# Identification of Lifestyle Behavior Patterns with Prediction of the Happiness of an Inhabitant in a Smart Home

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**Abstract**

With the rapid growth of the population and the increase in the elderly age group, there is a need to improve and maintain an independent, secure healthy lifestyle. A possible method to address this need is to apply intelligent technology using machine learning techniques in smart homes to remotely monitor an individual's activities. The MavHome project uses a system of basic sensors to monitor an inhabitant's in-home activity. We examine how smart homes can be used to detect behavioral and lifestyle patterns and from these findings provide suggestions to improve the lifestyle of the inhabitant.

## Introduction

In the United States, Medicare home health agency benefit payments increased between 2004 and 2005 from $10.5 billion to $12.5 billion. National individual health expenditures were $205 in 1965 and grew steadily to reach $5,670 by 2003 (Leavitt *et al*. 2005). The 2005 average daily rate for a private room in a nursing home is $203, $74,095 annually, an $11 increase over the 2004 rate of $192. The average daily rate for a semi-private room in a nursing home is $176, $64,240 annually, $7 more than the 2004 rate of $169. The average hourly rate for a Home Health Aide is $19 and the average hourly rate for a homemaker or companion is $17 (MetLife Survey 2005). The UN report also predicts the number of people 60 and over will triple, increasing from 606 million in 2000 to nearly 1.9 billion by 2050, which makes caring for the elderly a critical problem (The Population Institute 2003). Research has shown us that older Americans prefer an independent lifestyle (Hareven 2001). With a growing aging population that desires to maintain their independent living styles and the increase in healthcare costs, the need for, smart and cost effective, in-home health monitoring technology to replace the existing home caregivers arises.

A range of intelligent systems built for providing healthcare and wellness would enable people to live at home with an improved overall quality of life. The major challenges in these areas would be finding the physiological and psychological values in real-life conditions which could be used in the early prediction of health issues, such as chronic diseases or quality of life. Early prediction based on the observations made would aid the inhabitant to have an improved quality of life at home. The quality of life at home can be achieved with maximized privacy and also provide information on any concerned problems or deviations from normal patterns of activities. These deviations can be early indicators of health degradation. In addition, these variations could mark the early onset of diseases. Daily activities, with or without minute variations, can be examined as a possible indicator of the quality of daily life of the inhabitant.

This paper focuses on the problem of whether a system incorporating simple sensors which can detect and record behavior patterns on concerned health estimation parameters could provide the foundation for an approach to predict the quality of the day of the inhabitant. This involves analyzing the sensors for measuring values and combining the readings with a mapping to standard estimates and to develop prediction methods using machine learning techniques, which lead to the judging of the quality of life and wellness of the individual. On a long term basis, such real-time health monitoring could result in the generation of prediction models for the early onset of diseases and also in the generation of models to predict health variation patterns of the inhabitants.

Applying estimation techniques to the collected data can allow for the automation of the SF-36® health survey (SF-36 1996) by applying estimation techniques to the collected data. The SF-36® is a multi-purpose, short-form health survey with only 36 questions. It has been translated in more than 50 languages. It is a generic measure, as opposed to one that targets a specific age, disease, or treatment group. The SF-36® has proven to be useful in surveys of general and specific populations, comparing the relative burden of diseases, and in differentiating the health benefits produced by a wide range of different treatments. SF-36® was judged to be the most widely evaluated generic patient assessed health outcome measure in a bibliographic study of the growth of "quality of life" measures (Garrett *et al.* 2002).

## Related Work

Current research dealing with smart home and in-home health monitoring has two major areas. One is the set of technologies which assist home inhabitants in a timely manner (for example, auto reminders which reminds the timely intake of medical pills), and the other is those which target the health monitoring and behavioral monitoring for prediction of health quality and detection of early diseases. The Medical Automation Research Center (MARC) smart house project at the University of Virginia is focused on the issue of in-home monitoring for the elderly in order to promote the concept of *aging in place*. Their in-home monitoring system is made up of low-cost, non-invasive sensors (without cameras or microphones), and communications to establish telematics to authorized individuals (for example, family, personal physician).

