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Physiological and Motion Data to Extract Common Features of Procrastination Personas

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Abstract

Human beings are generally equipped with the trait of seeking escape from difficulties. Procrastination is a widespread problem in society. Especially, for educational settings, learner procrastination is a problem to be avoided. In this study, a new approach to finite procrastination traits is proposed that uses values from body sensor data. The proposed method creates a procrastination persona based on the relationship between the subject's motivation and their movements and physiological responses. The proposed method uses Nonnegative Matrix Factorization (NMF) to classify the collected data into clusters using an unsupervised machine learning model. The results of the experiment showed that subjects are divided into an average procrastination persona, a low procrastination persona, and a high procrastination persona. The need for intervention is lower for learners whose movement is less in the trunk and greater in both hands. Learners with low electrodermal activity and high heart rate require particularly active intervention. It is discovered that it is important to calm the heart rate and move the patient into a state of relaxation when intervening.

Keywords: machine learning, procrastination, EDA, heart rate, acceleration, cluster analysis

1. Introduction

People are generally equipped with the trait of seeking escape from difficulties. According to Harriott and Ferrari, 20% of adults procrastinate(Harriott & Ferrari, 1996). Ferrari and Diaz-Morales reported in 2007 that approximately 15% of adults procrastinate, regardless of cultural values, norms and practices (Ferrari et al., 2007).

Procrastination is a widespread problem in society. Many studies have analyzed this behavior(Feyzi Behnagh & Ferrari, 2022) (Rozental & Carlbring, 2014). Previous research has identified the causes of procrastination to some extent. Many of the studies have attempted to efficiently propose effective coping strategies for a finite number of procrastination traits. Rozental et al. used the Ward method and k-means to cluster the results of three questionnaires on the tendency to procrastinate and three questionnaires on depressive symptoms(Rozental et al., 2015) . The results show that the tendency to procrastinate is divided into five clusters. Rist et al. have selected six items from the questionnaires on the tendency to procrastinate and on mental health(Rist et al., 2023). Based on latent class analysis of responses to six items, they express procrastination tendencies using the probability of belonging to the six clusters. From several papers on procrastination, Steel states that factors that predict procrastination are, especially, task aversion, task delay, self-efficacy, impulsivity, conscientiousness, self-control, distractibility, organization and achievement motivation (Steel, 2010).

Learner procrastination is also a problem for educators to avoid. In the field of education, a small number of instructors often teach a large number of subjects. It is difficult for a small number of instructors to monitor the behavior of individual subjects. It is necessary to develop effective techniques for detecting learners with a strong tendency to procrastinate.

In this study, a new approach to finite characteristics is proposed, which uses the values of body sensor data. It is thought that individuals with procrastination behavior share common characteristics in their physiological signals and body movements. This study considers a group of users with typical characteristics of users with regard to procrastination behavior. This study makes the best use of personas, which are fictitious users representing each user group. The proposed method uses sensors to collect the movements and physiological responses of the subject that represent procrastination behavior. It uses Nonnegative Matrix Factorization to classify the collected data into clusters using an unsupervised machine learning model. The algorithm represents the matrix of observed data consisting of humans and attributes as the product of a feature matrix representing the characteristics of each persona and an attribution matrix representing the attributing degree of each subject to the characteristics of the feature persona. If the matrix of observed data can be approximated correctly, the belonging degree of each subject to a persona can be determined.

Procrastination behavior is related to the subject's motivation for the task to be performed. The proposed method involves a survey on procrastination behavior. The survey consisted of several questions about motivation related to procrastination. From the results of the survey, it is estimated what persona each vector in the feature matrix obtained from the Nonnegative Matrix Factorization corresponds to.

The proposed method creates a procrastination persona based on the relationship between the subject's motivation and their movements and physiological responses. The use of sensors enables instructors to identify individual learners' tendency to procrastinate, even when a small number of instructors are teaching many learners.

2. The Human Mind as Measured from Sensor Data

2.1 Sensors for measuring the human mind

Villa et al. reported remarkable results using biometrics and machine learning to track the attention of learners (Villa et al., 2020). According to this, sensor data used to measure the learner's attention are gaze, facial movements/expressions, body movements, electroencephalographic (EEG) signals, voice, and skin temperature.

