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RESEARCH ARTICLE

A Study of the Relationship Between Driving and Health Based on Large-Scale Data Analysis Using PLSA and t-SNE

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Ethics Committee of Hirosaki University School of Medicine.

ABSTRACT The purpose of this study is to facilitate knowledge discovery about the relationship between driving and health among the elderly. In the Iwaki Health Promotion Project that is an annual project conducted by Hirosaki University, we have included a survey on driving for the first time in 2019. After linking the data obtained from the survey with four years of health data for 2016–2019, we have utilized PLSA as a machine learning method to cluster those data in an integrated manner. As a result, we have found latent classes broadly classified according to whether the health level has been generally high or low. Also, when we have focused on a specific health item, for example, cognitive function, we have found some people with higher and lower maintenance of cognitive function over four years, even if they have belonged to a same latent class. To characterize these differences in detail, we have utilized t-SNE as a machine learning method. As a result, we have found that ''I like driving'' as a factor related to the Kansei (sensitivity) may characterize the high maintenance of cognitive function. For those who like driving, it is considered that the high maintenance of cognitive function may be occurred because they enjoy driving, have a wider range of activities, and increase the possibility of multitasking.

INDEX TERMS Cognitive function, driving, health, machine learning, PLSA, t-SNE.

I. INTRODUCTION

Japan is now facing a super-aged society. According to the World Health Organization (WHO), Japan has the highest life expectancy (LE) at birth in 2019 with 84.26 years [\[1\].](#page-44-0) Also, according to the Abridged Life Tables For Japan 2022, LE at birth in Japan is 81.05 years for males and 87.09 years for females [\[2\]. Th](#page-44-1)erefore, it is an important social issue to realize the extension of healthy life expectancy by ensuring

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transportation that allows people to go where they want to go, so that they can live a healthy and rich life for a long time, even if they grow older. In order to support the realization of the above, on the premise of providing safe and reliable cars from the standpoint of automotive industries, we believe that the ability to drive a car with one's own hands and feet may be a positive factor in promoting physical and mental vitality and maintaining health.

In fact, previous studies have reported that the cessation of driving among the elderly is associated with various health problems, including depression [\[3\], an](#page-44-2)d an increased risk of

functional decline with psychological frailty [\[4\]. In](#page-44-3) addition, a 6-week cognitive training program that simulates driving a car using a video game among the elderly has also been reported to be effective in maintaining cognitive function and improving mood [\[5\].](#page-44-4)

Conversely, a comprehensive review of the relationship between transportation and health [6] [has](#page-44-5) been reported from the standpoint that a lifestyle with low physical activity may have adverse effects on health and public health due to inactivity and reduced walking ability. In addition, it has also been reported that the risk of functional limitations may be alleviated among the elderly if they use public transportation or bicycles as an alternative means of transportation after driving cessation [\[7\]. Th](#page-44-6)erefore, it is difficult to simply link driving to health. However, we believe that a more detailed survey of daily driving, combined with a comprehensive health survey, may reveal factors related to driving that may trigger good health.

On the other hand, although a study on driving is not included, there are reports that, for example, having hobbies and purpose in life (PIL) are factors associated with maintaining survival among the community-dwelling elderly [\[8\].](#page-44-7) In other words, the above suggests that factors that stimulate the Kansei (sensitivity) associated with emotional needs may have a positive effect on health. The Kansei (sensitivity) is a Japanese word that does not have a direct translation in English, however, every translation (such as sensibility, sentiment, emotion, and feeling) captures just some of the aspects of Kansei [\[9\]. T](#page-44-8)herefore, it may be effective to conduct a survey on driving while actively taking into account factors related to the Kansei (sensitivity) in order to understand the relationship between driving and health in detail. However, as the number of survey items increases, classical statistical analysis has limitations in taking into account all items in an integrated manner and overlooking overall trends while dealing with nonlinearities and interdependencies in the data. In order to break through these limitations, in recent years, there have been an increasing number of reports in healthcare and other fields that have actively utilized machine learning based on ensemble methods, Bayesian statistics, and other approaches for a variety of data, including not only images and text, but also questionnaires and other surveys [\[10\],](#page-44-9) [\[11\],](#page-44-10) [\[12\],](#page-44-11) [\[13\],](#page-44-12) [\[14\],](#page-44-13) [\[15\],](#page-44-14) [\[16\]. M](#page-44-15)ore specifically, the reports in [\[10\],](#page-44-9) [\[11\], a](#page-44-10)nd [\[12\]](#page-44-11) are all examples of efforts to improve the accuracy in classification and prediction by using machine learning. In contrast, the reports in $[13]$, $[14]$, $[15]$, and $[16]$ correspond to efforts to ensure possibilities of knowledge discovery. In detail, [\[13\]](#page-44-12) reports an example of trying to find a source of information for classifying medical images from non-image knowledge (bag of words in the explanatory documents accompanying the images). In [\[14\], a](#page-44-13)n example of approaching knowledge discovery by ensuring explainability equivalent to the basis of classification results for medical images is reported. In [\[15\], a](#page-44-14)n example of approaching knowledge discovery by

structuring the interdependent relationships among factors related to disease risk is reported. In [\[16\],](#page-44-15) an example of approaching knowledge discovery by embedding and visualizing factors related to psychological motivation for sports participation on a 2-dimensional plane while dealing with nonlinearities is reported. The methods used in these examples need to be differentiated according to the type and amount of data, and the purpose of analysis, but all are effective options for knowledge discovery. Nevertheless, we have seen no previous examples of studies using machine learning as in the above approaches to handle large-scale data obtained from a set of health and driving surveys while taking the Kansei (sensitivity) into account.