MARC is designed to perform health status monitoring by analyzing behavioral patterns of its inhabitants using collected metrics (Barger et al. 2003). The data logged is used to observe general health and activity levels and using data mining techniques such as analysis of mixture models through which they have developed the metrics called the Activities of Daily Live (ADL). ADL also includes the measure of the index of well-being and a measure of the decline in ability over time. The data analysis component uses Estimation Maximization (EM) algorithms and Mixture Models (MM) to yield unique health status reports that can be made available by the inhabitants, their medical advisors and family members. ADL can also be beneficial in many ways like acting as early indicators for an onset of a disease. Moreover, their system provides identified activity levels, which could lead to reality-based decision making. Such a system would be beneficial if it were used to evaluate the quality of the day that a person could have, based on the previous observed activity levels, and suggest required changes and modifications in the daily activities patterns which would lead the inhabitant to experience a better quality of life (for example, the home perceives that the inhabitant has irregular sleeping patterns and this observations can be used to make corrections and suggestions, which could improve the inhabitant lifestyle and health).

There are also a number of systems which have been developed to help people compensate for physical and sensory needs. We see that most of them rely on computer based technologies incorporating artificial intelligence techniques (for example, schedule management using an autominder system) (Pollack 2002). A schedule management system for the elderly helps people who suffer from memory decline—an impediment that makes them forget their daily routine activities such as taking medicine, eating meals, or personal hygiene. Autominder, an *intelligent cognitive orthotic system* for people with memory impairment, employs techniques such as dynamic programming and Bayesian learning, a web-based interface for plan initialization and update to construct rich models of a inhabitant's activities—including constraints on the times and ways in which activities should be performed to monitor the execution of those activities, detect discrepancies between what a person is expected to do and what he or she actually is doing, and to reason about whether to issue reminders. Assistive technologies, when combined with the monitored information on daily activities of the inhabitant, can be used to measure the quality of a person's performance of their daily routine activities. A schedule management system such as this could generate an improved inhabitant life based on behavioral patterns designed to improve their daily performance (Pollack 2005).

## Environmental Sensing

The MavHome Project is a multi-disciplinary project at the University of Texas at Arlington, which has been engaged in the creation of adaptive and versatile home and workplace environments in the past few years (Youngblood *et al.* 2005, Cook 2003). The major goal of this project is to acquire and apply knowledge about inhabitants and their surroundings in order to adapt to the inhabitants and meet the goals of comfort and efficiency. In order to achieve these goals the house should be able to predict, reason, and adapt to its inhabitant.

In MavHome, the sensor network data is the primary source of data collection. The data collection system consists of an array of motion sensors which collect information through the Argus sensor network (Youngblood 2006). Argus and X-10 comprise the main perception and actuation control for the MavHome project. In this study we enhance collected information with web forms, which are used to collect critical health parameters (for example, weight, temperature, blood pressure, caloric intake) as well as a psychological questionnaire which targets the feelings of depression and pain (in accordance with the IRB protocols). The collected data is comprised of five main attributes associated with each sensor observation — name, location, time and date, state, level. The sensor data is collected based on sensor firing caused by the inhabitant interacting with the environment and the web form data is collected twice daily. The data collected for this study spanned a period of forty days, based on a single inhabitant living in the MavPad on-campus apartment.

Our evaluation environment is a student apartment with a deployed Argus and X-10 network. This environment is used for complete inhabitant immersion research of MavHome systems and provides the reality and deployment utilization grounding for our systems. There is a full-time, single inhabitant living in the MavPad. The MavPad consists of a living/dining room, kitchen, bath room, and bed room. There are over 150 sensors deployed in the MavPad that include light, temperature, humidity, and switches.

