

Effects of Nudge Reflecting Day-of-Week Pattern against Induction to Walk

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ABSTRACT

This study proposes a tailored intervention method that takes individual contexts into account to increase walking steps in a sustainable way. Continuous exercise is necessary to reduce the risk of lifestyle-related diseases. However, many people are too busy to take constant exercises. Many existing approaches take enforcing ways in their support neglecting individual contexts, which prevents them to motivate individuals to exercise spontaneously. The proposed method figures out the periodicity of walking steps within every week. It regards the variation of the walking comes from inevitable contexts in the individual style of work and life. Reflecting the context, it encourages individuals with messages containing nudges. In a 4-week experiment with 13 university students, messages on days of the week of low walking succeeded in the improvement of the consciousness toward a healthy life. The use of periodicity and nudges turns out to be effective to lead individuals to sustained exercise.

Keywords: eHealth; Nudge; Walking; Seasonal trend decomposition; STL; Exercise.

INTRODUCTION

In the modern world, where life is said to be 100 years long, we should consider maintaining our own health. It is essential for us to keep constant physical activities such as exercise and walking [1]. The World Health Organization (WHO) refers physical activities to all body movement during working time and private time. It is recommended to have constant physical activities in order to prevent lifestyle diseases. However, 1/4 of adults in the world seldom move their bodies [2]. They are far from constant physical activities. Lack of physical activities matters so much that overcoming against it has become a worldwide concern [3]. Lack of physical activities matters so much that overcoming against it has become a worldwide concern.

There are two main reasons for the lack. One comes from low awareness of people for the relationship of physical activities with their health. People seldom understand the healthful and comfortable life owes to abundant physical activities. Many people realize the importance of physical activities only after they suffer from lifestyle diseases. The other one is strongly associated with constraints against having physical activities. Many workers have regular working items for each day of the week. Some have long meetings on Tuesday, while others have to write a lot of reports at their desks on Friday.

Sensing with smartphones are put into practical usage for the recognition of physical activities [4]. It is also noteworthy that almost all people carry smartphones at any time in modern society. Smartphones can also be regarded as devices to bring IT solutions which enhance the awareness to achieve specific goals. Hill et al. discussed avatars interacting with users to promote specific activities [5]. It is troublesome that surrounding people must frequently motivate persons who are likely to be short of physical activities. However, avatars never mind it. It is avatars that can frequently issue messages to motivate them. Hamari motivated the target users by means of the badge [6].

This paper pays attention to a bias in busyness for each day of the week. Depending on the day of the week, people cannot take physical activities, even though they want, due to time constraints. This common problem with many workers. Existing IT solutions for health promotion have ignored the periodicity of busyness. IT solutions for the health promotion should motivate target users toward physical activities under constraints against physical activities in their environment. This study considers the amount of walking important because even busy workers can easily introduce walking into their life as their physical activities to improve health. The proposed method in the study let avatars on smartphone support that the users improve the amount of walking steps. To motivate walking, the avatars use Nudge, which is valued in behavioral economics [7]. The proposed method estimates the periodicity of walking steps each day of the week using seasonal trend decomposition. The avatar shows the target user the nudging message according to the periodicity of walking steps each day. Through an experiment, this method clarifies the periodicity of walking volume. It also investigates changes in walking volume due to messages with nudge reflecting the periodicity. All participants in the experiment are clustered by k-means++. This paper discusses the effectiveness of specific nudge messages against each cluster.

LACK OF PHYSICAL ACTIVITIES AND EXISTING METHODS

Current Conditions Of Health Care Support

Various solutions using IT are proposed for the lack of physical activities. The recent popularization of wearable devices enables us to measure movements and signals of human bodies without effort [8,9]. It has brought e-Health, which incorporates IT into medical care, to practical use [10,11]. The incorporation of IT into medical care is expected to reduce social costs that come from the health management of various populations [12].

Another expectation is gamification, which applies entertainment elements of games to other fields [6]. A prominent example in health care is Pokemon GO. It is a game where users hunt Pokemon monsters in the real-world using GPS information. Its contribution to the increment of walking steps is discussed in [13,14]. Rasche et al. state most users of Pokemon GO initiate the game because they are fans of Pokemon, a quite popular cartoon. Because of the weak motivation

towards health improvement, many of them are confirmed to quit playing the game shortly [15]. Several works address the effects of Pokemon GO toward health improvement, but it is not known what characteristics of users are likely to receive positive effects from Pokemon GO [16]. Some of Pokemon fans might hardly receive positive effects because of their characteristics. In order to improve health, it is desirable to provide an IT solution that increases physical activities constantly, not temporarily. The solution should take into consideration both of characteristics above of each user and constraints around each user mentioned in Chapter 1.

Nudge and Behavioral Change Wheel

Nudges, proposed by Thaler [7] in 2008 in areas of behavioral economics, have been developed for behavior modification. Nudges mean to poke lightly with an elbow. A nudge makes the best use of the characteristics and biases of target persons. It lets target persons select the expected option without coercion. The famous nudge example is the decoration of a fly on urinal flies at Schiphol Airport in Amsterdam, the Netherlands. Many men make fly's decoration their targets at urination, which has drastically reduced floor stains. The nudge has greatly contributed to a reduction in cleaning costs. A nudge that considers habits and characteristics causes people to act expectedly without enforcing them [17].

Nudge is also expected to contribute to increasing physical activities [18,19]. Nudge leading unconscious physical activities is expected to be more successful in making target persons continue exercising than exercise supports with enforcement. Blumenthal-Barby mentions many governments and insurance companies utilize nudges for health care [20]. Digital Nudge is a nudge that uses a user interface on computing devices [21,22]. Hummel states that Digital Nudge have similar effects as nudge [23]. Cherubini provided target users with monetary rewards and motivational messages to make target users continue exercises [24]. However, intrinsic exercise motivation was reduced in many target users.

Behavior modification has been studied in various fields. In each field, nudges whose effectiveness have been confirmed are put into practical use in a heuristic way [25]. There is no nudge valid in every context. Keywords and methods are different in each context. The Behavior Change Wheel (BCW) corresponds effective nudges with each context. BCW is a framework that summarizes the theory of behavior change [26]. BCW shows 9 elements of intervention to promote behavior modification. Focusing on increasing physical activities for health promotion, nine elements are illustrated along with examples of interventions for each element.