In this study, we have conducted a field survey with a wide range of health survey items as well as detailed driving questionnaire survey items related to the Kansei (sensitivity), such as driving preferences or usages. Our goal is to realize a car lifestyle that can assist healthy longevity according to each individual's attributes. In order to achieve this goal, the objective is to construct an approach that can not only understand the overall features of the elderly, but also focus on their specific characteristics as individual differences and scoop them up as findings, rather than simply ignoring them. Toward this, the purpose of this study is to facilitate knowledge discovery about the relationship between driving and health among the elderly by using machine learning to analyze the potential relationships among variables in the large-scale data obtained from the above. The driving survey itself, including items related to the Kansei (sensitivity), is unparalleled in prior research, and to our knowledge, this is the first study to acquire and analyze such items in combination with a large-scale health survey. As an approach to analyzing the data, although $[16]$ is the most helpful among the previous reports, since the number of items we handle is much larger, we have adopted an approach that analyzes overall features and specific characteristics by combining two different methods, which are PLSA [\[17\]](#page-44-16) and t-SNE [\[18\]. C](#page-44-17)ompared to other machine learning methods, PLSA can find latent classes by clustering samples and factors simultaneously and can easily obtain the factor contributions incidentally. Besides, since it is not bound to a prior distribution, latent classes are less abstract and can maximally incorporate the influence of the data. Therefore, we have selected PLSA because of its relative advantage in deepening our understanding of the current state of the data. In addition, since t-SNE can preserve the local rather than the global structure of the data, it has a high potential to be able to focus on and characterize some small number of subjects from the clustering results. Therefore, we have selected t-SNE because of its relative advantage in obtaining in-depth perspectives that are difficult to cover with other machine learning methods.

The remainder of this paper is organized as follows. Section [II](#page-2-0) describes the data and analysis methods we use in this study. Section [III](#page-10-0) describes the results obtained through

FIGURE 1. Overview of our analysis flow.

TABLE 1. Examples of basic statistics (maximum, minimum, mean and standard deviation) of the category ''Personal record form'' for subjects (1044 persons) in 2019.

our data analysis. Section [IV](#page-24-0) presents our discussion of the obtained results. Finally, Section [V](#page-31-0) presents our conclusions of this study and our future works.

II. RESEARCH METHODS

The general flow of our large-scale data analysis in this study is shown in Fig. [1.](#page-2-1)

A. DATA FOR ANALYSIS

In this study, we utilize data accumulated in the Iwaki Health Promotion Project [\[19\], a](#page-44-18) large-scale health survey conducted by Hirosaki University in Aomori Prefecture (Iwaki District, Hirosaki City) for approximately 1000 residents every year since 2005. Specifically, we link a single year's worth of data consisting of the driving questionnaire survey items obtained for the first time in 2019 to four years' worth of data consisting of the health survey items from the above project spanning 2016–2019. We then use our data restricted to the elderly (160 males and 252 females over 60 in 2019). As an overview of the data for all subjects, we take the subjects (1044 persons) in 2019 and show each aggregate result for ''Personal record form'', a kind of health checkup categories, **TABLE 2.** Examples of aggregated questionnaire responses regarding driving frequency, driving time, transmission (AT/MT) and likes/dislikes about driving for subjects (1044 persons) in 2019.

and some items of the driving questionnaire in Tables [1](#page-2-2) and [2,](#page-2-3) respectively.

Here we describe the details of the items handled in our analysis. First, the health survey items are shown in Table [3.](#page-6-0) We integrally handle items corresponding to the various health checkup categories of ''Personal record form'', ''Cognitive function'', ''Health questionnaire'', ''Vision test'', ''Blood examination'', ''Blood pressure measurement of the extremities'', ''Pulmonary function testing (Spirometry)'', "Heel bone density test", "Body composition measurement'', and ''Gravic body sway test (Otorhinolaryngology)''. Although there are multiple items of cognitive function in the actual health surveys (see $[19]$), in this study, we only handle the MMSE for our analysis. In the following description, RHH and RLH are described as relatively high and low levels of health, respectively.

1) PERSONAL RECORD FORM

For the following 3 items, we do not define any association with RHH or RLH. We define the level divisions for those data as follows.

- "Age [years old]": We define 7 divisions into 10-year increments from 20s to 80s.
- "Body height [cm]": We define 5 equal divisions between the maximum and minimum.
- ''Body weight [kg]'': We define 5 equal divisions between the maximum and minimum.

For the following 8 items, there are no explicit criteria for any of RHH and RLH. Therefore, as those analysis criteria, we define 2 sets of thresholds excluding the neutral center when divided into 5 equal divisions between the maximum and minimum. The specific threshold values corresponding to RHH and RLH are defined as follows.