The most used are gaze and EEG signals. However, equipment to measure gaze and EEG with high precision is expensive and highly invasive. This makes universal use difficult.

2.2 Electrodermal activity

Cognitive load, proposed by Sweller (Sweller, 1994), refers to the load imposed on the human cognitive system by performing a specific task. Cognitive load can be divided into the following three types.

Intrinsic Cognitive Load:

Caused by the difficulty of the task itself Extraneous

Cognitive Load:

Caused by factors external to the task

Germane Cognitive Load:

Caused by learning activities and mental processes that attempt to link the task content to a long-term knowledge schema

Nourbakhsh et al (Nourbakhsh et al., 2012) measured the Galvanic Skin Response (GSR) to measure cognitive load. GSRs are changes in electrical activity in the skin caused by strong sensory stimuli or emotional responses. GSR reflects changes in psychological states and is therefore used in lie detectors, experiments on conditioned reflexes, biofeedback, etc. GSR is caused by potential changes in sweat gland activity elicited via the sympathetic nervous system by a stimulus. GSR is one of the most sensitive markers of emotional arousal. A measure of GSR is known as skin conductivity (SC) or skin electrical activity (EDA) The higher the level of arousal, the higher the skin conductivity.

The study by Rajendra et al. measures the human mind from electrodermal activity (Rajendra & Dehzangi, 2017). This study uses a wearable sensor implemented as a wristband. This study measures GSR to detect distraction under natural driving conditions. The study detected distraction from electrodermal activity with high accuracy in a subject-dependent scenario.

As such, the level of arousal and the amount of cognitive load can be measured from electrodermal activity. Subjects with high electrodermal activity have a high level of arousal and cognitive load.

2.3 Heart rate

Draghici et al. state that heart rate fluctuates reflecting the effects of parasympathetic (vagal) and sympathetic stimulation (Draghici & Taylor, 2016). In general, the parasympathetic nervous system is activated during relaxation, whereas the sympathetic nervous system is activated during stress and excitement.

Lee et al. have attempted to build a model to measure panic symptoms from heart rate data with machine learning(Lee et al., 2023) .

Takada et al. have attempted to predict human error by measuring Heart Rate Variability (HRV) and EEG(Takada et al., 2022).

Both studies have successfully measured a person's internal state from heart rate variability. Subjects with higher heart rates are in a state of high stress or excitement.

2.4 Accelerometers

Accelerometers can sense the subject's mind in a less invasive way.

Raca et al. measured attention with head movements instead of eye tracking(Raca et al., 2015). As mentioned previously, sensors for eye tracking are expensive and invasive. Substituting eye tracking with head acceleration would facilitate the acquisition of more learner data.

Amada et al. used accelerometers to assess the psychological state of humans when viewing contents on smartphones(Amada et al., 2020). The study found that hand movements are decreased when browsing interested contents

2.5 Pure procrastination scale

The Pure Procrastination Scale is an established measure of the level of procrastination. Pure Procrastination Scale have been developing until now. The first common scales created is General Procrastination Scale(Lay, 1986). Over time, there has been a large discrepancy between the survey items and the general behavior of people today. Therefore, Pure Procrastination Scale(Steel, 2010) was created with more modern wording. A Japanese version was developed and validated(Kaneko et al., 2022). In this questionnaire, the subjects respond to 12 items using the five-factor method. The 12 questions are categorized into three factors. Factor 1 is procrastination in execution, Factor 2 is procrastination in decision-making and Factor 3 is untimeliness. Respondents with higher scores are assessed as higher tendency to procrastinate.

2.6 Self-efficacy

Self-efficacy is a concept proposed by A. Bandura. It refers to confidence in one's ability to carry out one's objectives(Bandura, 1982). The relation between self-efficacy and procrastination has been frequently discussed. Some studies have identified self-efficacy as one of the factors that distinguish procrastinators from non-procrastinators(Chu & Choi, 2005). The original version was published in 2001(Chen et al., 2001). This was translated into Japanese and validated(Shigematsu et al., 2022), which consists of eight items and is answered using the five-grade evaluation. The higher the score, the higher the self-efficacy.

