter identification (Figure 3), and was composed of the following sub routines.

1) Search domain definition

The domain of potential device positions (*x, y, z*) was constrained by the range within which the user could freely and comfortably take measurements.

2) Initial design solution

The physicians suggested the initial design solution should be based upon a position that the user would find comfortable.

3) Iterative search, optimization and definition of the final solution

The iterative search procedure consisted of three steps. The first step was to iterate a series of candidate design solutions within the domain of acceptable solutions. During this stage the measurement error was recorded. The second step was to fit the relationship (as outlined in section 3.1.2) and set up an explicit function expression (if possible). The third step was to solve the optimal solution according to the nonlinear optimization problem for the individual (Annex 3). If the functional expression could be fitted, it was; otherwise we manually selected local optima, through observation.

Evaluation and verification.

After the final solution was achieved (for each participant), the results were reviewed manually, with respect to how well the solution controlled / reduced noise. It was sometimes the case that measures taken on one day were inconsistent with preceding measures, in which case the data from the measurement session was discarded and another one was convened.

3.2.3 Validating the design

After the design was optimized for each individual, the solution needed to be generalized across the population. For each participant, the optimal solution for the "affecting factors" was determined through the design process, for example $\left(x_{bp}^{*}, y_{bp}^{*}, z_{bp}^{*}\right)$ for blood pressure. In order to derive the fitting curve for the optimal solution across the population, we needed to know which characteristics of the individuals were implicated (e.g. height, should-width, arm-length and/or BMI). For example, analysis revealed that the optimal x-position of the blood pressure monitor

was highly-correlated with the shoulder-width and the height of the individuals, so the population fitting curve over the x-position was based upon the should-width and height. If such a relationship could not be determined, it meant that there was too much noise in the measurement data and we needed to review the data, collect more or restart the measurement process.

4 RESULTS AND DISCUSSION

Results and analysis are presented for the blood pressure monitor, but a similar process was used for the other devices (identified separately as per theorem 1 – Annex 1).

4.1 Blood pressure monitor

There were three directions to optimize, i.e. x, y and z. The interval d was set to 5cm, and 5 trials were conducted across each direction. Each participant performed one measurement session, comprising of the three directions within one day; where possible, the sessions were arranged continuously, e.g. day by day. Sessions were scheduled to minimize the variation of the vital signs caused by the time. More than one month was spent conducting the experiment, and there were 20 measurement results at each coordinate for each participant.

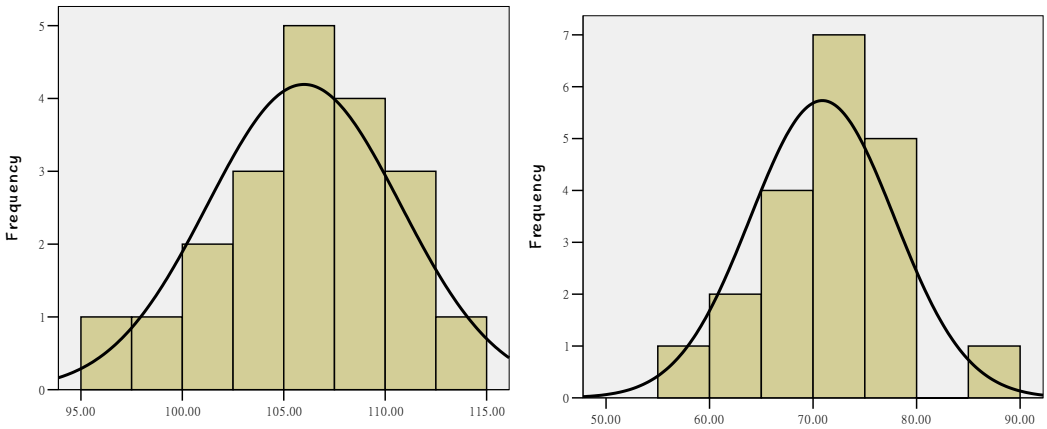
4.1.1 Assumptions of normality

Table 5 provides the systolic and diastolic pressures measured for an arbitrary participant for a given position during the 20 sessions.

Table 5: Blood pressure measurement results (20 sessions).

	Trial #Day 1 to 20						
Systolic	98	104	112	110	103	105	107
(Mean=106	105	101	101	106	104	108	96
SD=4.76)	109	108	107	109	112	115	
Diastolic	73	65	76	71	71	67	70
(Mean=71	78	55	67	63	78	72	63
SD=6.96)	67	70	78	87	72	75	

Overall data was compliant with the Normal distribution (Figure 6).



(a) (b)

Figure 6: The frequencies histograms of the data in Table 5: (a) the systolic pressures, and (b) the diastolic pressures.

The systolic and diastolic readings were compliant with the Normal distribution (p= 0.998 and 0.982) (Figure 7).