- "Grip strength (Right hand) [kg]": We define $>=$ 43.2 and < 30.8 for RHH and RLH criteria, respectively.
- "Grip strength (Left hand) [kg]": We define \ge = 36.8 and < 25.2 for RHH and RLH criteria, respectively.
- "Sitting trunk flexion \lceil cm \rceil ": We define \ge = 45 and < 33 for RHH and RLH criteria, respectively. Incidentally, see [\[20\]](#page-44-19) for a detailed methodology on this item.
- • ''Whole body reaction time [msec]'': We define $<$ 456.8 and $>=$ 685.2 for RHH and RLH criteria, respectively. Incidentally, see [\[21\]](#page-44-20) for a detailed methodology on this item.
- "Sit-to-stand test \lceil cm]": We define \geq 28 and < 22 for RHH and RLH criteria, respectively. Incidentally, see [\[22\]](#page-44-21) for a detailed methodology on this item.
- • "Timed up and go (TUG) test [sec]": We define $<$ 6.98 and $>=$ 9 for RHH and RLH criteria, respectively. Incidentally, see [\[23\]](#page-44-22) for a detailed methodology on this item.
- "Two-step test $\lceil \text{cm} \rceil$ ": We define \geq 262.8 and < 219.2 for RHH and RLH criteria, respectively.
- ''Maximal walking speed of 10 meters [sec]'': We define $<$ 5.62 and $>=$ 7.28 for RHH and RLH criteria, respectively.

2) COGNITIVE FUNCTION

For the following 1 item, we divide each value into 3 divisions based on Level 3 (27–30 points), Level 2 (22–26 points), which is neutral, and Level 1 (0–21 points). Then, referring to [\[24\], t](#page-44-23)he specific threshold values corresponding to RHH and RLH are defined as follows.

• ''Mini mental state examination (MMSE) score (0–30 points) [-]'': We define Level 3 and Level 1 for RHH and RLH criteria, respectively.

3) HEALTH QUESTIONNAIRE

For the following 2 items, we divide each value into 4 divisions based on 0, 1–5, 6–10, and 11 or more people, while including dummies. Then, referring to $[25]$, the specific threshold values corresponding to RHH and RLH are defined as follows.

- ''Social connections (Number of friends who feel comfortable) [-]'': We define non-zero and zero for RHH and RLH criteria, respectively.
- ''Social connections (Number of family members and relatives who feel comfortable) [-]'': We define non-zero and zero for RHH and RLH criteria, respectively.

For the following 1 item, we divide each value into 2 divisions based on 0–5 and 6–21 points. Then, referring to [\[26\], t](#page-44-25)he specific threshold values corresponding to RHH and RLH are defined as follows.

• "Pittsburgh sleep quality index (PSQI) total score $(0-21 \text{ points})$ [-]": We define $0-5$ and $6-21 \text{ points}$ for RHH and RLH criteria, respectively. Incidentally, see [\[27\]](#page-44-26) for a detailed methodology on this item.

For the following 1 item, we divide each value into 6 divisions based on 0–9, 10–19, 20–29, 30–39, 40–49, and 50–60 points, while including dummies. Then, referring to [\[28\]](#page-44-27) (or [\[29\]\),](#page-44-28) the specific threshold values corresponding

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to RHH and RLH are defined as follows. Here a division which intersects both RHH and RLH is considered neutral.

• "Depressive state: 20-item center for epidemiologic studies depression scale (CESD-20) score (0–60 points) [-]'': We define 0–15 and 16–60 points for RHH and RLH criteria, respectively. Incidentally, see [\[30\]](#page-44-29) for a detailed methodology on this item.

For the following 1 item, we divide each value into 10 divisions based on 0–9, 10–19, 20–29, 30–39, 40–49, 50–59, 60–69, 70–79, 80–89, and 90–100 points, while including dummies. Then, referring to [\[31\], t](#page-44-30)he specific threshold values corresponding to RHH and RLH are defined as follows. Here a division which intersects both RHH and RLH is considered neutral.

• "Locomotive syndrome: 25-question geriatric locomotive function scale (GLFS-25) score (0–100 points) [-]'': We define 0–15 and 16–60 points for RHH and RLH criteria, respectively. Incidentally, see [\[32\]](#page-44-31) for a detailed methodology on this item.

For the following 8 items, we divide each value into 10 divisions based on 0–9, 10–19, 20–29, 30–39, 40–49, 50–59, 60–69, 70–79, 80–89, and 90–100 points, while including dummies. Then, referring to [\[33\], t](#page-44-32)he specific threshold values corresponding to RHH and RLH are defined as follows. Here a division which intersects both RHH and RLH is considered neutral.

- • ''Medical outcomes study 36-item short-form health survey version 2 (SF-36v2) score (0-100 points) [-] - Subscale: Physical functioning (PF)'': We define 51–100 and 0–49 points for RHH and RLH criteria, respectively.
- • ''Medical outcomes study 36-item short-form health survey version 2 (SF-36v2) score (0–100 points) [-] - Subscale: Role physical (RP)'': We define 51–100 and 0–49 points for RHH and RLH criteria, respectively.
- ''Medical outcomes study 36-item short-form health survey version 2 (SF-36v2) score (0–100 points) [-] - Subscale: Bodily pain (BP)'': We define 51–100 and 0–49 points for RHH and RLH criteria, respectively.
- "Medical outcomes study 36-item short-form health survey version 2 (SF-36v2) score (0–100 points) [-] - Subscale: General health (GH)'': We define 51–100 and 0–49 points for RHH and RLH criteria, respectively.
- ''Medical outcomes study 36-item short-form health survey version 2 (SF-36v2) score (0-100 points) [-] - Subscale: Vitality (VT)'': We define 51–100 and 0–49 points for RHH and RLH criteria, respectively.
- ''Medical outcomes study 36-item short-form health survey version 2 (SF-36v2) score (0–100 points) [-] - Subscale: Social functioning (SF)'': We define 51–100 and 0–49 points for RHH and RLH criteria, respectively.
- ''Medical outcomes study 36-item short-form health survey version 2 (SF-36v2) score (0–100 points)