3. Procrastination Personas Discovered from Nonnegative Matrix Factorization

3.1 Procrastination Persona

When humans are unable to concentrate on the work they are engaged in, they try to extend the implementation of that work further. The hypothesis is that when humans are not concentrating, their body trunks sway and they are less efficient at working with their hands. Conversely, when they are concentrating, their body trunks stop swaying and they move their hands more frequently to perform tasks. Based on this hypothesis, this study estimates the user's procrastination traits from the movements of the trunk and both hands.

Personas represent imaginary users who identify with groups of people who share common characteristics. Users with strong procrastination traits have difficulty concentrating for only short periods when engaged in tasks that are difficult for them. On the other hand, patient users can maintain their concentration for a longer period on tasks that they have difficulty with. The personas may have common characteristics for procrastination traits. In this study, these will be referred to as procrastination personas. Since any person may extend work ahead of time, several types of these personas may exist

A number of recent studies estimate human psychological states from physiological signals. Electrodermal activity and heart rate are particularly useful for estimating psychological state. Electrodermal activity is observed to change when emotions change or when task intrinsic cognitive load is applied.

In this study, accelerometers and wristwatch digital biomarkers are used for sensing the user's mind. The digital biomarker measures electrodermal activity and heart rate. In this study, accelerometers are attached to the back of the subject's neck and both wrists. The former is to find out the movement of the trunk and the latter to monitor the movement of both hands. Additionally, a digital biomarker is used to check the changes in the emotion and the cognitive load of the subject.

This study estimates human procrastination traits from sensor data. The sensor data for monitoring the human mind are trunk acceleration, acceleration of both hands, electrodermal activity, and heart rate. These are independent features of each other. The sensors to measure these are less invasive and less costly.

3.2 Sensing Internal Status

Users with the same procrastination traits are likely to exhibit similar movements and physio logical responses when engaged in a particular task. Sensor data can be represented as a matrix showing each feature for each human. This matrix is decomposed into two matrices with Nonnegative Matrix Factorization (NMF). In Nonnegative Matrix Factorization, one matrix is a set of vectors representing typical human characteristics. This vector is called the feature vector and the matrix that is the set of vectors is called the feature matrix. Each feature of any subject is considered to be a weighted representation of the typical human characteristics represented by the feature vector. When the feature vectors are known, any feature values of any subject can be represented by a weighted sum of the corresponding elements of each feature vector. If the weights are chosen appropriately, any subject can be approximated by a weighted sum of typical human feature vectors. This weight is the belonging degree, which indicates how similar a particular subject is to a typical human. The other matrix, obtained by Nonnegative Matrix Factorization, represents the belonging degree to each feature vector. This matrix is called the belonging degree matrix.

Suppose that the Nonnegative Matrix Factorization gives a feature matrix and a belonging degree matrix. Each feature vector in a feature matrix is considered to represent a persona. On the other hand, the belonging degree matrix shows how close each subject is to each persona. If it is known what persona each feature vector represents in terms of work procrastination, it is possible to estimate the procrastination traits of each subject.

A method overview diagram of this study is shown in Figure 3.1.