One-Sample Kolmogorov-Smirnov Test

		VAR00010
N		20
Normal Parameters [a,b]	Mean	106.0000
	Std. Deviation	4.75727
Most Extreme Differences	Absolute	.087
	Positive	.064
	Negative	-.087
Kolmogorov-Smirnov Z		.389
Asymp. Sig. (2-tailed)		.998

		VAR00009
N		20
Normal Parameters [a,b]	Mean	70.9000
	Std. Deviation	6.95777
Most Extreme Differences	Absolute	.104
	Positive	.104
	Negative	-.099
Kolmogorov-Smirnov Z		.464
Asymp. Sig. (2-tailed)		.982

a. Test distribution is Normal.

b. Calculated from data.

Figure 7: K-S tests for normality based on the systolic and diastolic values in Table 5.

4.1.2 Outlying data

Measurements taken from two of the participants contained outlying data for systolic (one case) and diastolic readings (one case) (Table 6). Figure 8 provides a schematic of the outlying data (boxplot form), alongside Q-Q plots. The outlying data

was filtered via the Grubbs' test. There was 2.39% of outlying data across the whole measurement dataset.

Table 6: The multiple measurement results with outlying data.

	Trial #Day 1 to 20						
Systolic	99	100	102	94	101	99	92
(Mean=102	105	102	100	99	104	110	103
SD=6.5)	122	100	103	107	96	95	
Diastolic	71	69	69	75	61	71	72
(Mean=68	68	73	74	51	61	75	82
SD=6.8)	60	66	67	64	68	72	

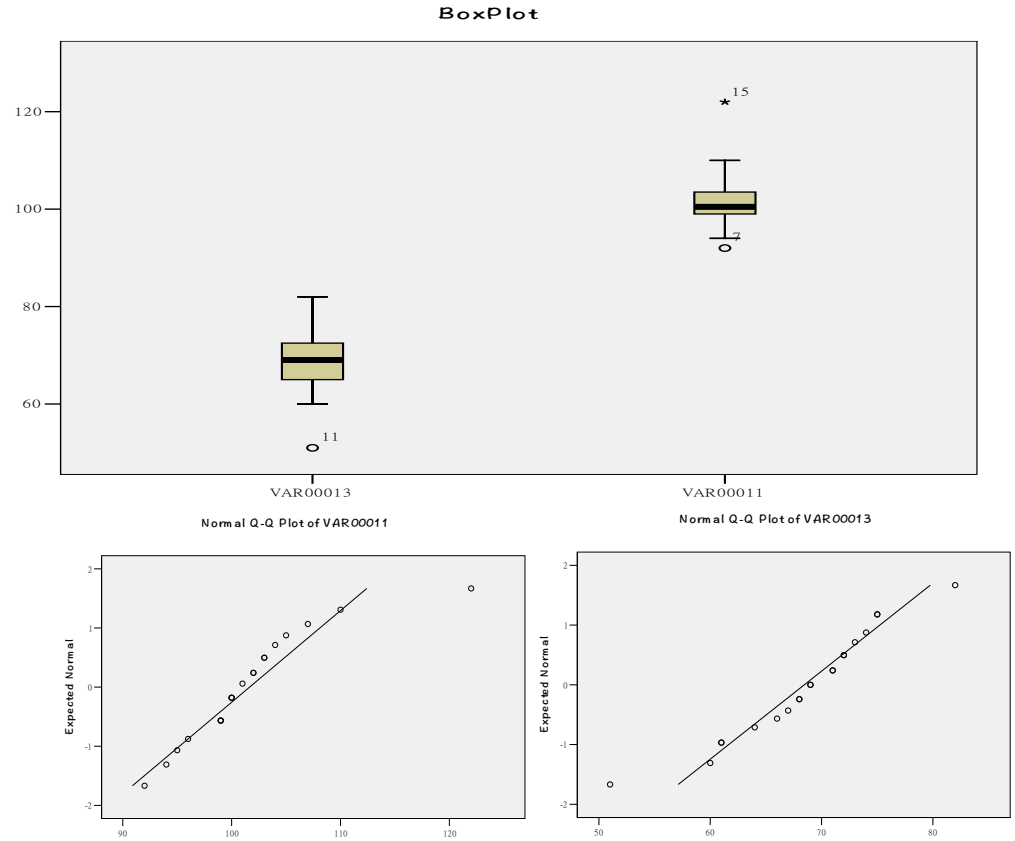


Figure 8: Boxplots showing three outlying data points; they were 92 (No. 7) and 122 (No. 15) - systolic data and 51 (No. 11) - diastolic data. The Normal distribution with Q-Q plots showed similar results.