[-] - Subscale: Role emotional (RE)'': We define 51–100 and 0–49 points for RHH and RLH criteria, respectively.

• ''Medical outcomes study 36-item short-form health survey version 2 (SF-36v2) score (0–100 points) [-] - Subscale: Mental health (MH)'': We define 51–100 and 0–49 points for RHH and RLH criteria, respectively.

4) VISION TEST

The compact vision meter "CA-1000" (TOMEY Corporation, Nagoya City, Japan) [\[34\]](#page-44-33) is used for this test. For the following 6 items, we divide each value into 2 divisions based on more than or less than 1.0. Then, referring to [\[35\], t](#page-44-34)he specific threshold values corresponding to RHH and RLH are defined as follows.

- "Distance vision (Right eye) $[-]$ ": We define \ge = 1.0 and others for RHH and RLH criteria, respectively.
- "Distance vision (Left eye) $[-]'$: We define $>= 1.0$ and others for RHH and RLH criteria, respectively.
- "Distance vision (Both eyes) $[-]$ ": We define $>=$ 1.0 and others for RHH and RLH criteria, respectively.
- "Near vision (Right eye) $[-]$ ": We define \ge = 1.0 and others for RHH and RLH criteria, respectively.
- "Near vision (Left eye) $[-]$ ": We define \geq = 1.0 and others for RHH and RLH criteria, respectively.
- "Near vision (Both eyes) $[-]$ ": We define \ge = 1.0 and others for RHH and RLH criteria, respectively.

5) BLOOD EXAMINATION

For the following 15 items, we divide each value into 2 divisions referring to public information [\[36\]](#page-44-35) (LSI Medience Corporation, Tokyo, Japan) (but only for Fischer's ratio, see [\[37\]\).](#page-44-36) The specific threshold values corresponding to RHH and RLH are defined as follows.

- • ''Total bilirubin [mg/dL] (for liver diagnosis)'': We define 0.2–1.2 and others (abnormal) for RHH and RLH criteria, respectively.
- ''Asparate aminotransferase (AST) (Glutamic oxaloacet ic transaminase (GOT)) [U/L] (for liver diagnosis)'': We define 10–40 and others (abnormal) for RHH and RLH criteria, respectively.
- "Alanine aminotransferase (ALT) (Glutamic pyruvate transaminase (GPT)) [U/L] (for liver diagnosis)'': We define 5–45 and others (abnormal) for RHH and RLH criteria, respectively.
- ''Gamma-glutamyl transferase (γ -GT) (Gamma-glutam yl transpeptidase (γ -GTP)) [U/L] (for liver diagnosis)'': For males, we define \leq 80 and others (abnormal) for RHH and RLH criteria, respectively. For females, we define <= 30 and others (abnormal) for RHH and RLH criteria, respectively.
- ''Total protein [g/dL] (for nutrition diagnosis)'': We define 6.7–8.3 and others (abnormal) for RHH and RLH criteria, respectively.
- "Creatinine [mg/dL] (for kidney diagnosis)": For males, we define 0.61–1.04 and others (abnormal)

for RHH and RLH criteria, respectively. For females, we define 0.47–0.79 and others (abnormal) for RHH and RLH criteria, respectively.

- ''Uric acid [mg/dL] (for gout diagnosis)'': For males, we define 3.8–7.0 and others (abnormal) for RHH and RLH criteria, respectively. For females, we define 2.5–7.0 and others (abnormal) for RHH and RLH criteria, respectively.
- ''Triglyceride (TG) [mg/dL] (for lipid diagnosis)'': We define 30–149 and others (abnormal) for RHH and RLH criteria, respectively.
- • "High-density lipoprotein (HDL) cholesterol [mg/dL] (for lipid diagnosis)'': For males, we define 40–85 and others (abnormal) for RHH and RLH criteria, respectively. For females, we define 40–95 and others (abnormal) for RHH and RLH criteria, respectively.
- ''Albumin (ALB) by improved bromcresol purple (BCP) method [g/dL] (for nutrition diagnosis)'': We define 3.8–5.2 and others (abnormal) for RHH and RLH criteria, respectively.
- "White blood cell count $[μ L]$ (for immunodiagnosis)": We define 3300–9000 and others (abnormal) for RHH and RLH criteria, respectively.
- "Hemoglobin [g/dL] (for anemia diagnosis)": For males, we define 13.5–17.5 and others (abnormal) for RHH and RLH criteria, respectively. For females, we define 11.5–15.0 and others (abnormal) for RHH and RLH criteria, respectively.
- • ''Hemoglobin A1c (HbA1c) based on the national glycohemoglobin standardization program (NGSP) [%] (for diabetes diagnosis)'': We define 4.6–6.2 and others (abnormal) for RHH and RLH criteria, respectively.
- "Fischer's ratio [-] (for amino acid diagnosis)": We define 2.31–4.29 and others (abnormal) for RHH and RLH criteria, respectively.
- "Cortisol $[\mu g/dL]$ (for stress diagnosis)": We define 3.7–19.4 and others (abnormal) for RHH and RLH criteria, respectively.