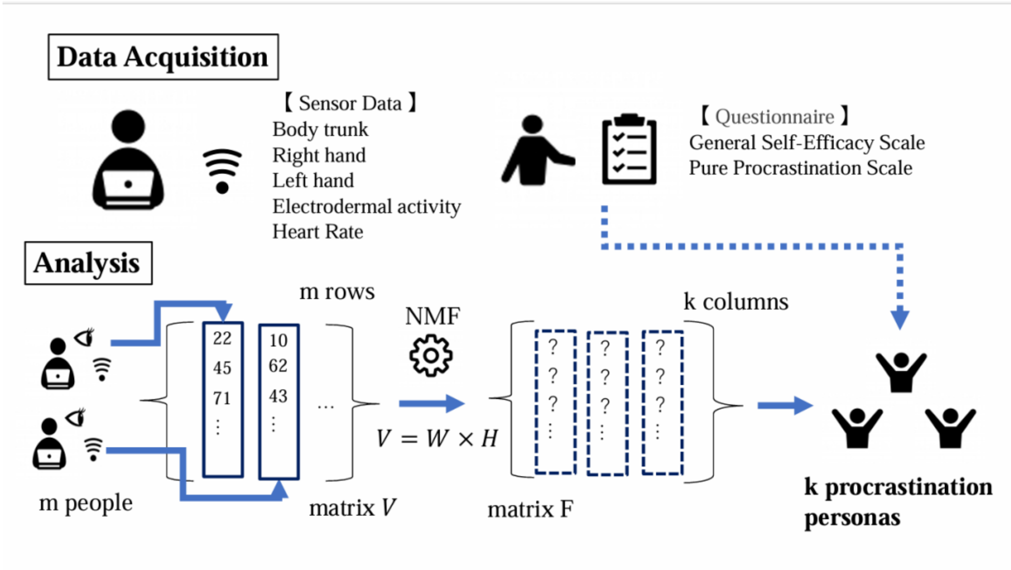

Figure3.1. A Method Overview Diagram

In this study, feature matrices and belonging degree matrices are calculated from the sensor data matrices by Nonnegative Matrix Factorization. The correspondence of each feature vector to any procrastination persona can be investigated by means of a pure procrastination scale and a questionnaire on self-efficacy to examine procrastination traits. However, the survey imposes extra burdens on the targets. However, if sensor data and survey results for procrastination traits are obtained from a sufficient number of subjects, it is possible to estimate procrastination traits for further subjects by collecting sensor data only, without the burden of questionnaire responses.

3.3 Persona Identification Based on Nonnegative Matrix Factorization

This study uses Nonnegative Matrix Factorization to decompose the matrix of sensor data obtained from the subject into a feature matrix and a belonging degree matrix. Nonnegative Matrix Factorization is an unsupervised clustering method. If a person has n sensor data values, then n time-series sensor data can be obtained for m persons. When the prepared sensor data is stored in a matrix V with n rows and m columns, V can be represented by a matrix F with n rows and k columns and a matrix B with k rows and m columns. Hence the equation $V = F \times B$ holds. k is the number of personas and F is the feature matrix. Feature matrices are features of the sensor data for each persona. B is the belonging degree matrix. The belonging degree matrix shows the degree to which m people belong to each cluster. The higher the value, the higher the belonging degree to that persona.

4. Three Procrastinator Personas Discovered from Sensor Data

4.1 Work Assignment

Experiments are conducted with 16 subjects. All subjects are males in their twenties, six are senior undergraduate students and ten are postgraduate students. All subjects have studied programming at undergraduate and postgraduate levels. Their programming experience is between 3 and 6 years. Subjects are given some assignments in C programming. Several parts of the codes are blank in the assignments. The task is to fill in the blanks in the code in a contextual way. The shortest task is 19 lines and the longest task is 89 lines. The fewest number of blanks is 2 and the largest number is 14. Each subject takes 16 identical tasks. To check if subjects procrastinate on their work, subjects were told that the task could be completed in two sessions. If the task is split into two sessions, the second programming session is on a different day. For each subject, the first session of programming tasks is called the first task and the second session of programming tasks is called the second task.

The first task had a maximum duration of 90 minutes and a minimum duration of 43 minutes, the second task had a maximum duration of 53 minutes and a minimum duration of 0 minutes. 8 subjects completed all programming on the first task. The second task time for subjects completing all blanks in the first task is 0 min.

4.2 Time-based Pre-processing

Acceleration is taken by attaching sensors to three positions. The sensor is TWILITE2525A produced by MonoWireless (*Acceleration sensor wireless tag TWELITE 2525A-Twilight Nico Nico - MONO-WIRELESS.COM*, n.d.) . It is attached to the back of the neck and both wrists. Electrodermal activity and heart rate are taken by the Embrace+, produced by the company Empatica (*EmbracePlus | The World's Most Advanced Smartwatch for Continuous Health Monitoring*, n.d.). It is worn on any of the arms.