4.1.3 Fitting the error function and optimizing for an individual

After the outlying data was filtered, expectations were calculated for each of the coordinates (readings were compliant with the normal distribution). Table 7 gives an example, for one participant, of the mean and standard deviations for each trial coordinate. For this example, they were calculated for systolic readings (mean=113, SD=5.64) and diastolic readings (mean=69, SD=5.61). The standard deviation is a little bigger than the 5 (mmHg) recommended manufacturing error for clinical blood pressure monitors.

Table 7: Means and SDs for an arbitrary participant (23 testing locations); each mean value was calculated from 20 readings.

BP: Systolic readings on 23 coordinates (Mean ± SD)				
104±5.8	104±5.8	105±4.8	117±4.7	108±4.8
102 ±5.5	104±5.1	111±5.5	108±6.3	109±4.9
105±5.9	101±5.1	103±4.9	106±6.0	107±4.8
114±5.8	108±5.2	112±4.8	101±4.7	105±4.5
93±6.0	95±5.8	90±4.7		

After expectations were calculated from the distribution of measurements taken for each position, the explicit form of the objective function $f_i(X)$ (the error function of blood pressure) was fitted. X is composed of the Cartesian coordinate variables x, y and z. As per Equation (8) and (9) (Annex 3), the square form $f^2_B(X)$ was employed to guarantee differentiability. An example is provided for an arbitrary participant. Systolic and diastolic fitting functions are shown in Figure 9 with explicit functions provided in the legend.

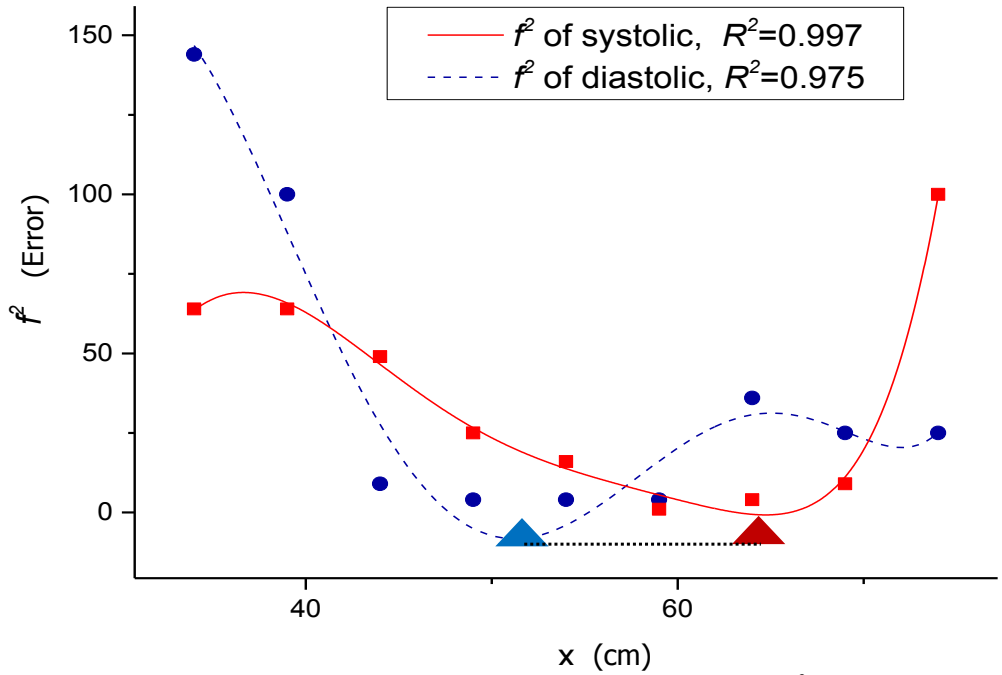


Figure 9: The x-axis denotes the device position (Figure 4), and f^2 is the error function of BP. The red solid curve is for the systolic BP, which has the fitted form (using polynomial fitting): $f_B(x) = 0.0000654x^6 - 0.00017x^5 + 0.0184x^4 - 0.957x^3 + 24.38x^2 - 240.983x$ (R^2=0.997, p=0.00); the blue dashed curve is for the diastolic BP, which has the fitted form: $f_B(x) = 0.0000786x^6 - 0.00021x^5 + 0.0224x^4 - 1.134x^3 + 27.247x^2 - 243.039x$ (R^2=0.975, p=0.001).

Following estimation of the curve functions, and the KTT points, optimal solutions were solved and selected according to Equation (10) (Annex 3). There was inconsistency between the optimal solution (e.g. the best position) for the systolic and diastolic pressures (indicated by two triangles in Figure 9). In these cases the measures were obtained via the same monitoring device, but the optima were different. Although we would expect the optima to be different, there was also potential for variation as a result of the positional interval being relatively coarse (5cm). We decided that the optimal positions should be a *range* rather than a *point*.

The optimal position for an individual was selected as the middle point of the range as indicated by the blue and red arrowheads.