- Education: Teaching the importance of health.
- Persuasion: Persuading with the fun of exercise.
- Incentivization: Giving reward each time, you reach your goal.
- Coercion: If you fail, you will be punished.
- Training: Teaching people who do not usually exercise how to stretch and exercise.
- Restriction: Enforcing exercise by coach.
- Environmental restructuring: Creating an environment where you can exercise
- Modeling: Presenting a successful example.
- Enablement: Using supplements or support devices

The effectiveness of the nine interventions may vary with characteristics of the target persons. For example, Intervention including an element of Education given to persons who have already known the importance of exercises would never produce any behavior modification towards health improvement.

Seasonal Trend Decomposition

Since the busyness varies from day to day, many people have a periodic increase or decrease in their physical activities. We should avoid deciding interventions only from the change of daily physical activities of a specific person. Instead, we should make it clear what kinds of periodicity is contained in the time series of the physical activities.

The seasonal trend decomposition makes seasonal fluctuations apparent in the time-series. For example, the time-series of the crop commodity price fluctuates periodically due to the influence of climate. The seasonal trend decomposition is useful for analysis of periodic price fluctuations or fluctuations that cannot be explained by seasonal aspects.

The seasonal trend decomposition decomposes time series D into three components: seasonal variation component S , trend component T , and irregular variation component I .

$$D = S + T + I \quad (1)$$

The trend component is free from seasonal variation. Note that the last component brings fluctuation unexplainable with the two former components. There are multiple methods to realize the seasonal component decomposition, such as the moving averages and Seasonal and Trend decomposition using Loess (STL) founding on locally weighted smoothing [27].

Let us consider an example where the seasonal trend decomposition is applied to a time series showing the decrease of the prices of a specific item. The seasonal component shows the periodicity of price declines due to year-end sales, while the trend component expresses low consumer demand because it excludes the seasonal component. The irregular variation component may correspond to a sudden recession. As the example shows, the seasonal trend decomposition contributes to understanding a time series from multiple aspects [28]. Rowlands et al. have confirmed that the number of daily steps of any person has periodicity with the seasonal component decomposition [29].

Target Users

Many health improvement programs focus on walking because of its simplicity. Walking does not require special skills or equipment. It is an easy physical activity to sustain in daily life [30]. Even in a busy time, anyone can increase walking steps, just being conscious of taking short walking during working. Another advantage of walking is that there is almost no financial burden.

Harries has suggested that feedback on the number of walking steps using smartphone applications can increase physical activities [31]. However, the effect of feedback may vary with persons. An individualized approach is important to increase walking volume.

As an individualized approach, we should have a clear target because there are various kinds of people. Positive and negative factors should be taken into account to classify people from

viewpoints of engagement in walking. The former is represented with the consciousness of exercises, while the latter includes constraints coming from time and money. If you are highly conscious of exercise, you are spontaneous to walk. On the other hand, it is hard for you to walk if you do not have enough time and money. Therefore, people are classified according to their consciousness of exercise, which is an internal factor, and their time and money, which are environmental constraints.

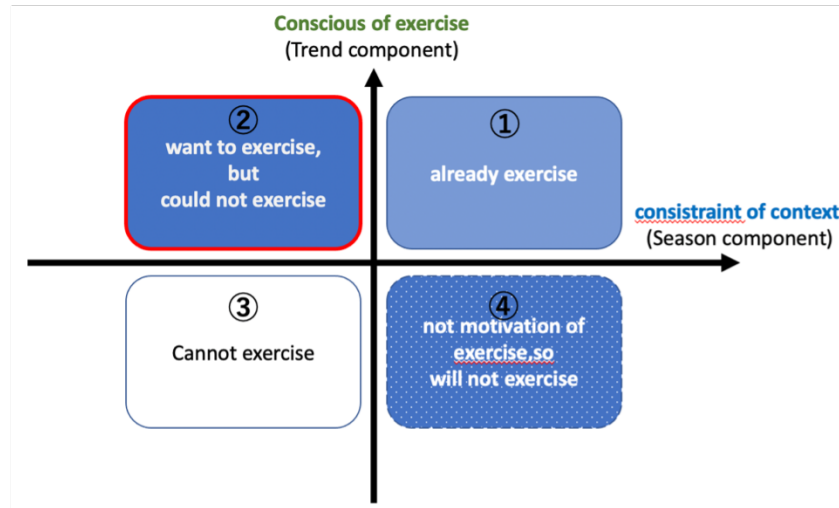


Figure 16 Classification based on internal and environmental constraints

Figure 1 shows the labeling of the four classes by internal factors and external constraints. People highly conscious of exercise with enough time and money have already started engagement in exercises. Those who are highly conscious of exercise but have limited time and money cannot engage even though they want to. People with low conscious of exercise do not exercise even if they have time and money to spare. Those who are low in consciousness with constraints are far from exercising. This study targets people who cannot exercise despite their desires. It examines whether interventions considering environmental constraints can induce them toward walking.

IMPROVEMENT OF WALKING STEPS BY NUDGE CONSIDERING BUSYNESS

Context Component And Intrinsic Component

The proposed method encourages the target users to sustain improvement in walking steps, taking individual environmental constraints into account. It makes them maintain a high level of consciousness of their own exercise.

This method collects walking steps of a target user with a smartphone or a smartwatch. The walking steps are recorded as a time-series with a daily timestamp. To consider an individual environment, the method decomposes the time series into seasonal variation components and a trend component by the seasonal component decomposition. The method associates the seasonal variation components and the trend component with the individual environment and the exercise consciousness of the target user, respectively.

Constraints each person has for each day of the week vary with the personal environment. They depend on contexts of each person. This study assumes the effects of constraints on days of the week appear as the seasonal variation components. In this study, the seasonal variation

components are referred to as context components. On the other hand, the walking steps that are not intervened by environmental factors represent the original walking potential of the target user. The study regards the consciousness of exercise of the target user appears as the trend component. In this study, the trend component is referred to as the intrinsic component. When the health consciousness is high in a user, the intrinsic component is also high inherently.

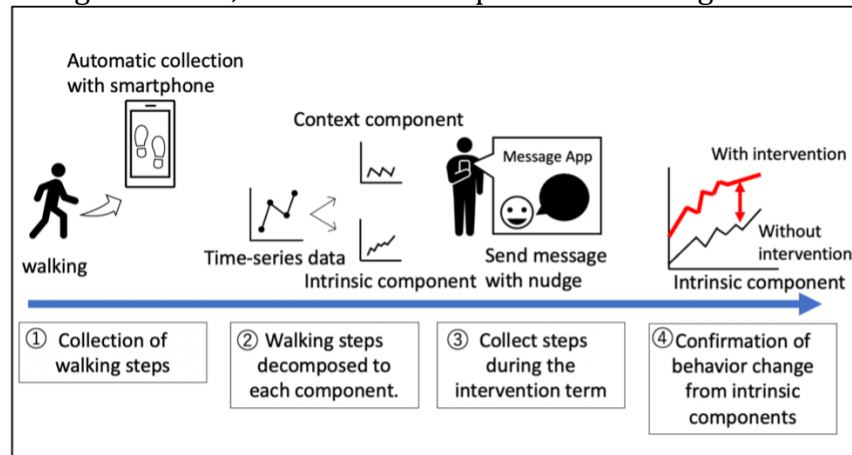


Figure 17 Schematic of the method

The proposed method presents a message containing a nudge to the target user through a smartphone. The message encourages walking, based on the BCW. It is chosen, considering the individual environment. The effect of the message is measured from the change of the intrinsic component associated with the consciousness of exercise. The method repeats messages found to be more effective. Repetition of the tasks in Figure 2 is expected to improve the walking of the target user.