For each task, the start time is different for all sensors, so the start and end times are aligned to ensure that the length of the time series data in which the observations are recorded is the same for each subject. The start time is adjusted to the latest of each task. The end time is adjusted to the earliest of each task. These give time-series data for a single period for each subject.

Each subject takes different lengths of time to fill in all blanks. Data for Nonnegative Matrix Factorization must be the same length for all subjects. Therefore, the number of time-stamped snapshots of time-series data is pre-processed to be the same for all subjects. For example, if subject A has 50 neck acceleration data and subject B has 100 neck acceleration data, extract the 2,4,6...100th data from the subject B data. This allows data lengths to be reduced without compromising data change behavior.

4.3 Clusters Discovered By Nonnegative Matrix Factorization

Nonnegative Matrix Factorization requires specifying the number of clusters *k*. In the analysis that follows, it is assumed that individual subjects belong to the cluster with the highest belonging degree. Setting the number of clusters *k* to 4 or more causes the clusters with no subjects of highest belonging degree to be found. Therefore, in this study, the number of clusters is assumed to be 3 for the Nonnegative Matrix Factorization. Table 4.1 shows the belonging degree matrix B derived from the Nonnegative Matrix Factorization.

Table 4.1. Belonging Degree Matrix B

	Data/K002	Data/K003	Data/K004	Data/K006	Data/K007	Data/K008	Data/K009	Data/K010
0	0.00	17.79	0.00	14.26	8.97	1.05	16.30	12.86
1	9.96	0.00	27.24	7.25	23.52	14.84	1.91	7.76
2	14.15	4.81	7.86	6.01	2.78	11.64	8.44	7.96

	Data/K012	Data/K013	Data/K014	Data/K015	Data/K017	Data/K018	Data/K019	Data/K021
0	19.12	20.71	4.72	9.45	9.75	12.60	12.81	10.69
1	18.43	0.00	24.24	23.24	0.95	3.58	24.93	0.00
2	0.00	4.29	7.04	3.71	12.50	9.16	0.90	12.09

Each column corresponds to an individual subject. It represents the subject's belonging degree to the three clusters. The higher the number, the higher the belonging degree to the cluster. The table head shows the ID of the subjects and the table side shows the clusters. Significantly higher belonging degrees to cluster 0 were subject ID 3,6,9,12,13. Significantly higher belonging degrees to cluster 1 were subject ID 4,7,14,19. A significantly higher degree of belonging to cluster 3 was subject ID 2.

Table 4.2 shows the frequency of occurrence of the values of the elements that make up each cluster of the feature matrix F obtained by non-negative matrix factorization. It shows the total sample of the frequency distribution divided into four parts with the values in each range. It shows in which range the values of each explanatory variable occur most frequently for each cluster. The electrodermal activity and the pulse rate are scalar values, whereas the acceleration is a three-dimensional vector value, so that the norm is calculated. The total may not add up to 100 because significant figures are rounded to two digits.

Table 4.2. Percentage of the Feature Matrix belongs to Each Quartile

(a) Neck

	0	1	2
75∼100%	0	0	74
50∼75%	43	6	26
25∼50%	56	20	0
0∼25%	0	75	0

(b) Left-Hand

	0	1	2
75∼100%	0	0	75
50∼75%	45	5	25
25∼50%	48	28	0
0∼25%	8	67	0

(c) Right-Hand

	0	1	2
75∼100%	0	0	75
50∼75%	0	50	25
25∼50%	40	36	0
0∼25%	59	14	0

(d) Electrodermal Activity

	0	1	2
75∼100%	10	37	27
50∼75%	14	47	16
25∼50%	37	16	20
0∼25%	39	0	37

(e) Heart Rate

	0	1	2
75∼100%	0	0	75
50∼75%	51	0	25
25∼50%	49	24	0
0∼25%	0	76	0

In cluster 0, more than 90% of the neck and left hand acceleration data are in the second and third quartile ranges.All right-hand accelerations are in the first and second quartile ranges.More than 75% of the electrodermal activity data is distributed in the first and second quartile ranges. All data of the heart rate are found in the second and third quartile ranges.