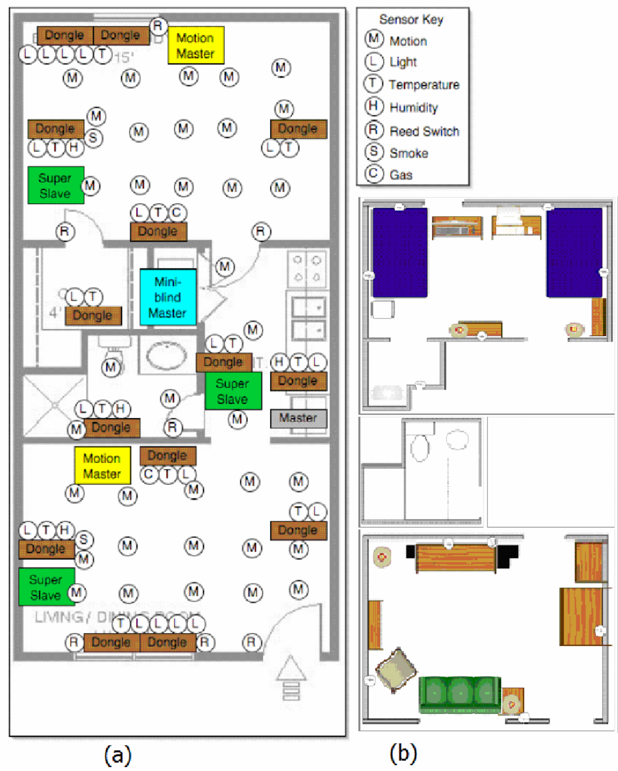

Figure 1: (a) MavHome Argus Sensor Network
(b) MavHome Apartment Environment. (Youngblood 2005)

## Health Metrics

Several performance and sensor readings were evaluated to form the metrics for analysis. These metrics are a form of classification performed on complex datasets to extract patterns for analysis. The health metrics consist of the higher metrics and the mid-level metrics which are calculated from lower level metrics (described later). The lower lever metrics constitute the collected data from the sensor network and the web forms used. A total of forty days of data collected from the MavHome motion sensors during a six week period were used in the formulation of the metrics presented here. This collected data is inhabitant centric and pertains to the current inhabitant of this smart home. The data would vary for different inhabitants.

The low-level data is used to generate the mid-level data which consists of parameters such as motion in the home, sleep duration, bathroom usage, shower duration, sleep restlessness, and so forth. An example of a mid-level metric is the number of visits to bathroom, measured by the number of times the sensors fire in the bathroom indicating a visit and this visit includes the sensor firing either for a shower, to wash the inhabitant's face, or even just a casual visit to look in the mirror. The basic motion sensor data was used in estimations of major parameters of the mid-level metrics. The high-level metrics mainly consist of the overall sensor activity and the overall X-10 based activities, which are simply motion sensor firings for that particular day and the instrumental activities performed. The metrics are essential as they can be used to find correlations among various parameters in these metrics.

## Experimentation Evaluation

Experimentation is broken into two studies. In the first experiment, we look for correlations and perform t-tests to find any similarities among the classification metrics. The second experiment uses the machine learning technique, the **k**-nearest neighbor algorithm, to predict the state of wellness the inhabitant will experience on the following day. For this second task, the learning algorithm is trained on historical data for which the outcome is known for each record. It is then applied to a new data set in order to predict the outcome for each record.

T-tests are used for determining the similarity or difference between two sampled populations. The value observed is called a t-statistic which should be used in its absolute value form. The smaller the value, the more similar are the two samples. If the t-statistic is greater than this number, then we can reject the null hypothesis (that the two samples are the same), and say that there is a statistically significant difference between the two samples. The p-value (two-tail) obtained gives the exact probability of mistakenly rejecting the null hypothesis when we shouldn't have. A p-value less than 0.05 mean the same thing as having a t-statistic greater than the t-critical value, and thus allow us to reject the null hypothesis as above.

A correlation is a way to statistically measure the association between two variables. A correlation produces an r-value**,** which tells how closely correlated the two variables are. r-Values range from 0-1(signed), with 0 indicating completely unrelated variables and 1 indicating a perfect (linear) relationship between the two. If we square the r-value ($r^2$) we get a number that can be expressed as a percentage, telling us how much of the change in one variable can be explained by the other.

For the correlations and t-tests the mid-level metrics have been classified as groups of parameters for better understanding. The classifications are motion in bed, motion in various rooms (kitchen, closet, and bathroom), the inhabitant-specified levels of happiness and health, and objective health parameters and so forth. The mid-level and high-level metrics were analyzed in their raw form. The analysis produced the following results which are shown in figures 2, 3, 4, 5, 6.