Decomposition Of Walking Steps

Seasonal trend decomposition extracts patterns of periodic data from a time series. This method assumes the walking steps include periodic fluctuations corresponding to each day of the week. For example, people would commute to work on weekdays, while go shopping on weekends. Walking steps required for commuting and shopping would be constant in most cases. Apart from it, regular meetings are usually held on certain days of the week. On such days, the amount of walking is inevitably small. In this study, the periodicity of the seasonal trend decomposition is set to 7 days, to extract such periodic components corresponding to each day of the week.

Seasonal component decomposition using simple moving averages results in missing data at both ends of a time series. One way to compensate for missing data estimates them from ones around the ends. However, it causes a bias. To solve the problem, the method adopts STL, which calculates seasonal and trend components using locally weighted linear regression. This allows the STL to decompose the components without loss.

Another advantage of STL is its ability to follow for seasonal components to change over the time. In general, it is considered that the periodicity in the walking steps changes in the course of time. The SLT optimizes the decomposition gradually so as to accommodate any change that has a

significant impact on periodicity. For example, even if the way of commuting changes, the seasonal component gets to show the right periodicity as the weeks go by.

Walking Steps Coming From Days Of The Week

The context component in this method means the number of steps specific to each day of the week. The context component is calculated as either a positive or a negative value. The context components of a user are shown in Figure 3. For example, a user obliged to working at home every Tuesday, Thursday, and Friday has negative values on those days. It attributes to the working at home. Walking steps required for commuting is reduced on the days.

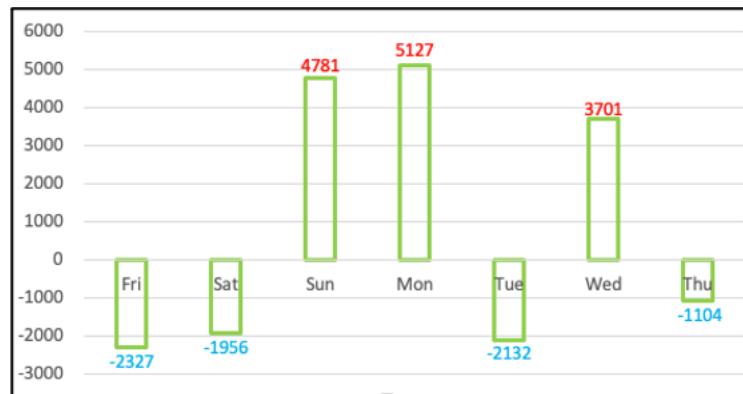


Figure 18 Example of context component

The difference in walking steps that occurs periodically inevitably occurs in the course of daily life on each day of the week because users cannot change environmental constraints such as weekly meetings and designated working days at home. It comes from the habits of target users regarding working and living. Context components can be regarded to represent the target user's busyness specific to days of the week.

This method uses the context component in two ways. First, it is used to create a message that tells the day of the week short in walking. In the other way, it is used to determine when to send a message to take the individual environment into account. We can assume 2 kinds of days for message-sending: ones with positive context components and ones with negative context components. The proposed method can test which message-sending is more effective to increase the walking steps.

Estimation Of Consciousness Of Walking

The intrinsic component is obtained by the removal of the context component and the irregular variation component from the walking steps data. Figure 4 shows an example of the original walking steps along with its intrinsic component. The figure indicates the context component and the irregular variation component make short period waves and large peaks in the original walking steps. On the other hand, the intrinsic component has a gentle and flat waveform. The Intrinsic component, which is free from the context component, is considered to be walking steps the target user himself unconsciously takes in a certain environment. The intrinsic component which is walking steps under unconsciousness indicates how well the walking custom is established in the target user.

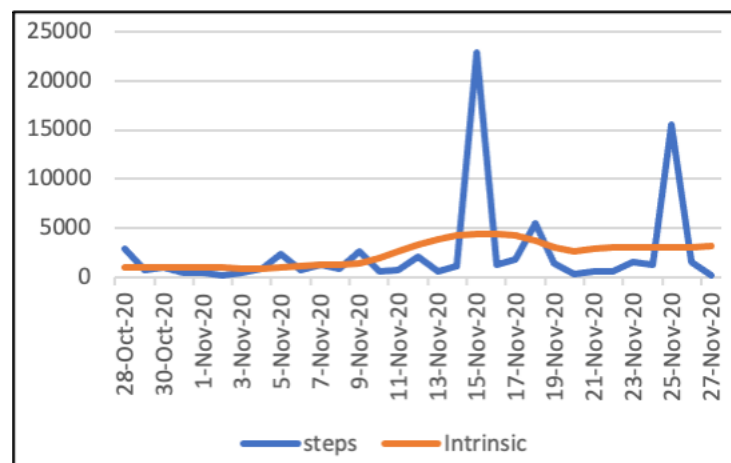


Figure 19 Graph of walking steps and intrinsic component

It is significant to examine the increase or decrease in the intrinsic component, not in the original walking steps. Suppose that walking steps increase temporally due to the influence of an encouraging message. Since the effect of a message generally declines over time, subsequent messages are necessary for people to sustain the high level of walking steps. However, if the message greatly raises the consciousness of people toward their healthy life, they will engage in healthy behaviors spontaneously even without subsequent messages. If the consciousness is figured out from the original walking steps, it would include walking steps increased by contexts or events that require walking by chance. It would make the relationship of the consciousness with the walking steps ambiguous. The proposed method expresses pure walking steps caused by the consciousness toward a healthy life, through the examination of the intrinsic component obtained through the decomposition of the original walking steps.