For the following 1 item, we divide each value into 5 divisions based on 0 to less than 0.1, 0.1 to less than 0.2, 0.2 to less than 0.3, 0.3 to less than 0.4, and more than 0.4, while including dummies. Then, referring to $[38]$, the specific threshold values corresponding to RHH and RLH are defined as follows.

• "High sensitive C-reactive protein (CRP) [mg/dL] (for inflammation diagnosis)": We define < 0.4 and >= 0.4 for RHH and RLH criteria, respectively.

6) BLOOD PRESSURE MEASUREMENT OF THE EXTREMITIES For the following 4 items, we divide each value into 2 divisions referring to [\[39\]](#page-45-0) (or [\[40\]\).](#page-45-1) The specific threshold values corresponding to RHH and RLH are defined as follows.

• "Right brachial-ankle pulse wave velocity (RbaPWV) [cm/s] (for atherosclerosis diagnosis)'': We define

< 1400 and others (abnormal) for RHH and RLH criteria, respectively.

- "Left brachial-ankle pulse wave velocity (LbaPWV) [cm/s] (for atherosclerosis diagnosis)": We define < 1400 and others (abnormal) for RHH and RLH criteria, respectively.
- "Right ankle-brachial index (Rabi) [-] (for artery occlusion diagnosis)": We define > 0.9 and others (abnormal) for RHH and RLH criteria, respectively.
- "Left ankle-brachial index (Labi) [-] (for artery occlusion diagnosis)'': We define > 0.9 and others (abnormal) for RHH and RLH criteria, respectively.

7) PULMONARY FUNCTION TESTING (SPIROMETRY)

For the following 1 item, we divide each value into 2 divisions referring to $[41]$ (or $[35]$). The specific threshold values corresponding to RHH and RLH are defined as follows.

• ''Gaensler's forced expiratory volume in one second percent (FEV1.0%G) [%] (for obstructive pulmonary disease diagnosis)": We define \geq 80 and others (abnormal) for RHH and RLH criteria, respectively.

8) HEEL BONE DENSITY TEST

For the following 1 item, we divide each value into 2 divisions referring to $[42]$ (or $[43]$). The specific threshold values corresponding to RHH and RLH are defined as follows.

• "T-score (YAM) derived from the osteo sono-assessment index (OSI) [%] (for osteoporosis diagnosis)'': We define \ge = 80 and others (abnormal) for RHH and RLH criteria, respectively.

9) BODY COMPOSITION MEASUREMENT

For the following 1 item, we divide each value into 3 divisions referring to $[44]$ (or $[45]$, $[46]$). The specific threshold values corresponding to RHH and RLH are defined as follows.

• ''Body fat percentage [%]'': For males, we define 10–19 and others (non-standard) for RHH and RLH criteria, respectively. For females, we define 20–29 and others (non-standard) for RHH and RLH criteria, respectively.

10) GRAVIC BODY SWAY TEST (OTORHINOLARYNGOLOGY)

The Gravicorder (ANIMA Corporation, Tokyo, Japan) [\[47\]](#page-45-8) is used for this test. For the following 1 item, there are no explicit criteria, and for this one, the actual diagnostic levels (common or large) divided by otorhinolaryngologists in clinical testing are directly used for divisions. Incidentally, see [\[48\]](#page-45-9) for a detailed methodology on this item.

• "Evaluation of large sway (1: Large or 0: Common) [-]'': We define 0 and 1 for RHH and RLH criteria, respectively.

We show the main items for 2019 in Table [3,](#page-6-0) while we also handle the same items for 2016–2018. Although some items are continuous variables and some are discrete variables, in this study, we handle each item as a discrete

variable categorized into several levels. As a threshold for categorization, we establish a criterion to separate relatively high or low levels of health in the numerical values of each item. In addition, we also calculate the four-year slopes for each item over 2016–2019 for each subject, categorize them into discrete variables according to a level divided into 5 equal parts between the maximum and minimum values, and handle them together.

Next, the driving questionnaire survey items are shown in Table [4.](#page-9-0) We handle the items ''Driving frequency'', ''Driving time'', ''Transmission: Automatic (AT) or Manual (MT)'', "Likes or dislikes about driving", "Moments when you feel better while driving'', ''Scenes where you have felt better while driving", "Excitements ("Waku-Waku" in Japanese) that you can relate to'', and ''Purpose of driving''. Since all of the above items have response options, they are all discrete variables.

The items in Table [4](#page-9-0) and their response options are detailed below. These are all of our own design. However, only in the design of the item ''Purpose of driving'', some factors such as shopping, working, leisure and hobby, which are considered in [\[49\]](#page-45-10) in relation to health, are referred to as response options. On the other hand, there are no previous studies that incorporate the other items in detail. For example, although there is a known study using driving style questionnaires (DSQ) designed to analyze the association with traffic accidents $[50]$, they do not fit our purpose of actively analyzing the association with health and the Kansei (sensitivity). Therefore, we have designed generally all of our own, with the exception of the item ''Purpose of driving''.