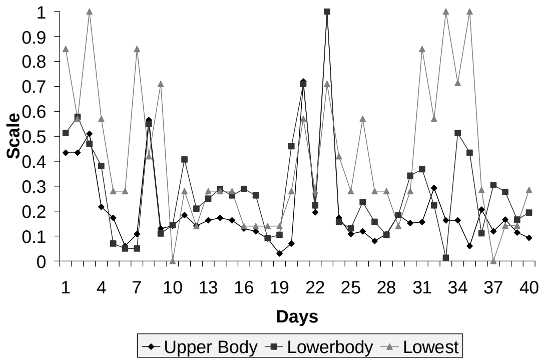


Figure 2: Comparison of Upper, Lower and Lowest body motion in bed.

The above figure represents the comparison of the upper, lower and lowest body motion on bed which are observed by the motion sensors over the bed. The plotting has the number of days on the X-axis and the scale of 0 to 1 on the Y-axis. The below tables 1 and 2, represent the correlation and t-test performed on these values. We have observed form these values that there exist very close similarity between upper and lower body motion.

Table 1: Correlation comparison (r) values between Upper, Lower and Lowest body motion in bed.

| | Upperbody | Lowerbody | Lowestbody |
|---|---|---|---|
| Upperbody | 1 | | |
| Lowerbody | 0.805138 | 1 | |
| Lowestbody | 0.369965 | 0.343273 | 1 |

Table 2: t-test similarity (P) values between Upper, Lower and Lowest body motion in bed.

| | Upperbody | Lowerbody | Lowestbody |
|---|---|---|---|
| Upperbody | 1 | | |
| Lowerbody | 0.52903 | 1 | |
| Lowestbody | 1.68E-07 | 0.025584 | 1 |

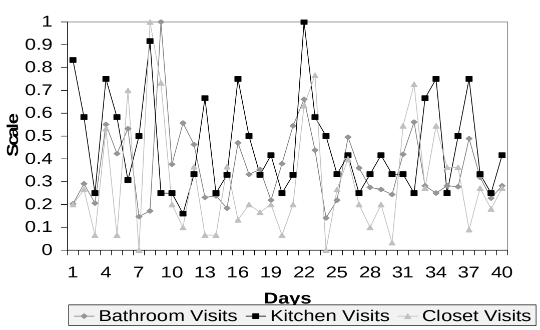


Figure: 3 Comparison of number of visits to the bathroom, closet and kitchen.

The above figure represents the comparison of the number of visits to the bathroom, closet and kitchen. The plotting has no of days on the X-axis and the scale on the Y-axis. Tables 3 and 4 show that there is a very slight correlation between closet visit and bathroom visit.

Table 3: Correlation comparison (r) values between Bathroom, Closet and Kitchen visits.

| | Bathroom | Kitchen | Closet |
|---|---|---|---|
| Bathroom | 1 | | |
| Kitchen | -0.05421 | 1 | |
| Closet | 0.424568 | 0.250582 | 1 |

Table 4: t-test similarity (P) values between Bathroom, Closet and Kitchen visits

| | Bathroom | Closet | Kitchen |
|---|---|---|---|
| Bathroom | 1 | | |
| Closet | 0.198345 | 1 | |
| Kitchen | 0.028979 | 0.00305 | 1 |

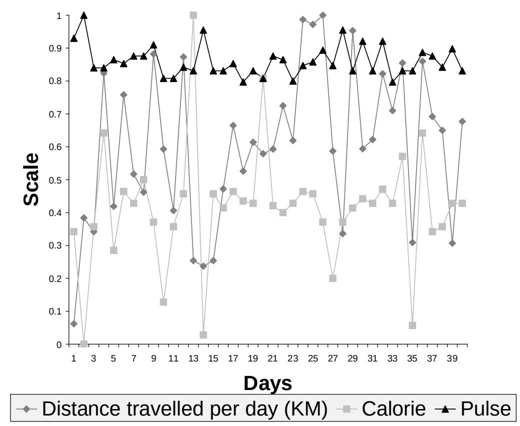


Figure: 4 Comparison of Distance traveled in home, calorie intake and monitored pulse.

The above figure represents a comparison of the total distance traveled in a home, calorie intake and monitored pulses which are observed by the motion sensors and digital instruments. The plotting has the number of days on the X-axis and the scale of 0 to 1 on the Y-axis. The below tables represent the correlation and t-test performed on these observed data. We have observed form these values that there are not many similarities observed in these values. There are very slight correlations observed amongst them.