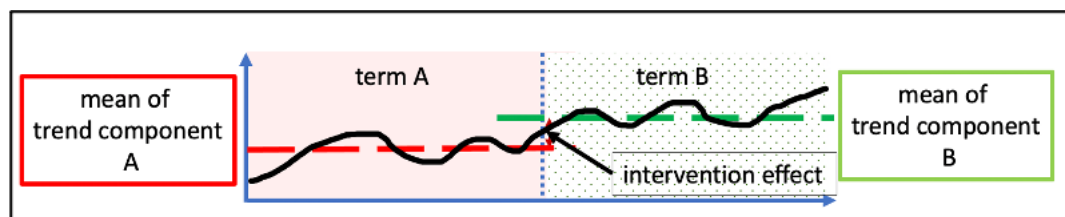


Figure 20 Intervention effects due to differences in mean intrinsic components

The long-term observation of the intrinsic component tells us the changes in the consciousness of the target users. The proposed method sends messages several times in a fixed period to check how much the average value of the intrinsic component has changed. Figure 3.4 shows the method used to check the change in consciousness of exercise due to the intrinsic component. The horizontal axis and the vertical axis represent the time and the walking steps of intrinsic component, respectively. Nothing is done to the target user in period A, while messages are sent to the user to improve the walking step in period B. The difference of the intrinsic components in the two periods indicates the change of the consciousness due to the messages.

Messages Using Nudges To Improve Walking Steps

It is not a good idea to assign someone to monitor whether a target user is engaged in continuous exercises. It would be a mental burden on the target user. It would also need many persons to monitor the target users. It is infeasible from the viewpoint of social implementation.

The paper proposes an avatar that sends promotion messages toward walking to the target user. The proposed method makes it important the target user agrees with the messages as a basic principle to change the consciousness of the target user. There are many barriers to imposing healthful behaviors on people. It is useless to oblige excessively busy persons to visit a sports gym. To achieve for the target users to keep efforts for the improvement of their health, the study esteems concept "nudges" in behavioral economics [7]. Nudges lead them to take expected behavior, through suggesting options that sound preferable to them. In this method, the avatar presents a message using nudges considering the situations of each target user. The messages gradually lead the consciousness of the target user to improve the health.

BEHAVIOR CHANGE EXPERIMENT WITH MESSAGES

Experimental Environment And Purpose

To verify the effectiveness of the proposed method, an avatar is installed on the target user's smartphone. The avatar presents messages which work as nudges to target users. The daily walking steps of the target user are counted using a smart phone. The experiment examines relationships of the number of walking steps with the nudge intervention. Any message presents one of the nudge elements of the BCW.

The purpose of the experiment consists of the following 3 points. It tests the impact of the intervention by nudges. It further examines the impact of nudges in the two cases: under the negative context components and the positive ones. It examines in which case nudges work better. It figures out what kind of nudges works well for a specific group of persons. It investigates the magnitude of the effect of nudges on variations of each of the context component and the intrinsic component. Figure 4.1 shows the duration of the experiment.

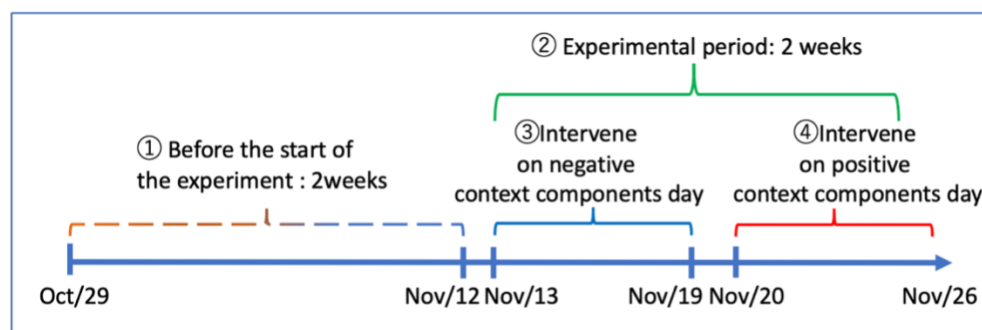


Figure 21 Range of data in this experiment

Differences Of Walking Steps By Intervention

Purohit et al. stated that timing is critical to the success of Digital Nudge [32]. In this experiment, digital nudges intervene to enable the target user to continuously increase the walking steps.

The assumption of the study is that the walking steps increases if the avatar presents nudges using messages. To verify it, regardless of the positive or negative context components, a statistical test is conducted to see if there is a significant difference of the walking steps in the two weeks under the experiment from those in the two weeks prior to the experiment. If there is, the presentation of the nudge is expected to increase the walking steps. For each of the cases where the context component is either negative or positive, a significant difference is also tested before and after the nudge intervention. The timing to send messages indicating nudges turns out if there is a significant difference in one of the cases.

The effect of nudges is then tested on the difference of the intrinsic component with nudge from that without nudge. After the test neglecting the context component, the nudge effect is again tested under the distinction of the positive context component from the negative one. The test turns out how much nudges affect the intrinsic component, which is a manifestation of the consciousness of the target user toward the health improvement.

Clustering Target User

The target users are clustered based on the variation of the walking steps under the difference of the context components and the nudge intervention. Days of the week with negative context components are regarded as busy days, for some reasons reduce the walking steps every days of the week. The explanatory variables in the clustering are shown in Table 1

Table 5 Explanatory variables and means

explanatory variables	means
Mes-B (Message and Busy)	Average walking steps when messages are sent on a busy day
Mes-Nb (Message and Not Busy)	Average walking steps when messages are sent on a less busy day
Nmes-B (No Message and Busy)	Average walking steps when no messages were sent on a busy day
Nmes-Nb (No Message and Not Busy)	Average walking steps when no messages were sent on a non-busy day
Mes-Nmes-B (Message - No Message on Busy)	The difference of average walking steps between sending a message on a busy day and not sending a message.
Mes-Nmes-Nb (Message - No Message on Not Busy)	The difference of average walking steps between sending a message on a non-busy day and not sending a message.

Symbol B (Busy) in the explanatory variable name stands for days with a negative context component, while NB (Not Busy) represents days with a positive context component. Symbol Mes(Message) and Nmes(No Message) stands for days with messages and those without messages, respectively. The clustering lets us know whether users in each cluster increases their walking steps on busy or less busy days depending on messages.

Creating a Message

Table 2 lists nudges presented in messages to increase the walking steps along with the type of BCW corresponding to each of them. Any nudge should never enforce any particular behavior. They only convey useful information to the target user. Target users can decide whether or not they increase the walking steps.

Informing users of the days of the week when they walk less, the persuasion nudge in Table. encourages them to increase their walking steps. The nudge makes the users aware of the context component to see what changes occur in the walking steps.