4.1.4 Testing the affecting factors

After optimal solutions had been determined for each participant, the factors that were related to the blood pressure measurement data were determined, allowing for population fitting. The factors listed in Table 3 (age, height, weight, BMI, shoulder width and arm length) were tested for correlation over the optimal positions x, y and z.

Correlations

		gender	height	weight	bmi	arm_len	shoulder_wid	bp_x
gender	Pearson Correlation	1	.666**	.518*	.331	.592*	.917**	.604*
	Sig. (2-tailed)		.005	.040	.210	.016	.000	.013
	N	16	16	16	16	16	16	16
height	Pearson Correlation	.666**	1	.662**	.297	.799**	.724**	.664**
	Sig. (2-tailed)	.005		.005	.263	.000	.002	.005
	N	16	16	16	16	16	16	16
weight	Pearson Correlation	.518*	.662**	1	.910**	.739**	.658**	.398
	Sig. (2-tailed)	.040	.005		.000	.001	.006	.127
	N	16	16	16	16	16	16	16
bmi	Pearson Correlation	.331	.297	.910**	1	.487	.473	.169
	Sig. (2-tailed)	.210	.263	.000		.056	.064	.530
	N	16	16	16	16	16	16	16
arm_len	Pearson Correlation	.592*	.799**	.739**	.487	1	.611*	.411
	Sig. (2-tailed)	.016	.000	.001	.056		.012	.114
	N	16	16	16	16	16	16	16
shoulder_wid	Pearson Correlation	.917**	.724**	.658**	.473	.611*	1	.720**
	Sig. (2-tailed)	.000	.002	.006	.064	.012		.002
	N	16	16	16	16	16	16	16
bp_x	Pearson Correlation	.604*	.664**	.398	.169	.411	.720**	1
	Sig. (2-tailed)	.013	.005	.127	.530	.114	.002	
	N	16	16	16	16	16	16	16

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Figure 10: Correlation test with the characteristics of the participants in the testing group.

Based upon the correlation tests, the measurement error for blood pressure readings across the x-direction was most correlated with the shoulder width (denoted as s, coefficient 0.72 with p=0.002), then the height (denoted as h, 0.664 with p=0.005) and then gender (denoted as g, 0.604 with p=0.13). As one would expect, some of these factors were also correlated; for example, gender and shoulder width (0.917 with p=0.00). A similar analysis was performed for the y and z directions (Table 8).

Table 8: Correlation results for the x, y and z directions. BP_x, BP_y and BP_z are the measurement errors of the blood pressure in x, y and z directions respectively.

	gender (*g*)	**arm-len (a)**	**shoulder_w (*s*)**	**height (*h*)**
BP_x	0.604(0.13)	\	**0.720(0.002)**	0.664(0.05)
BP_y	\	**0.704(0.002)**	\	0.604(0.013)
BP_z	**0.772(0.00)**	\	\	0.739(0.001)

In the *y* direction, the most correlated factors (with measurement error) were the arm length and the height. In *z* direction, it was the gender and then the height. There were differences between the optimal positions for female (mean = 54.3 ± 1.5cm) and males (mean = 64.6 ± 2.5cm).

4.1.5 Population fitting and testing

Population fitting was performed for three directions based on the affecting factors outlined in the previous section. The following equation gives the final fit functions in the three directions based on the affecting factor height (*h*), arm length (*a*), shoulder width (*s*) and gender (*g*), which was generated from a similar process like that in Figure 9 (polynomial fitting).

$$\begin{cases} x = 0.1h - 1.97g + 0.41s & (R^2 = 0.997 \;\; p = 0.00) \\ y = 0.1h + 0.73a & (R^2 = 0.997 \;\; p = 0.00) \\ z = 0.33h + 5.78g & (R^2 = 0.998 \;\; p = 0.00) \end{cases}$$

There are actually two possible forms in fitting the function of the *z*-direction: one is the piecewise form upon the gender and the other is the continuous form based upon the height. A constant-based piecewise function was chosen for the *z*-direction function due to the minimal standard deviation. The population-fitting functions provided high determination (*R-square*) and significance (*p*). After the population fitting was conducted for the training group, the testing group was employed. The testing group consisted of 16 people (6 female). For each person, the optimal positions were calculated, according to the population-fitting function in Equation (6). We then took three continuous measurements. The mean value of the readings was recorded and designated as the test reading for that person. At the same time, a physician took three continuous measurements using a clinical blood pressure monitor, to obtain the mean value of the readings for a reference blood pressure. The measurement error was calculated according to the test reading and reference reading. These results showed the average error was 3.94 ± 1.28 mmHg, which is in line with clinical standards (5mmHg).