11) DRIVING QUESTIONNAIRE

The following 3 items are general questionnaires about daily driving.

- "Driving frequency": We define the response options as ''Every day'', ''5–6 days a week'', ''3–4 days a week'', ''Less than 2 days a week'', and ''None''.
- "Driving time": We define the response options as ''Less than 30 minutes'', ''30 minutes to 1 hour'', ''1–2 hours'', and ''More than 2 hours''.
- ''Transmission: Automatic (AT) or Manual (MT)'': We define the response options as ''Only AT'', ''Only MT'', and ''Both AT and MT''.

The following 1 item is a questionnaire that takes into account a key factor that may be strongly related to the Kansei (sensitivity) leading to active driving.

• ''Likes or dislikes about driving'': We define the response options as ''Like'', ''Rather like'', ''Rather dislike'', and ''Dislike''.

The following 4 items are questionnaires that take into account other factors that may be related to the Kansei (sensitivity) for driving. For each item, the response options allows multiple answers.

• ''Moments when you feel better while driving'': We define the response options as ''When hearing the sound

TABLE 3. Overview of our health checkup categories, items, their analysis criteria, and division explanations for subjects (1044 persons) in 2019.

TABLE 3. (Continued.) Overview of our health checkup categories, items, their analysis criteria, and division explanations for subjects (1044 persons) in 2019.

TABLE 3. (Continued.) Overview of our health checkup categories, items, their analysis criteria, and division explanations for subjects (1044 persons) in 2019.

of the engine running'', ''When putting your foot on the accelerator'', ''When hearing the engine accelerating'', ''When feeling enough acceleration'', ''When driving around a series of curves'', ''When turning the curves as you want'', ''When seeing the shining body of your car'', ''When feeling the texture of the interior'', ''When feeling that your car's design stands out from others'', ''When achieving fuel-efficient driving'', and ''None''.

• ''Scenes where you have felt better while driving'': We define the response options as ''Where feeling that you have your own space'', ''Where discovering a new route'', ''Where chatting and laughing with everyone'', ''Where traveling or driving with everyone'', ''Where spending time in the car with your family", "Where driving alone", "Where smelling the natural scent of the sea or greenery'', ''Where

seeing the natural scenery of the sea or greenery'', and ''None''.

- "Excitements ("Waku-Waku" in Japanese) that you can relate to'': We define the response options as ''The sense of speed'', ''Handling'', ''The harmony with nature", "Exploring new routes", "The standout design'', ''Achieving fuel efficiency'', ''Your own space'', and ''Chatting and laughing with everyone''.
- ''Purpose of driving'': We define the response options as ''Commuting'', ''Shopping'', ''Working'', ''Farming'', ''Picking up and droping off'', ''Going for the leisure'', ''Going to the hospital'', ''Going for the hobby'', ''Going for the entertainment'', and ''Driving''.

We transform the discrete variables for driving and health described above into one-hot vectorized variables (i.e., binary variables with 1s for the corresponding attributes and 0s otherwise) according to their levels, and use them in an integrated manner in our analysis. Even if the original discrete variables have some missing values, since the binary variables corresponding to the levels representing the missing values can be generated simultaneously by one-hot vectorization, we remove the missing values as part of all binary variables. Each overview of the set of binary variables used for the analysis corresponding to males and females over 60 is shown in Tables [5](#page-10-1) and [6,](#page-11-0) respectively (partially displayed due to the large number of binary variables).

B. ANALYSIS METHOD (STEP 1: LATENT CLASSES EXTRACTION)

In order to extract the relationships between driving and health, we cluster the data of over 1000 variables (onehot vectorized binary variables) as shown in the previous section in an integrated manner. For this purpose, we use the Probabilistic Latent Semantic Analysis (PLSA) method [\[17\],](#page-44-16) a machine learning technique (see Appendix [A\)](#page-33-0). The PLSA is a method originally proposed to extract several latent topics (latent classes) in the field of natural language processing for text clustering. Since the essence of PLSA is to soft cluster data structured as a co-occurrence matrix of documents (rows) and words (columns), it can be applied not only to text but also to questionnaires, images, and other similar data [\[12\],](#page-44-11) [\[13\]. T](#page-44-12)he hyperparameters in PLSA include the number of latent classes K and the threshold ε related to the termination condition of the EM algorithm, which are used as $K = 5$ (for easy interpretability) and $\varepsilon = 10^{-8}$ in this study, respectively. The C language is used for our program implementations of PLSA.

Moreover, although PLSA is a soft clustering method, in this study, to facilitate the interpretation of each latent class, we derive *K* latent classes $C^{(k)}$ ($k = 1, ..., K$) obtained from samples (subjects)

$$
d \in D = \{d_1, \dots, d_N\}
$$

with $N = \begin{cases} 160 & \text{(for males over 60)}, \\ 252 & \text{(for females over 60)} \end{cases}$ (1)

TABLE 4. Overview of our items of driving questionnaire and their response options for subjects (1044 persons) in 2019.

and factors (binary variables)

$$
w \in W = \{A_1, \dots, A_M\}
$$

with $M = \begin{cases} 1038 & \text{(for males over 60)}, \\ 1088 & \text{(for females over 60)} \end{cases}$ (2)

as a pair $C^{(k)} = \left(C_d^{(k)}\right)$ $\left(\begin{array}{c} (k) \\ d \end{array}\right)$, $C_w^{(k)}$ of the set $C_d^{(k)}$ $\frac{d^{(k)}}{d}$ of component samples *d* and the set $C_w^{(k)}$ of component factors *w* with

TABLE 5. Overview of a set of binary variables by one-hot vectorization (for males over 60).