Seasonal factors have been introducing into the nudge of autumn leaves and the nudge of calorie consumption. The nudge of autumn leaves tells it is a time where the autumn leaves are beautiful, expecting the walking steps will increase due to visiting any spots of the autumn-leaf viewing. In the nudge of calorie consumption, after the calorie content of chestnuts is explained, it tells the number of walking steps required to consume the calories. Seasonal elements are introduced to make the content of the message more related to the target user's own life, which gives users intimacy to the message.

Modeling, one of the BCW elements, is used for the three nudges: baker's serendipity, tips on how to keep exercising, and promotion of simple exercise. Modeling is a method of communicating ideal behaviors and successful experiences in the form of stories to encourage similar behaviors and experiences.

The proposed method adopts an implementation where an avatar sends a message. Avatars are expressed using emoticons. It is essential to create nudges carefully, keeping in mind the recipients of the message never feel forced towards specific behavior. Any avatar is set as a health-conscious person. It is also set as an imperfect personality trying to act ideally but often failing to. In the nudges to promote simple exercises, avatars present their own exercise trials which result in failures. The setting human-like characteristics for avatars makes messages more friendly to target users.

Table 6 Experimental Message

BCW	Message title	Contents of message
Persuasion	Informing them of the days of the week when they were walking less	There tends to be less walking on Saturdays.
Persuasion, Environmental restructuring, Incentivisation	The nudge of autumn leaves	The mountains are changing color and the autumn leaves are in full bloom. Why don't you take a break from your busy schedule and enjoy the autumn colors?

Modeling, Persuasion	Baker's Serendipity	The other day, I dared to walk home from an unknown street, and I happened to find a delicious bakery! Sometimes, taking a different road may lead to a wonderful encounter.
Education	The nudge of calorie consumption by walking step.	The autumn of appetite and sports is almost over, but did you know that chestnuts, which are in season in autumn, have 160 kcal per 100 grams? By the way, it is said that it takes 5,000 steps to consume 160 kcal by walking slowly on a flat road. Why don't you walk a lot and enjoy the taste of autumn?
Education, persuasion	Risk of lifestyle-related diseases and benefits of exercise	Let me tell you about the risks of inactivity today! In fact, 50,000 people in Japan die every year from diseases caused by lack of exercise. In fact, 50,000 people in Japan die every year from diseases caused by lack of exercise. According to one study, habitual and rigorous exercise can reduce the risk of death by as much as 30%. To live a long and healthy life, we need to start exercising now....
Training, Education, modeling	Tips on how to keep exercising	Of course, it is important to set a goal and make a plan in order to continue exercising, but it is also important to check your daily results in order to increase your motivation. Check your pedometer every day. Get on the scale. Take a good look at your body in the mirror. These are just some of the ways you can check and praise yourself for your efforts!
Training, Education, modeling	Promotion of simple exercise	Do you usually exercise? I tend to slack off, so instead of doing strenuous exercise, I have been trying to do light exercise such as stretching little by little. Why don't you start doing light exercise when you suddenly notice it, such as standing on your toes while standing on the train, or walking with a wider stride than usual?

Experiment On Students

An experiment was conducted on 13 male college students. Their ages ranged from 20-24 years old. All of them are users of the health care feature of the iPhone. They provided their walking steps recorded in 2 weeks just before the experiment. In advance, it was confirmed they have no plan that would significantly affect the walking steps. The proposed method extracts the context component and the intrinsic component from each time series of their walking steps. It created two cases: one in which messages were sent only on days with negative context components, and the other in which messages were sent only on days with positive context components.

In this experiment, messages were sent according to the Wizard of Oz method, where an experimenter operates a computer behind the user as if avatars have dialogues with users in a responsive manner. The experimenter transmitted the nudge messages to make the target users believe the avatars responded to them.

The message was sent around 9:00 a.m. so that the target users may behave according to the messages on the day. Target users were asked to be sure to check the messages sent by avatars at that time. After the experiment, the target users provided the walking data again as well as took questionnaires and interviews on the messages.

RESULT

Statistical Tests Of Walking Steps

The normality of the data should be checked first. For each target user, let one clump be the daily walking steps. Figure 7 depicts a stacked bar graph showing the frequency of the occurrences of clumps colored with individual users. The figure shows not only the distribution of the walking steps is skewed to the left, but also the range of the distribution varies with the users.

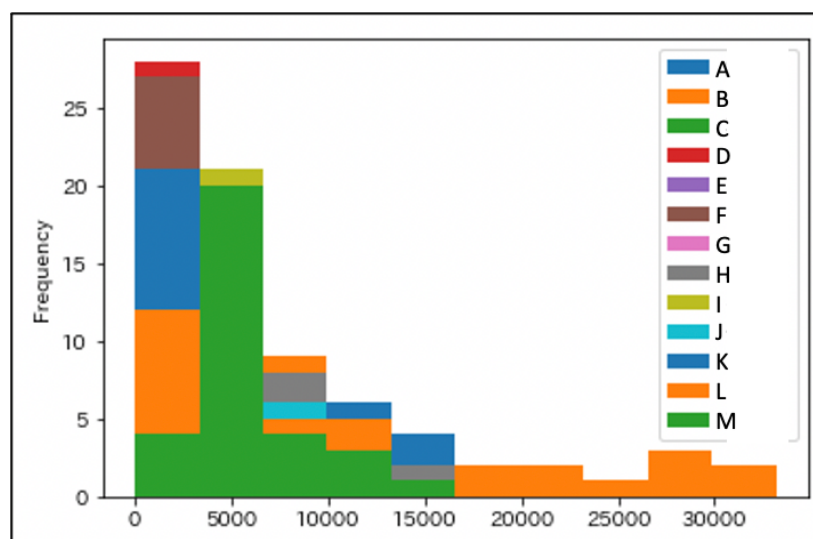


Figure 22 The daily walking volume of each target user is considered as a lump

A q-q plot for the walking steps for all users is shown in Figure 8. The red line represents the waveform of the walking steps following a normal distribution, while the blue points represent the

walking steps collected in the experiment. As the figure shows, the blue point is far from the red line in both edges. The Shapiro-Wilk test turns out the test statistic is 7.9×10^{-23} . The Shapiro-Wilk test lets the null hypothesis be that the population of sampled data follows a normal distribution. The test result rejects the null hypothesis, which indicates the sampled data is not considered to follow a normal distribution.