5 CONCLUSION

Although a design kiosk design solution was achieved (based on the three devices), there was a need for compromise in creating a general solution. We know that different users had different optimal solutions (e.g. according to the population-fitting functions , based upon the blood pressure results). It was hard to provide both a general and optimal solution when different users had different heights, shoulder widths and genders. There are two ways to resolve the issue: one is to provide a design that adapts for different users, the other is to use (published) data relating to population level anthropometry, biomechanics or ergonomics. In this study, we collected our own data from our target population. The anthropometric characteristics were as follows: height 169.31cm, arm length 54.43 and the shoulder length 43.42cm. Our blood pressure monitor was located at x = 33.74, y =56.66 and z = 58.76 (cms). The prototype design and the corresponding implementation based on the anthropometric data are shown in Figure 11. Based on the population-fitting functions of the optimal device configuration, an automatic device adaption could be realized for any specific user. However, addressing the practicality of both obtaining

the user parameters and automatically configuring the devices requires additional work.

Figure 11: The finalized design and the implementation of the healthcare kiosk.

This study proposes a methodology that allows for both the development and optimization of a self-service physiological kiosk. For this domain, very few design studies provide a formalization of the problem, means to optimize it, and demonstration using a general, and compelling design problem. The use of a dedicated design model and corresponding design and optimization methodology helps guarantee the accuracy of the implementation.

Accurate physiological measurements in ubiquitous scenarios are a challenging issue; we provide a demonstration of how formal mathematical proofs can be applied to support them. To extend these methods we need formulations with additional variables that take into account more factors. In future work there may be ways to decrease the testing burden by "smartly" controlling noise. For example, deciding whether to accept or reject multiple measurements based on variability in the data. Given a generalizable and sufficiently accurate solution, the self-service healthcare kiosk could offer accurate physiological measurements that meet medical standards and serve large populations efficiently. The system could allow users to engage with the system over a period of time, to help support long-term monitoring. Before this can be realised, there are still a few practical issues to resolve. They form the basis for future work:

1) *Population adaption*. We implemented the design based on a restricted population (e.g. the training and testing groups were recruited in a university campus). A more general solution would require additional testing. We need to find an appropriate balance between the generalizability of the solution and the cost of involving multiple user groups during the testing.
2) *The Graphical User Interface (GUI)*. Irrespective of the device configuration presented in this paper, the GUI needs to be optimized separately. We considered some factors for controlling the measurement noise, but a well-designed GUI also plays a role in guiding the user to complete operations correctly (e.g. providing video based instruction on how to attach the sensors). The role of the GUI is important when it comes to preparing users (e.g. calming them prior to a measurement being taken). It can also be used to provide educational instructions e.g. tutoring on lifestyle options and healthy living.
3) *Maintenance*. We need to consider the mechanisms for supporting the kiosk (e.g. training, cleaning, hardware and software support).

4) *Integration with the wider health service*. For the kiosk to be of maximum benefit, it needs to form part of a wider series of systems and services. For example: the kiosk could be used to collect data to support medical practice; it could provide the basis for telemedicine; it could support preventative medicine and community health initiatives; it could form forming the basis for wider social networks consisting of both community members and clinical professionals.

6 ACKNOWLEDGEMENTS

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(All the numbers of the Equations and Figures in the annex are consistent with those in the main texts from section 1 to 5.)

ANNEX 1, Sequenced Sub-Problems

It is possible to provide proof of equivalence as per the following definitions:

Definition 1 (**sequenced sub-problems**): $\forall i \in V$, we can define the sequenced sub-problem for each vital sign as Equation (6) shows:

$$\min. \quad \Phi_i = \left|\delta_i(X_i)\right| \quad (6)$$

Theorem 1 (Equivalence based on sequenced sub-problems):
$X^* = \bigcup_{i \in V} X_i^*$ is the optimal solution of the problem in Equation (4) $\Leftrightarrow$ $\forall i \in V$, X_i^* is the optimal solution of the sub-problem of the vital sign *i* in Equation (6) .

Proof: $\Rightarrow$ proof by contradiction.

Suppose $\exists i \in V$, X_i^* is not the optimal. So we can assume there is X_i^0 satisfying:

$$|\delta_i(X_i^0)| < |\delta_i(X_i^*)|$$

Therefore the following must hold:

$$|\delta_i(X_i^0)| + \sum_{j \in (V - \{i\})} |\delta_j(X_j^*)| < \sum_{i \in V} |\delta_i(X_i^*)|$$

which means X^* is not the optimal solution of Equation (4). This contradicts with the known proposition. So the supposition is false.

$\Leftarrow$proof by contradiction.

Suppose X* is not the optimal solution of Equation (4). So we can assume there is $X^0 = \bigcup_{i \in V} X_i^0$ satisfying:

$$\sum_{i \in V} |\delta_i(X_i^0)| < \sum_{i \in V} |\delta_i(X_i^*)|$$

Therefore there must be an $i \in V$ satisfying:

$$|\delta_i(X_i^0)| < |\delta_i(X_i^*)|$$

which results in the contradiction of the proposition that X_i^* is the optimal solution of the sub-problem for vital sign *i* (Equation (6)).