In cluster 1, more than 90% of the neck and left hand acceleration data are in the first and second quartile ranges. More than 85% of the right hand acceleration is distributed in the second and third quartile ranges. More than 80% of the electrodermal activity data are in the third and fourth quartile ranges. All data of the heart rate is present in the first and second quartile ranges.

In cluster 2, all of the neck, left hand and right hand accelerations are contained in the third and fourth quartile ranges. More than 55% of the electrodermal activity data are distributed in the first and second quartile ranges. All of the heart rate data are present in the third and fourth quartile ranges.

The clustering results from the NMF model show that cluster 0 has more data with medium neck and left hand movements and less data with small left hand movements. In addition, they perceive a tendency towards low electrodermal activity and high heart rate. Cluster 1 has more data with small neck and left hand movements and medium right hand movements. Those in cluster 1 often have high electrodermal activity and a moderate heart rate. And finally, those in cluster 2 often have more movement of the neck, left hand and right hand. They are also characterised by low electrodermal activity and high heart rate.

We then clustered them using the acquired sensor data, assuming that each subject belonged to the cluster with the highest degree of affiliation. Table 4.3 shows the number of data in each quartile as a percentage of the total.

The total may not add up to 100 because significant figures are rounded to two digits.

Table4.3. Percentage of the Collected Data belongs to Each Quartile

(a) Neck

	0	1	2
75∼100%	25	18	33
50∼75%	23	31	21
25∼50%	32	24	14
0∼25%	21	27	31

(b) Left-Hand

	0	1	2
75∼100%	19	31	24
50∼75%	23	27	26
25∼50%	29	26	18
0∼25%	28	16	33

(c) Right-Hand

	0	1	2
75∼100%	27	29	11
50∼75%	13	29	44
25∼50%	25	24	27
0∼25%	34	17	18

(d) Electrodermal Activity

	0	1	2
75∼100%	17	38	16
50∼75%	26	24	24
25∼50%	29	18	25
0∼25%	27	21	34

(e) Heart Rate

	0	1	2
75∼100%	30	5	47
50∼75%	28	23	24
25∼50%	23	25	26
0∼25%	19	48	3

In cluster 0, about 55% of the neck acceleration data in feature matrix F are in the second and third quartile ranges. In the real clusters, however, the number of data in the third and fourth quartile ranges is more proportionate at about 58%. The feature matrix F therefore captures the high occurrence of moderate values in the neck acceleration of cluster 0, whereas the actual data is more moderate to high. About 52% of the left-hand acceleration data in feature matrix F are in the second and third quartile ranges. In the real clusters, however, the number of data in the first and second quartile ranges is more proportionate at about 57%. The feature matrix F therefore captures that many medium values occur in the left-hand acceleration of cluster 0, whereas the actual data is low to medium. About 59% of the right hand acceleration data are in the first and second quartile ranges. This is consistent with the values suggested by the feature matrix F and the values of the real clusters. More than 56% of the electrodermal activity data in feature matrix F is in the first and second quartile ranges. However, in real clusters, the number of data in the second and third quartile ranges is about 55% and hardly different. Therefore, the feature matrix F considers people in cluster 0 to often have a low degree of electrodermal activity in their left hand, whereas the actual data is often low to moderate. 51% of the heart rate data in feature matrix F are in the second and third quartile ranges. In the real clusters, however, the third and fourth quartile ranges have a higher proportion of data at about 58%. The model therefore sees the left-hand acceleration in cluster 0 as predominantly moderate, whereas the actual data is predominantly moderate to high.