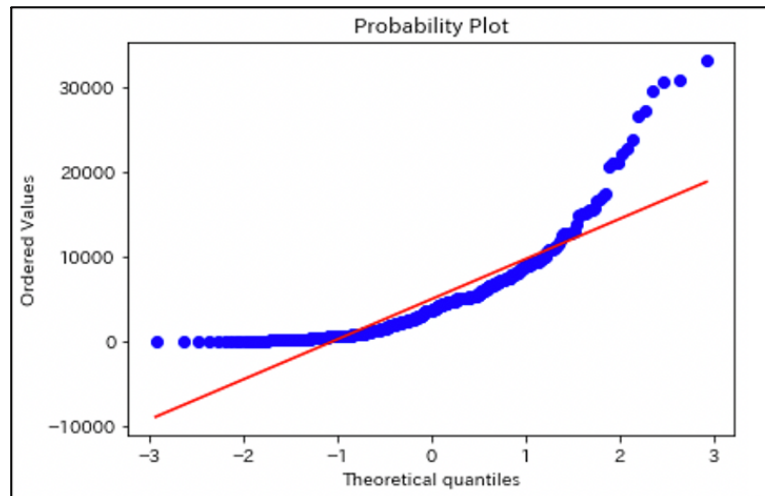


Figure 23 Q-Q plot

Since the population does not follow a normal distribution, a nonparametric test is necessary. In this test, Wilcoxon's signed rank sum test is used for the corresponding data, while unpaired data are tested using the Mann-Whitney U test. The significance level is set to 10% in both tests.

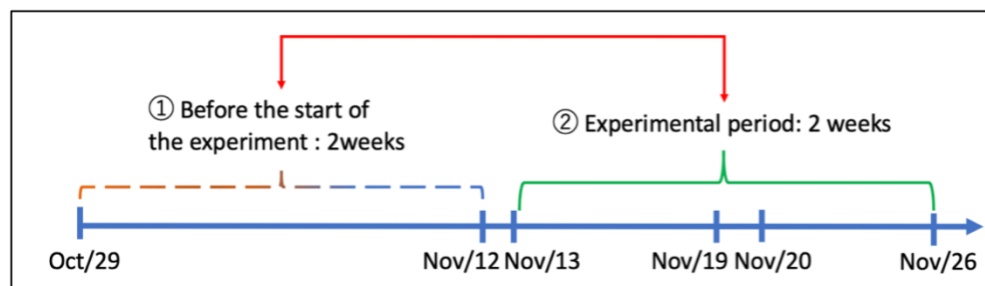


Figure 24 Period of time with or without intervention

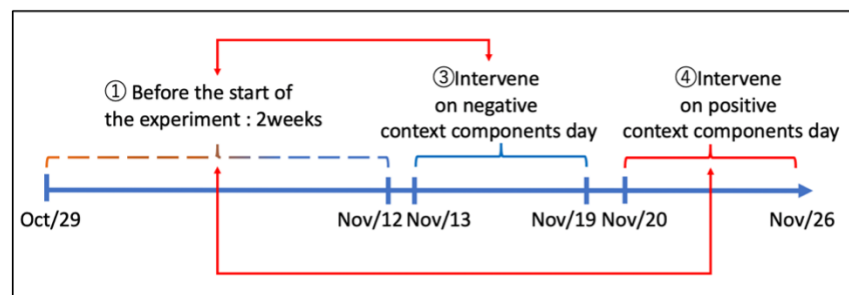


Figure 25 Target period when context component is taken into account

Let us confirm how much the presence or absence of the message affects the walking steps. The time period of the data covered in this analysis is depicted in Figure 9. The null hypothesis is that there is no significant difference of the walking steps in the two weeks with the message intervention from those in the two weeks without the message intervention. The test result is 0.127 for all target users. No significant difference is found for all users.

Next, let us test whether there is a significant difference when messages are sent on either of days with the positive context components or days with the negative ones. Figure 5.4 shows the combination of data handled in the test. Since there is no correspondence in the data for the periods considering the context component, the U test was adopted as the testing method. The first null hypothesis is that there would be no significant difference of the two weeks prior to the experiment from the week where messages were sent only on days with negative context components. The second null hypothesis is that there would be no significant difference of the two weeks prior to the experiment from the week where messages were sent only on days with positive context components. The test result for all users is 0.089 and 0.636 for days with a negative context component and for days with a positive context component, respectively. The message is sent on a day with a negative context component may cause a significant difference. When the significance level is set at 10%, the first null hypothesis is rejected. Therefore, we can regard there is a significant difference when the message is sent on days with negative context components.

Effect Of Nudges On Intrinsic Components

The intrinsic component, which does not include the context component, indicates how much the target user would walk without influence from the environment. It is worthwhile to find out how much the target user's walking increased before and after receiving the nudge. Nudges using messages sent from avatars can influence the target user's consciousness toward health. The difference in the average of intrinsic components for all users indicates the change of the consciousness before and after receiving the nudge. The table 3, 4, and 5 shows the difference in the intrinsic components during each period.

Table 7 Difference in average intrinsic components with and without intervention

Basic Statics	Difference in intrinsic components
Mean	1423.03
Dispersion	5739828.69
MIN	-1396.96
MAX	5085.93

Table 8 Average intrinsic component difference when the context component is negative

Basic Statics	Difference in intrinsic components
Mean	1517.40
Dispersion	6524445.42
MIN	-2432.64
MAX	6074.71

Table 9 Average intrinsic component difference when the context component is positive

Basic Statics	Difference in intrinsic components
Mean	1328.66
Dispersion	5888875.64
MIN	-1417.12
MAX	5775.41

The largest difference in the intrinsic component is found when the users were intervened when the context component was negative. In terms of both results of the test and the difference in the intrinsic component, we can expect that intervention when the target users are busy will bring an increase in the walking steps.

Clustering Results

The target users were clustered using the explanatory variables listed in Table 1. The results of using the elbow method to determine the number of clusters are shown in Figure 11. If the sum of squares of errors (SSE) within a cluster bends like an elbow in the graph, we know that the degree of error reduction has become smaller for that number of clusters. As the degree of decrease in SSE becomes smaller, it turns out that further decomposition will not result in meaningful clusters. Figure 11 suggests that 3 or 4 would be appropriate. The results of clustering with K-means++ method for the case where the number of clusters is 4 are shown in Figure 12.