So the supposition is false and the theorem holds.

The optimization problem relating to the error sum in Equation (4) can be transformed to an equivalent series of optimization sub-problems for each vital sign (as per Equation (6)).

ANNEX 2, Independent Sub-Problems

Definition 2 (**Independent set**):
A variable set X is an independent set $\Leftrightarrow \forall X_i, X_j \in X$ satisfies when X_i and X_j are independent with each other.

Although linear and nonlinear correlations can be revealed using statistical methods, for this paper, independent sets of variables (listed in Equation 5) are stated and assumed as follows:

- $\{X_S, X_P\}$ are not an independent due to the strong linkage between sensory process and mental activity.
- The set $\{X_B, X_T, X_A, X_E\}$ is assumed independent.

Let $X_{SP}= X_S \cup X_P$, so the independent set of the affecting variables can be written as a hyper-set $X_{Ind}=\{X_B, X_T, X_A, X_E, X_{SP}\}$ where the independence between X_{SP} and the rest are assumed. We can also write E_{Ind} = {Body posture, Sensory and Psychological activities, Time, Space, Environment} accordingly.

There are two properties on the independent set X_{Ind}:

- $\forall X_i, X_j \in X_{Ind} : X_i \cap X_j = \varnothing$ (no overlapping)
- $\bigcup_{s \in X_{Ind}} s = X_{Aff}$ (the same affecting variables)

The proofs are omitted here.

Definition 3 (**Independent sub-problems**): The independent sub-problems with respect to the independent variable sets are defined as:

$$\begin{aligned}
&\forall i \in E_{ind}: \ \min. \ \ \Psi_i = \left|f_i(X_i)\right|, \ \textit{i.e.}\\
&\min. \ \ \Psi_B = \left|f_B(X_B)\right|\\
&\min. \ \ \Psi_T = \left|f_T(X_T)\right|\\
&\min. \ \ \Psi_A = \left|f_A(X_A)\right|\\
&\min. \ \ \Psi_E = \left|f_E(X_E)\right|\\
&\min. \ \ \Psi_{SP} = \left|f_S(X_S)\right| + \left|f_P(X_P)\right|
\end{aligned} \tag{7}$$

Theorem 2 (Equivalence based on independent sub-problems):
$X^* = \bigcup_{i \in E} X_i^* = \left\{X_B^*, X_S^*, X_P^*, X_T^*, X_A^*, X_E^*\right\}$ is the optimal solution of the problem in Equation (5) $\Leftrightarrow$ $X_B^*, X_T^*, X_A^*, X_E^*$ *and* $X_S^* + X_P^*$ are the optimal solutions of the independent sub-problems in Equation (7).

Proof: proof by contradiction is similar with that in Theorem 1 and omitted here.

The original optimization problem can therefore transformed into a series of smaller optimization problems surrounding each set of affecting factors defined in the set X_{Ind}.

ANNEX 3, Measurement Error Optimization

The objective function in Equation (7) can result in issues of non-differentiability. In this case, it is possible to use the square form. There are also constraints relating to

the domain of the function. So the finalized optimization problem takes these aspects into account (Equation (8)):

$$\begin{aligned} &\min. \quad \Psi_i = f_i(X_i)^2 \\ &\text{s.t.} \quad F_i(X_i) = 0 \end{aligned} \tag{8}$$

When constrained, the function $F_i(X_i)$ can be a vector function and it can also cover situations of the unequal, such as "≤" and "≥". In the case of unequal forms, the equation can be converted by introducing redundant variables, e.g. $f(x) \leq 0$ can be converted to $f(x) + x_r = 0, x_r \geq 0$.

Discrete models and functions of this type are often used when deriving biological models. There are many techniques that can be used to generate continuous functions based upon the use of discrete data and models, including smoothing and interpolating (Faires and Burden, 2012), fitting (Hauser, 2009), and stochastic process (Øksendal, 2003). Techniques such as piecewise derivatives and fractional derivatives (Podlubny, 1999) can also be used to convert the functions to ones which are differentiable. So we can make the assumption that all the functions in Equation (8) are differentiable (or partially differentiable). We cannot judge how much approximation there would be at this point since we do not know ground truth. However, the approximation maintains generality and is provided on a theoretical basis.