Table 5: Correlation comparison (r) values between distances traveled in home, calorie intake and monitored pulse.

| | *Distance* | *Pulse* | *Calorie* |
|---|---|---|---|
| Distance | 1 | | |
| Pulse | -0.19926 | 1 | |
| Calorie | 0.227047 | -0.35315 | 1 |

Table 6: t-test similarity (P) values between distances traveled in home, calorie intake and monitored pulse.

| | *Distance* | *Calorie* | *Pulse* |
|---|---|---|---|
| Distance | 1 | | |
| Calorie | 0.000143 | 1 | |
| Pulse | 1.44E-09 | 4.81E-25 | 1 |

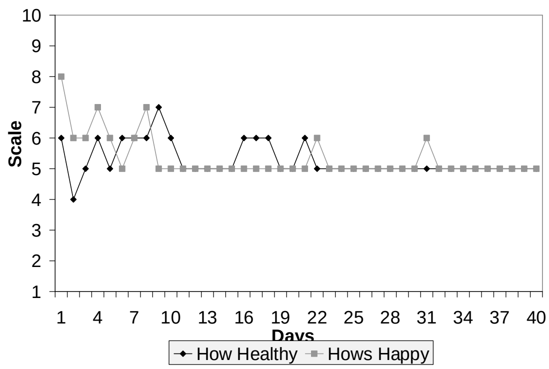


Figure 5: Comparison of Happy Vs Health state of Inhabitant.

The above figure represents the comparison of the inhabitant's emotional feelings of happiness and healthiness which is plotted with number of days on the X-axis and a scale of 1 to 10 on the Y-axis. The tables below that there is good similarity in them and the values are correlated slightly.

Table 7: Correlation comparison (r) values between Happy Vs Health state of Inhabitant.

| | Healthy | Happy |
|---|---|---|
| Healthy | 1 | |
| Happy | 0.299772 | 1 |

Table 8: t-test similarity (P) values between Happy Vs Health state of Inhabitant.

| | Healthy | Happy |
|---|---|---|
| Healthy | 1 | |
| Happy | 0.722704 | 1 |

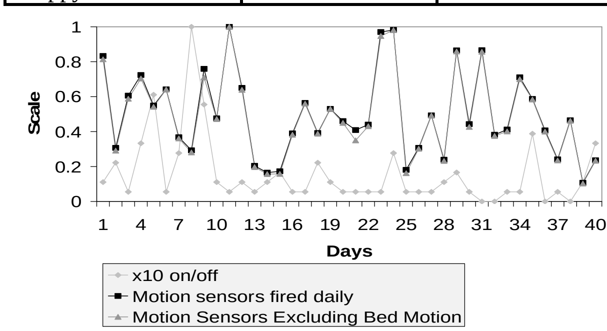


Figure 6: Comparison of X10 readings and sensor firing which constitutes the high level metrics.

The above figure represents a comparison of X10 readings and sensor firings which constitutes the high level metrics which are observed by the motion sensors. The plotting has the number of days on the X-axis and the scale of 0 to 1 on the Y-axis. The below tables represent the correlation and t-test performed on these observed data. We have observed from these values that there is infact a much smaller correlation between the x10 activity and motion sensors firing.

Table 9: Correlation comparison (r) values between X10 devices turned on/off and Motion sensor firings.

| | X10 on/off | Motion sensors |
|---|---|---|
| x10 on/off | 1 | |
| Motion sensors | -0.00315 | 1 |

Table 10: t-test similarity (P) values between X10 devices turned on/off and Motion sensor firings.

| | X10 on/off | Motion sensors |
|---|---|---|
| x10 on/off | 1 | |
| Motion sensor | 4.09E-21 | 1 |

From the above analysis we noticed that there are correlations among lower and upper body movements during sleep, closet and bathroom visits. The similarity test showed us that calorie intake has similarity with the distance traveled in the home. There is also similarity in room visits by the inhabitant. There is less correlation in health and happy states for the inhabitant. We need to remember that the data collected here was based on a single inhabitant and has some effect by the present condition these parameters were collected. We note, however, that the prediction model would also be based on data for the particular inhabitant currently in the environment.

In our prediction experiment, we use predictive accuracy as the performance measure. It is defined as the number of correctly classified instances divided by the total number of instances. We also look at the error rates during the experimentation. Most of the experimentation is run using the Weka environment (Witten 2005) and in all of the experiments reported here percentage split was used as the evaluation technique. This consists of dividing the data into two subgroups. The first subgroup, called the training set, is used for building the model for the classifiers. The second subgroup, called the test set, is used for calculating the accuracy of the constructed model.