In cluster 1, about 51% of the data for the neck acceleration of the feature matrix F are in the first and second quartile ranges. In the real clusters, however, the second and third quartile ranges have a higher proportion of data at about 55%. Therefore, while the feature matrix F considers many low degrees of neck acceleration in Cluster 1, the actual data is predominantly low to medium. About 42% of the left-hand acceleration data in feature matrix F are in the first and second quartile ranges. In the real clusters, however, the third and fourth quartile ranges have a higher proportion of data at about 55%.Therefore, the feature matrix F captures a high number of low degrees of acceleration for the left hand in cluster 1, whereas the actual data has a high degree of acceleration. About 53% of the right-hand acceleration in feature matrix F is in the second and third quartile ranges. In the real clusters, however, the number of data in the third and fourth quartile ranges is more proportionate at about 58%. Therefore, while the feature matrix F captures a high medium level of acceleration in the right hand of cluster 1, the actual data is medium to high. About 59% of the electrodermal activity data are in the third and fourth quartile ranges. The values indicated by the feature matrix F match the values of the real clusters. About 73% of the heart rate data are in the first and second quartile ranges. The values suggested by the feature matrix F agree with the values of the real clusters.

In cluster 2, about 54% of the neck accelerations are in the third and fourth quartile ranges in both the feature matrix F and the real cluster. About 51% of the left hand acceleration is in the third and fourth quartile ranges for both the feature matrix F and the real cluster. In feature matrix F, about 55% of the right hand accelerations are in the third and fourth quartile ranges. However, in the real clusters, the number of data in the second and third quartile ranges is about 71% with a higher proportion. Therefore, the feature matrix F captures that many high values occur in the right-hand acceleration of cluster 2, whereas the actual data has many medium values. About 59% of the electrodermal activity data are in the first and second quartile ranges for both feature matrix F and real clusters. About 71% of the heart rate data are in the third and fourth quartile ranges for both feature matrix F and real clusters.

For cluster 0, the feature matrix F estimation of the right hand acceleration matrices matched the real clusters. In cluster 1, the estimated feature matrix F of electrodermal activity and heart rate matrices coincided with the values in the real clusters. In cluster 2, the estimated feature matrix F for neck, left hand acceleration, heart rate and EDA coincided with the values in the real cluster. Cluster 1 left-hand side of the feature matrix F differs significantly in value between the estimation and the actual data.

Table 4.4. Survey Results

(a) Pure Procrastination Scale

ID	Procrastination	Cluster
17	51	2
2	49	2
14	46	1
3	45	0
10	44	0
21	44	2
6	41	0
13	40	0
8	38	1
18	35	0
4	32	1
9	31	0
12	30	0
15	28	1
19	28	1
7	25	1

(b) New General Self-Efficacy Scale

ID	Self-Efficacy	Cluster
2	38	2
4	31	1
3	29	0
21	29	2
19	28	1
7	27	1
6	26	0
9	26	0
12	24	0
10	22	0
13	22	0
8	22	1
18	21	0
15	21	1
14	19	1
17	16	2

4.4 Survey Data for Clusters

Table 4.4 shows the results of the New General Self-Efficacy Scale (Shigematsu et al., 2022) and the Pure Procrastination Scale(Kaneko et al., 2022) survey. Table 4.5 shows the scores of the 3 factors that construct the Pure Procrastination Scale. ID refers to the subject's ID and Custer refers to the cluster to which the subject belongs. Subjects answered this survey once after completing all tasks to avoid preconceived notions. Highest scores are 60 on the Pure Procrastination Scale and 40 on the New General Self-Efficacy Scale survey.

On the Pure Procrastination Scale, Factor 1 is procrastination in execution, Factor 2 is procrastination in decision making, and Factor 3 represents timeliness. The highest scores for each Factor are 25, 15, and 20.

The procrastination scores of subjects belonging to cluster 0 are between 30~40. The tendency to procrastinate is moderate to relatively high. Self-efficacy scores are between 20~30 and are moderate to relatively high.