For the system in Equation (8), the Lagrange Multipliers method (Bertsekas, 1999) can be employed to convert the constraints into the objective function by introducing the Lagrange Multipliers method. This optimization problem can be converted to a Lagrange function as Equation (9) shows:

$$\min. \ L_i = f_i(X_i)^2 + \lambda_i F_i(X_i) \tag{9}$$

The function may be a nonlinear function and the necessary condition of the Karush-Kuhn-Tucker (KKT) (Karush, 1939; Kuhn and Tucker, 1950). KTT points are often employed to give candidate optimal solutions in such cases; that is, to find out all the stationary points by letting the gradient equal to zero as Equation (10) shows.

$$\begin{aligned} &\nabla L_i = \left[\frac{\partial L_i}{\partial X_i}, \frac{\partial L_i}{\partial \lambda_i} \right] = 0 \ \Rightarrow \\ &\begin{cases} \dfrac{\partial L_i}{\partial X_i} = 2 f_i(X_i) \dfrac{\partial f_i}{\partial X_i} + \lambda_i \dfrac{\partial F_i}{\partial X_i} = 0 \\ \dfrac{\partial L_i}{\partial \lambda_i} = F_i(X_i) = 0 \end{cases} \end{aligned} \tag{10}$$

After the solutions have been achieved for Equation (10), the final solution can be obtained from these candidate optima.

ANNEX 4, Magnitude of Different Factors Affecting Measures

Insensitive factors

Some of the "affecting factors" contribute to biological systems but in a way that had little consequence for the measures that were taken. For example, vital signs such as blood pressure, pulse rate, even the height and weight can vary across different

times (Stewart et al., 2009) or locations. However, such variations may be very slight when considered in a very short-time frame. For example, the vital signs in set V = {BP, SpO_2, PR, BG, ECG, Height, Weight} can be approximated as invariant in a short time Δt, i.e.:

$$\frac{\Delta f_i}{\Delta X_i} \approx 0 \Rightarrow \frac{df_i}{dX_i} \approx 0 \qquad (11)$$

which means the gradient value of the f_T on a given point in Equation (10) is zero. Similar situations arise when considering the functions f_A (space) and f_E (environment).

Factors {sp*a*ce, *E*nvironment} are hence classified as *insensitive factors*. This implies 1) a minimal contribution to measurement error and 2) the optimization process can be replaced by specifying constants. For example, for environmental variables such as temperature and humidity, small changes will result in a negligible change to the measurement error. This assumes that the measurement process can be done before the constants are invalidated, say, the temperature changes a lot, too much time passes, the space changes dramatically, etc. The kiosk usage scenarios means that it is unlikely this type of constant will be invalidated. We approximated for several "insensitive factors" during the implementation.

Shielding factors

In section 2.4 it was assumed that factors relating to sensory input and psychological activity (e.g. mental state) were sufficiently related that they could be modelled as a common variable in independent set E_{Ind}. In our case, it was difficult to measure and quantify psychological activities (for example, emotions relating to happiness, sadness, anger, etc. (Ekman et al., 1972)), and difficult to elucidate a specification for the computational OCC categories (Ortony et al., 1998), which could be used to define and control these factors or variables. It was hard to establish their impact on measurement error.

We considered sensory input and psychological activities together, as *shielding factors*, where we wanted to reduce their impact on measurement error and maintain constancy as much as possible. We chose to do this in line with standard clinical practice, taking into account guidelines to reduce effects from the psychological activities, or keeping any effect constant. For example, a silent and clean space is required for ECG monitoring; at least 5-minutes rest is required before monitoring blood pressure, etc.

Another means to reduce the impact of shielding factors was via the GUI. There were two approaches that were used:

1) Making sure that the user knew what to do (e.g. using simple instructions).

2) Making sure that the user knew what was going on and what was about to happen (e.g. which measurement was about to be taken, giving them time to prepare).

The shielding factors affected the measurement results, but did not affect the optimization process. This was according to Theorem 2 (independent sub-problems). The reason why we needed to control the shielding factors is that the vital signs could not be divided into their ideal sub-parts (corresponding to the independent sets); they could only be read as a whole. For example, the blood pressure could be read from the monitor and the error component calculated (e.g. using the reference value), but the source of the error components could not be deduced. So the relationship between the

dominant factors and the measurement errors could only be observed when other shielding factors were controlled (e.g. kept constant). Such control didn't seek to avoid the influence of the shielding factors, but instead aimed to keep them constant. The following control strategies were applied following reference to the guidelines in (Campbell and McKay, 1999; MacWilliam, 1933; Madden and Savard, 1995; Pickering et al., 2005):

Insensitive vital signs

As measurement of both height and weight is relatively straightforward in both ubiquitous (general) and clinical scenarios they don't form the focus of this paper. Measures of height and weight may be influenced by body posture but are easy to correct for. Measures of blood glucose (BG) were also assumed to be insensitive to any of the affecting factors described in this paper. For these measures the process and resulting accuracy was outside of our scope and so the measurements are considered as *insensitive vital signs* and ignored during the optimization process.