Binary	Names of variables (corresponding to the 2016-2019 health		
variables w (for	checkup results and their four-year slopes, and the 2019 driving questionnaire results, one-hot vectorized by those		
males	levels)		
over 60)			
Al	"60-69" Y19 <personal form="" record=""> Age [years old]</personal>		
A2 A3	Y19 <personal form="" record=""> Age [years old] "70-79" Y19<personal form="" record=""> Age [years old] "80-89"</personal></personal>		
$\overline{A}4$	Y19 <personal form="" record=""> Grip strength (Right hand) [kg] ">=18.4 and <30.8"</personal>		
A5	Y19 <personal form="" record=""> Grip strength (Right hand) [kg] "$>=$ 30.8 and <43.2"</personal>		
A6	Y19 <personal form="" record=""> Grip strength (Right hand) [kg] $">=43.2$ and <55.6"</personal>		
A7	Y19 <personal form="" record=""> Grip strength (Right hand) [kg] "$>=(Min)6$ and <18.4"</personal>		
A8	Y19 <personal form="" record=""> Grip strength (Left hand) [kg] "$>=$25.2 and $<$36.8"</personal>		
A ₉	Y19 <personal form="" record=""> Grip strength (Left hand) [kg] "$>=$36.8 and <48.4"</personal>		
A10	Y19 <personal form="" record=""> Grip strength (Left hand) [kg] $">=13.6$ and <25.2"</personal>		
A11	Y19 <personal form="" record=""> Grip strength (Left hand) [kg] ">=48.4 and <= (Max)60"</personal>		
A12 \vdots	Y19 <personal form="" record=""> Grip strength (Left hand) [kg] "$>=(Min)2$ and <13.6"</personal>		
A719	Y16 <health questionnaire=""> SF-36v2 score (0-100 points) [-] : MH _">=90 and <=$(Max)100"$</health>		
A720	Y16 <health questionnaire=""> SF-36v2 score (0-100 points) [-] : MH $">=60$ and <70"</health>		
A721	Y16 <health questionnaire=""> SF-36v2 score (0-100 points) [-] : MH _">=70 and <80"</health>		
A722	Y16 <health questionnaire=""> SF-36v2 score (0-100 points) [-]: MH _">=50 and <60"</health>		
A723	Y16 <health questionnaire=""> SF-36v2 score (0-100 points) [-] : MH ">=80 and <90"</health>		
A724	Y16 <health questionnaire=""> SF-36v2 score (0-100 points) [-] : MH ">=30 and <40"</health>		
A725	Y16 <health questionnaire=""> SF-36v2 score (0-100 points) [-] : MH ">=40 and <50"</health>		
A726	Slope <personal form="" record=""> Grip strength (Right hand) [kg] ">=-4.4 and <-0.6"</personal>		
A727	Slope <personal form="" record=""> Grip strength (Right hand) [kg] $">=0.6$ and <3.2"</personal>		
A728	Slope <personal form="" record=""> Grip strength (Right hand) [kg] ">=3.2 and <= $(Max)7"$</personal>		
A729	Slope <personal form="" record=""> Grip strength (Right hand) [kg] "$>= 8.2$ and ≤ 4.4"</personal>		
A730	Slope <personal form="" record=""> Grip strength (Right hand) [kg] ">=(Min)-12 and <-8.2"</personal>		
÷ A980	Slope <health questionnaire=""> SF-36v2 score (0-100 points) [-]</health>		
	: MH _">=-7.4 and <3.2"		
A981	Slope <health questionnaire=""> SF-36v2 score $(0-100 \text{ points})$ [-] : MH _">=3.2 and <13.8"</health>		
A982	Slope <health questionnaire=""> SF-36v2 score (0-100 points) [-] : MH _">=(Min)-18 and <-7.4"</health>		
A983	Slope <health questionnaire=""> SF-36v2 score (0-100 points) [-] : MH ">=13.8 and <24.4"</health>		
A984	Slope <health questionnaire=""> SF-36v2 score (0-100 points) [-] : MH _">=24.4 and <= (Max)35"</health>		
A985	Y19Car <driving questionnaire="">Driving frequency_"Every day"</driving>		
A986	Y19Car <driving questionnaire="">Driving frequency "5-6 days a week"</driving>		
A987	Y19Car <driving questionnaire=""> Driving frequency _"3-4 days a week"</driving>		
A988	Y19Car <driving questionnaire=""> Driving frequency _"Less than 2 days a week"</driving>		
A989	Y19Car <driving questionnaire=""> Driving frequency "None"</driving>		
A1029	Y19Car <driving questionnaire=""> Purpose of driving</driving>		
A1030	"Commuting" Y19Car <driving questionnaire=""> Purpose of driving "Shopping"</driving>		
A1031	Y19Car <driving questionnaire=""> Purpose of driving "Working"</driving>		