Table 4.5. Scores of the 3 Factors

(a) Procrastination in Execution

ID	Factor1	Cluster
2	24	2
17	22	2
10	21	0
13	21	0
14	21	1
3	19	0
18	19	0
21	18	2
19	18	1
6	18	0
8	18	1
9	17	0
4	16	1
12	14	0
15	12	1
7	10	1

(b) Procrastination in Decision

ID	Factor2	Cluster
14	13	1
17	12	2
3	11	0
8	11	1
2	10	2
21	10	2
6	10	0
13	9	0
10	8	0
12	8	0
15	8	1
7	8	1
18	7	0
9	7	0
4	6	1
19	3	1

(c) Timeliness

ID	Factor3	Cluster
2	14	2
17	12	2
10	12	0
3	11	0
21	11	2
6	11	0
14	10	1
13	9	0
8	8	1
18	8	0
4	8	1
15	7	1
12	6	0
7	6	1
9	6	0
19	4	1

Cluster 1 had the highest number of people with procrastination scores below 30. The distribution of self-efficacy scores was varied and not distinctive. The cluster is a highly timely cluster, as the scores for timeliness are less than 10.

Subjects belonging to cluster 2 have a high procrastination score of 44 and above. For self-efficacy, the subjects with the highest and lowest scores belong to this cluster together, which shows very extreme values. From the table for decision procrastination, the subjects with the highest scores belong to cluster 2. The scores for procrastination in execution are higher than 10. Non-timeliness is relatively high, being above 11.

5. Handling Personas

5.1 Heart Rate and Electrodermal Activity

Cluster 1, to which subjects with high electrodermal activity and low heart rate during task execution belong, is the persona with the lowest tendency to procrastinate. Personas with a low tendency to procrastinate can engage in tasks at the right time and are therefore a lower priority for intervention.

Subjects belonging to cluster 0, the persona in which both electrodermal activity and heart rate are low during task execution, have a moderate tendency to procrastinate. Subjects belonging to cluster 0, the persona in which both electrodermal activity and heart rate are low during task execution, have a moderate tendency to procrastinate.

Cluster 2, the persona with a high tendency to procrastinate, has many subjects with low electrodermal activity and high heart rate during the task. Personas in cluster 2 can be expected to have a low cognitive load and be in a stress state with a predominant sympathetic nervous system.

Personas with a high tendency to procrastinate need to be brought closer to a relaxed state with parasympathetic dominance to reduce their tendency to procrastinate. Then if they can increase their cognitive load, they can move closer to a persona with a lower tendency to procrastinate.

5.2 Acceleration

Cluster 1 has smaller trunk movements during the task. Cluster 1 is a persona with a low tendency to procrastinate, according to the results of the survey.

Focus on learners who have greater trunk movement during task execution and who also have greater movement of the left hand. They are personas with a high procrastination tendency, so special attention should be paid to them.

Learners with large movements of the left hand but not much movement of the right hand have a moderate tendency to procrastinate. If the persona with a moderate procrastination tendency is to become more like a persona with a low procrastination tendency, it is necessary to intervene.

5.3 Limitations

The digital biomarkers this study uses are less invasive and more accurate, but they are still expensive. The feature matrices do not fully capture the trends in the real data, as there are differences between some of the feature matrices and the trends in the real data.

Nonnegative Matrix Factorization enables a more universal clustering with more subjects. As the number of subjects in this study was 16, sample bias is suspected.

Surveys are conducted to analyze the characteristics of the personas. However, this survey is only taken once for each subject. In addition, the distribution of self-efficacy does not capture the characteristics of the procrastination persona very well. The results may be arbitrary. Surveys taken over a long period and at regular intervals may capture more of the characteristics of the subjects.

Finally, in previous studies (Rist et al., 2023; Rozental et al., 2015). in which surveys are clustered, the number of clusters is greater than 3. The number of clusters could be set to 5 or 6 if the number of subjects is increased. Increasing the number of clusters amounts to subdividing the persona. Subdivisional clustering may be able to estimate procrastination tendencies with good accuracy.

6. Conclusion

The purpose of this study is to create procrastination personas by machine learning of sensor data. The results of the experiments show that subjects are divided into an average procrastination persona, a persona with a low procrastination tendency, and a persona with a high procrastination tendency. The need for intervention is lower for learners whose movement is less in the trunk and greater in both hands. Learners with low electrodermal activity and high heart rate require particularly active intervention. It is discovered that it is important to calm the heart rate and move the patient into a state of relaxation when intervening.

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Authors' contributions

Kirii,Y. is responsible for data collection and analysis. Prof.Shimakawa is responsible for study design and revising.

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