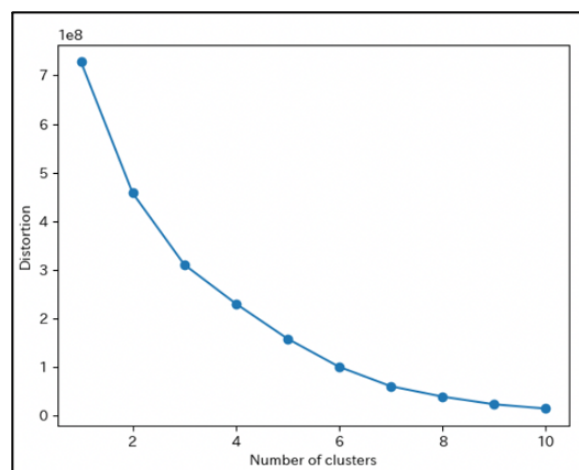


Figure 26 The results of using the elbow method

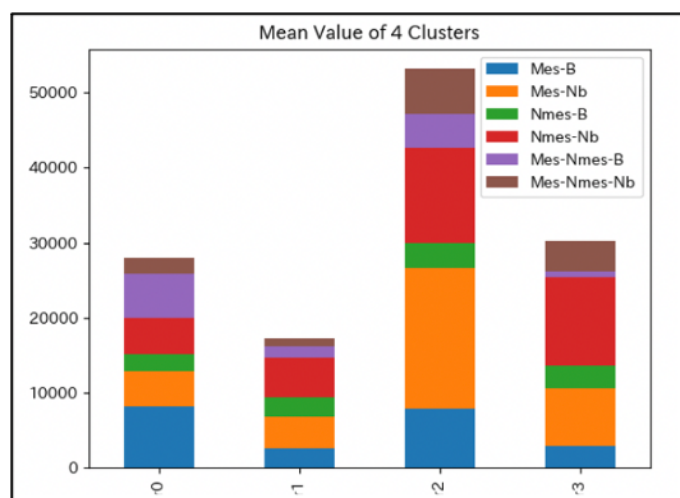


Figure 27 Average of the components of each cluster

Table 10 Number of people assigned to the cluster

Identified Cluster	0	1	2	3
number of target users	5	5	1	2

The number of people assigned to each cluster is shown in Table 6. There are many users in clusters 0 and 1, while only 1 and 2 people are assigned to clusters 2 and 3. For the explanatory variables specified this time, it is likely that the majority of target users are classified into clusters 0 and 1. Target users whose explanatory variables have outliers compared to those of the other target users seems to be assigned to clusters 2 and 3.

DISCUSSION

Clustering Based On Response To Messages

Target users do not always behave in the same way when they receive a specific message. The clustering results of the target users in section 5.3 classifies the target users by their responses to the messages. Let us compare clusters 0 and 1, which have many members.

Among the explanatory variables that make up the cluster, the blue Mes-B and the purple Mes-Nmes-B in cluster 0 have larger values than those in cluster 2. Mes-B represents the walking steps in the case where a message was sent on days of the negative context component, which means the walking steps would be fewer on those days of the week. This paper regards the days where the walking steps is reduced as busy days. Mes-Nmes-B represents the difference of the walking steps with messages on busy days from those without message on busy days. From the major components of the explanatory variables in cluster 0, we can see that messages on busy days are more effective to increase walking steps than no message on those days. Cluster 0 can be regarded as a group of people whose walking steps increase by messages on busy days.

Since the number of people belonging to clusters 2 and 3 is small, only the characteristics of their members are discussed without the comparison of them with other clusters. Many walking steps of the person in Cluster 2 implies his high health consciousness. Since Mes- Nb is more than Nmes-

Nb in Cluster 2, we can expect to increase the walking steps by sending messages on less busy days. Cluster 3 has more walking steps on less busy days. In cluster 3, Nmes-Nb is more than Mes-Nb, which suggests that they reduced walking steps on busy days due to messages. They might be inherently health conscious. Though they had spontaneously walked a lot, they might have degraded their motivation with the messages enforcing further increment of their walking steps.

Effective Messages As Nudges

This section discusses the results of the interviews for each nudge. See Table 2 for the nudge items in this experiment.

There was a negative opinion on the nudge, which periodically notified the target user of the days of the week when he walks less. The target user was aware of few walking steps on the days. The notification made him sick of walking. To avoid creating meddlesome nudges, it is necessary to intervene reflecting the target user's awareness of walking steps. Nudges must not force behavior on the target users. Nudges that may seem to criticize the target users would not only fail to suggest expected behavior but also bring worse effects.

On the other hand, in the nudge of autumn leaves, there were several target users who actually went to see the autumn leaves, which increased their walking steps. Some commented that the seasonal messages were easy to imagine and increased their desire to go. Further- more, in terms of calorie consumption by the walking steps, several target users began to pay more attention to calories when eating. They tried to walk more consciously in order to consume the calories they had taken in. As these two examples imply, it is important to create nudge messages that make it easy for receivers to imagine the action to be taken. They usually empathize with such messages.

In the nudges about the risk of lifestyle-related diseases and the benefits of exercise, some target users felt that the messages were someone else's problem. To increase the efficacy of the message, it is necessary to specify the risk of disease caused by lack of exercise is really related to the target user themselves.

CONCLUSION

In this paper, a method is proposed to improve the walking steps using a smart phone for the improvement of the inactivity. The proposed method creates messages based on nudges in order to motivate target users to exercise without difficulty.

The proposed method applies the seasonal trend decomposition to the walking steps in order to consider the environment of target users. It decomposes the walking steps into context components and the intrinsic component. The context components are the difference in the walking steps for each day of the week. Constraints coming from workstyle or lifestyle bring the difference. Therefore, the context component can be regarded as a component that represents the busyness caused by the environment specific to each target user. The intrinsic component represents the walking steps per week free from the context components. The intrinsic component is the walking steps due to the target user consciousness toward the exercise.

An experiment was conducted to send messages indicating nudges using smart phones. A significant difference is observed in the walking steps during the week with messages sent only on days of the negative context component. It implies messages on days of the week when the

walking steps is periodically low are effective to improve the walking steps. The target users are classified into 2 major clusters based on the characteristics of the walking steps. It turns out the walking steps of one cluster increase with messages on busy days while those of the other do not change with the message. The result shows that messages on busy days generally do not fail to improve the walking steps. Examination of the target users' opinions over the messages figures out effective messages to make the target users conscious of exercise.

The proposed method, which takes the target user environment into account, make target users conscious of the need for exercise. In the future, we will apply the proposed method not only to walking steps but also to data of various physical activities. In order to increase the reliability, we plan to conduct experiments with a large number of target users. Long term experiments are also needed to see how long the effects of the messages last.