On the collected data the inhabitant was asked to scale their level of happiness at particular times of the day. This was later classified into three (yes–happy, ok–mediocre, no–not happy) possible sets from an original scale of one to ten. Here we have considered values 6 to ten to be yes, 5 to be ok, and below 5 is no.

We use a **k**-nearest neighbors' classifier (Aha 1991), which returns the most common value among the **k** training discrete values by default and we can also select appropriate value of **k** based on cross-validation. This is robust to noisy data. This algorithm performs well and is most suited to this scenario as it uses a matching method to select **k** reviewers with high similarity measures (Witten 2005).

Using **k**-nearest neighbors' the accuracy is 78.5714% and the error is 21.4286%, here error is a measure of inaccurately classification. We see from the results that the learning performed well, although there is room for improvement. We anticipate that the algorithm could perform much better as more data becomes available. We also note that the inhabitant did not have extreme happiness or extreme sorrow which when obtained would facilitate more accurate prediction.

Table 11 shows a sample prediction which also shows the comparison of the actual value to the predicted value.

Table 11: Sample predictions on test split.

| Instance | Actual | Predicted | Error | Distribution |
|---|---|---|---|---|
| 1 | 1:yes | 3:ok | + 0.333 | 0.012 *0.654 |
| 2 | 3:ok | 3:ok | 0.012 | 0.012 *0.975 |
| 3 | 3:ok | 3:ok | 0.333 | 0.012 *0.654 |
| 4 | 3:ok | 3:ok | 0.012 | 0.012 *0.975 |
| 5 | 3:ok | 3:ok | 0.333 | 0.012 *0.654 |
| 6 | 1:yes | 1:yes | 0.333 | 0.333 *0.33 |
| 7 | 2:no | 3:ok | + 0.012 | 0.333 *0.654 |
| 8 | 3:ok | 3:ok | 0.333 | 0.012 *0.654 |
| 9 | 3:ok | 1:yes | + 0.654 | 0.333 * 0.01 |
| 10 | 3:ok | 3:ok | 0.333 | 0.012 *0.654 |
| 11 | 3:ok | 3:ok | 0.012 | 0.012 *0.975 |
| 12 | 3:ok | 3:ok | 0.333 | 0.012 *0.654 |
| 13 | 3:ok | 3:ok | 0.012 | 0.012 *0.975 |
| 14 | 3:ok | 3:ok | 0.012 | 0.012 *0.975 |

We performed similar experiments with various other techniques which included a J48 pruned tree and IB1 which is a lazy nearest neighbor classifier. Table 12 shows the comparison accuracy results. The **k**-Nearest Neighbor algorithm performed better as it uses a matching method to select **k** reviewers (here reviewers are data points) with high similarity measures. The votes from these reviewers, which are suitably weighted, are used to make predictions and recommendations. This method of matching was not used in the other algorithm which improved its performance.

Finally we perform an SVM classification using Weka on the available datasets and found that the accuracy was less compared to the **k**-Nearest Neighbor's.

Table 12: Comparison of Accuracy of prediction techniques.

| Learning Algorithm | Accuracy (%) |
|---|---|
| J48 | 57.1429 % |
| IB1 | 64.2857 % |
| SVM (SMO) | 65% |
| KNN | 78.5714 % |

## Conclusions and Future Work

The above results indicate that the **k**-nearest neighbor technique can be used for predicting an individual's state of happiness using collected smart home data (Youngblood 2006). Performance of the classifier would be expected to improve given a larger collected dataset. The result of this analysis demonstrates that a simple sensor network in smart home can be used to detect lifestyle patterns (such as frequent rooms visited, distance traveled in the home, health parameters, and so forth) of inhabitants in smart home. The **k**-nearest neighbor technique performed better than J48 Pruned tree and IB1 on our datasets. The basic goal of this work is to be able to predict the state of happiness which will aid the inhabitant to improve their lifestyle which would contribute to lead a healthy and happy life.

Our datasets still have many interesting findings to be found and patterns to be analyzed as collection continues. We also plan to address the problem of automating the SF-36® health survey form which would represent a breakthrough for smart home research.

## Acknowledgements

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