Conversely, collecting measures of blood pressure (BP), blood oxygen saturation (SpO_2), pulse rate (PR) and ECG, was not straight-forward and could be influenced by position of the device relative to the user. Therefore postural factors that could influence the set of vital signs V_E={BP, SpO_2, PR, ECG} in Equation (7) were selected as the problems to optimize. Other aspects relating to *insensitive factors* and *shielding factors* were controlled / accounted for as described in the following design plan. The final design solution was near-optimal due to the approximation required for shielding factors and insensitive factors. This situation could have been resolved through additional investigation and improvements in the methods used to measure and control factors relating to "psychological activity" / "mental state".

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8 AUTHOR PROFILES

Yongqiang Lyu, Ph.D., is an assistant professor in Research Institute of Information Technology at Tsinghua University. His research interest focuses on the hardware-software fusion architecture and system design with innovative technologies in computer system architecture and human-computer interaction. He leads an interdisciplinary team at Tsinghua University working on the innovative cyber-physical architectures and systems from a fusion perspective of computer science, art and medicine. The team also works with several international companies for consumer electronics and healthcare services to make their production applied in emerging applications.

Chris Vincent is a postdoctoral research associate working on the CHI+MED project at the UCL Interaction Centre (UCLIC). Chris aims to understand how industry can benefit from research practice and support methods that contribute towards safer interactive medical devices. Chris works with several international medical device providers to understand the processes, tools or techniques that are of greatest value to support interaction design. He has published research papers reporting factors that underpin the successful design and development of interactive medical devices. He has also spent four years working in the aviation industry, with a focus on Human Factors and Ergonomics.

Yu Chen, Ph.D., is an associate professor of the Department of Computer Science and Technology at Tsinghua University. His research areas include operating systems, embedded systems, pervasive computing, and parallel computing. Recently, Yu Chen has been focusing on the OS&VMM optimization for multi-core computer architecture and high performance I/O devices in emerging cyber-physical systems. His research production has been widely used in domestic healthcare device vendors and service providers.

Yuanchun Shi, Ph.D., is a professor of the Department of Computer Science, the director of Institute of Human Computer Interaction & Media Integration, and the

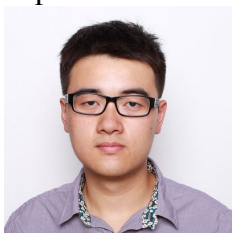
director of Pervasive Computing Division of Tsinghua National Lab of Information Science and Technology, Tsinghua University, China. Her research interests include human computer interaction, pervasive computing and multimedia communication. She has publications in IEEE Pervasive Computing, TPDS, TKDE, ACM CHI, MM, UIST, etc. She also chaired several conferences like the ACM Ubicomp2011 and chaired the Technology Committee on Pervasive Computing of CCF (China Computer Federation) from Jun. 2005 to Jan. 2012.

Yi-Da Tang, M.D., Ph.D., is an associate professor of medicine and the deputy director of department of cardiology, FuWai Hospital, Chinese Academy of Medical Sciences. Dr. Tang received his M.D. degree in Hunan Medical University in 1995 and his M.S. degree and Ph.D. in 2000 and 2003 respectively, both in Peking Union Medical College. His work is at the intersection of endocrinology and cardiology, anti-platelet therapy, the prognosis of myocardial infarction and interventional therapy for coronary heart disease. As PI, he has several basic and clinical projects supported by the main national nature science foundations in China.

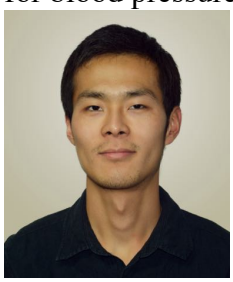
Wenyao Wang is a postgraduate student in Peking Union Medical College working with Yi-Da Tang. His major is cardiology and his work mainly focuses on the relationship between the metabolic dysfunction and cardiovascular diseases, anti-platelet therapy after PCI and test for platelet function.

Wei Liu is a graduate student in an exchange program between Beijing University of Technology and Tsinghua University. His research done in Tsinghua University focuses on the smart healthcare systems, including the self-service terminals, the SOA based cloud-services, and smart spaces.

Shuangshuang Zhang is a graduate student majored in interaction design combined training by the School of Computer Science and the Academy of Arts & Design, Tsinghua University. She focuses on the research fields about human-computer interaction, intelligent medical and service design, and is determined to contribute to the public health cause. In practice, through Health Kiosk design, she has had experience of product design for chronic disease management and some results of exploration for healthcare service model.



Ke Fang is a graduate student of Academy of Art and Design, Tsinghua University. He majors in the interdisciplinary study of computer science and design, including HCI, product design, interaction design, etc. His production includes an adaptive chair for blood pressure measurement, an aesthetics oriented programmable camera, etc.



Ding Ji is a graduate student in the Interdisciplinary Project of Information Design Department at Tsinghua University, from which he got undergraduate degree as well. He is interested in novel interactive system design and has developed several known interactive web applications which have more than 100k users.