References

1. Katrina L Piercy, Richard P Troiano, Rachel M Ballard, Susan A Carlson, Janet E Fulton, Deborah A Galuska, Stephanie M George, and Richard D Olson. The physical activity guidelines for americans. *Jama*, 320(19):2020–2028, 2018.
2. World Health Organization. Global action plan on physical activity 2018-2030: more active people for a healthier world. World Health Organization, 2019.
3. Regina Guthold, Gretchen A Stevens, Leanne M Riley, and Fiona C Bull. Worldwide trends in insufficient physical activity from 2001 to 2016: a pooled analysis of 358 population-based surveys with 1.7 million participants. *The Lancet Global Health*, 6(10):e1077-e1086, 2018.
4. Jennifer R Kwapisz, Gary M Weiss, and Samuel A Moore. Activity recognition using cell phone accelerometers. *ACM SigKDD Explorations Newsletter*, 12(2):74–82, 2011.
5. Jennifer Hill, W Randolph Ford, and Ingrid G Farreras. Real conversations with artificial intelligence: A comparison between human-human online conversations and human- chatbot conversations. *Computers in human behavior*, 49:245-250, 2015.
6. Juho Hamari. Do badges increase user activity? a field experiment on the effects of gamification. *Computers in human behavior*, 71:469–478, 2017.
7. Richard H Thaler and Cass R Sunstein. *Nudge: Improving decisions about health, wealth, and happiness*. Penguin, 2009.
8. Yangjian Huang, Junkai Xu, Bo Yu, and Peter B Shull. Validity of fitbit, jawbone up, nike+ and other wearable devices for level and stair walking. *Gait & Posture*, 48:36–41, 2016.
9. S Baskar, P Mohamed Shakeel, R Kumar, MA Burhanuddin, and R Sampath. A dynamic and interoperable communication framework for controlling the operations of wearable sensors in smart healthcare applications. *Computer Communications*, 149:17– 26, 2020.
10. Abby C King, Eric B Hekler, Lauren A Grieco, Sandra J Winter, Jylana L Sheats, Matthew P Buman, Banny Banerjee, Thomas N Robinson, and Jesse Cirimele. Harness- ing different motivational frames via mobile phones to promote daily physical activity and reduce sedentary behavior in aging adults. *PloS one*, 8(4):e62613, 2013.
11. Supraja Sankaran, Paul Dendale, and Karin Coninx. Evaluating the impact of the hearthab app on motivation, physical activity, quality of life, and risk factors of coronary artery disease patients: multidisciplinary crossover study. *JMIR mHealth and uHealth*, 7(4):e10874, 2019.

12. Farshad Firouzi, Bahar Farahani, Mohamed Ibrahim, and Krishnendu Chakrabarty. Keynote paper: from eda to iot ehealth: promises, challenges, and solutions. *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*, 37(12):2965–2978, 2018.
13. Farshad Firouzi, Bahar Farahani, Mohamed Ibrahim, and Krishnendu Chakrabarty. Keynote paper: from eda to iot ehealth: promises, challenges, and solutions. *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*, 37(12):2965–2978, 2018.
14. Tim Althoff, Ryen W White, and Eric Horvitz. Influence of pokémon go on physical activity: study and implications. *Journal of medical Internet research*, 18(12):e315, 2016.
15. Peter Rasche, Anna Schlomann, and Alexander Mertens. Who is still playing pokemon go? a web-based survey. *JMIR serious games*, 5(2):e7, 2017.
16. Claudio R Nigg, Desiree Joi Mateo, and Jiyoung An. Pokemon go may increase physical activity and decrease sedentary behaviors. *American journal of public health*, 107(1):37, 2017.
17. Saurabh Bhargava and George Loewenstein. Behavioral economics and public policy 102: Beyond nudging. *American Economic Review*, 105(5):396–401, 2015.
18. Andreas Lieberoth, Niels Holm, and Thomas Bredahl. Selective psychological effects of nudging, gamification and rational information in converting commuters from cars to buses: A controlled field experiment. 2018.
19. Meng Li and Gretchen B Chapman. Nudge to health: Harnessing decision research to promote health behavior. *Social and Personality Psychology Compass*, 7(3):187–198, 2013.
20. Jennifer Swindell Blumenthal-Barby and Hadley Burroughs. Seeking better health care outcomes: the ethics of using the “nudge”. *The American Journal of Bioethics*, 12(2):1–10, 2012.
21. Markus Weinmann, Christoph Schneider, and Jan Vom Brocke. Digital nudging. *Business & Information Systems Engineering*, 58(6):433–436, 2016.
22. Randi Karlsen and Anders Andersen. Recommendations with a nudge. *Technologies*, 7(2):45, 2019.
23. Dennis Hummel and Alexander Maedche. How effective is nudging? a quantitative review on the effect sizes and limits of empirical nudging studies. *Journal of Behavioral and Experimental Economics*, 80:47–58, 2019.
24. Mauro Cherubini, Gabriela Villalobos-Zuniga, Marc-Olivier Boldi, and Riccardo Bonazzi. The unexpected downside of paying or sending messages to people to make them walk: Comparing tangible rewards and motivational messages to improve physical activity. *ACM Trans. Comput.-Hum. Interact.*, 27(2), 2020.
25. Ryan E. Rhodes, Desmond McEwan, and Amanda L. Rebar. Theories of physical activity behaviour change: A history and synthesis of approaches. *Psychology of Sport and Exercise*, 42:100 – 109, 2019. 50 years of FEPSAC: Current and future directions to sport and exercise Psychology research.
26. Susan Michie, Maartje M Van Stralen, and Robert West. The behaviour change wheel: a new method for characterising and designing behaviour change interventions. *Implementation science*, 6(1):42, 2011.
27. Robert B Cleveland, William S Cleveland, Jean E McRae, and Irma Terpenning. Stl: A seasonal-trend decomposition. *Journal of official statistics*, 6(1):3–73, 1990.
28. Song S Qian, Mark E Borsuk, and Craig A Stow. Seasonal and long-term nutrient trend decomposition along a spatial gradient in the neuse river watershed. *Environmental Science & Technology*, 34(21):4474–4482, 2000.
29. Alex V. Rowlands, Sjaan R. Gomersall, Catrine Tudor-Locke, David R. Bassett, Min-soo Kang, Francois Fraysse, Barbara Ainsworth, and Tim S. Olds. Introducing novel approaches for examining the variability of individuals’ physical activity. *Journal of Sports Sciences*, 33(5):457–466, 2015.
30. Jeremy N Morris and Adrianne E Hardman. Walking to health. *Sports medicine*, 23(5):306–332, 1997.
31. Tim Harries, Parisa Eslambolchilar, Ruth Rettie, Chris Stride, Simon Walton, and Hugo C Van Woerden. Effectiveness of a smartphone app in increasing physical activity amongst male adults: a randomised controlled trial. *BMC public health*, 16(1):1–10, 2016.

32. Aditya Kumar Purohit and Adrian Holzer. Functional digital nudges: Identifying optimal timing for effective behavior change. CHI EA '19, page 1 – 6, New York, NY, USA, 2019. Association for Computing Machinery.