TABLE 5. (Continued.) Overview of a set of binary variables by one-hot vectorization (for males over 60).

maximum membership probabilities. That is, we derive $C_d^{(k)}$ *d* and $C_w^{(k)}$ as

$$
C_d^{(k)} = \left\{ d \in D | P(z_k | d) = \max_{z \in Z} P(z | d) \right\},
$$

$$
C_w^{(k)} = \left\{ w \in W | P(z_k | w) = \max_{z \in Z} P(z | w) \right\}.
$$
 (3)

C. ANALYSIS METHOD (STEP 2: ADDITIONAL ANALYSIS FOCUSED ON CHARACTERISTIC LATENT CLASSES)

As an additional analysis for the latent classes extracted by PLSA, when one of the latent classes is selected, we integrate its main component factors (binary variables) and several other target variables (binary variables) defined to focus on as a data set, and analyze the relationships between the component factors and target variables. For this purpose, we use the t-distributed Stochastic Neighbor Embedding (t-SNE) method [\[18\], a](#page-44-17) machine learning (especially a manifold learning) technique (see Appendix B), as an approach that can evaluate similarities among all variables even if the target variables are defined as sparse (consisting of a few 1s) one-hot vectors. The t-SNE is a method that allows dimensional compression and visualization of data in a way that maximally satisfies the preservation of local structures of data (i.e., keeping data close together at close distances), while also ensuring that global structures of data are as intact as possible. Since the essence of t-SNE is to characterize data with distance-based similarities, it can be widely applied to a variety of data [\[14\],](#page-44-13) [\[16\]. T](#page-44-15)he hyperparameters in t-SNE include the dimension n' after compression, the perplexity, the maximum number of iterations t_{max} , the learning rate η , and the momentum $\alpha(t)$, which are used as $n' = 2$, *perplexity* = 5, $t_{\text{max}} = 1000$, $\eta =$ 200, and $\alpha(t) = 0.5(t \le 250)$ or $0.8(t > 250)$ in this study, respectively. We have determined these values by referring to typical values in [\[18\]](#page-44-17) as a guide. The R language is used for our program implementations of t-SNE.

TABLE 6. Overview of a set of binary variables by one-hot vectorization (for females over 60).

TABLE 6. (Continued.) Overview of a set of binary variables by one-hot vectorization (for females over 60).

III. RESULTS

A. RESULTS OF PRELIMINARY ANALYSIS TO DETERMINE THE NUMBER OF PLSA'S LATENT CLASSES, INCLUDING COMPARISON WITH CLASSIC STATISTICAL PLOTS USING EXISTING ITEMS

We first show the results of the preliminary analysis using PLSA described in the previous section and simple statistical plots (stratified scatter plots). Before analyzing the relationship between driving and health among the elderly over 60, we have examined whether there are driving questionnaire items that can simply stratify health, once using only 2018 gender-inclusive data for example, which also includes those aged 20–60. However, due to large variances in most health item data, we have been able to find no cases where they can be simply stratified by any of the driving items. As some examples, in Fig. [2,](#page-13-0) we show preliminary analysis results with scatter plots for all males and females over 20 in 2018, stratified by ''Driving frequency'', ''Driving time'', ''Transmission: Automatic (AT) or Manual (MT)'', and ''Likes or dislikes about driving'', respectively. In this figure, for each stratification, the left side plots age on the horizontal axis and CESD-20 score on the vertical axis, while the right side plots age on the horizontal axis and GLFS-25 score on the vertical axis. From this figure, it can be immediately understood that the data is difficult to adequately capture relationships using average values or conventional linear analysis (e.g., correlation analysis). Therefore, in order to efficiently extract the relationship with driving while also setting a large number of other health items, it is essential to deal with uncertainty and cluster the items and subjects simultaneously to find some stratifiable categories in a flexible manner other than the predefined driving items. This has led us to use PLSA as a kind of probabilistic modeling method.

We note here that it is necessary to consider how many latent classes to set in PLSA. As a reference, it has long been known that the Akaike information criterion (AIC) can be applied to regular models that are guaranteed to have asymptotically Gaussian distributions in the maximum likelihood estimators of model parameters [\[51\]. H](#page-45-12)owever, it is not strictly applicable in PLSA involving latent class models that do not necessarily have such guarantees. Therefore, in this study, we have decided to determine the number of latent classes by making several specific changes. As a result, as shown in Fig. [3,](#page-13-1) we have confirmed that increasing the number of latent classes up to approximately $K = 10$ makes stratification by these latent classes relatively easier. In fact, for example, at least in the upper left and lower right parts of the plot (i.e., the parts easily understood as declining health from young to old), we can see that relatively different latent classes (especially $C^{(7)}$ and $C^{(2)}$) appear and support stratification, respectively. Based on these results, we have believed that if we focus on subjects over 60, the target of our analysis, we should set the number of latent classes to approximately $K = 5$ and analyze the data by gender to capture the reality of the data relatively more easily, although this is a qualitative judgment. Although this does not correspond to an objective approach to determining the number of latent classes, it has been our priority to ensure ease of understanding and interpretability in accordance with the actual data situation.

B. RESULTS OF LATENT CLASSES EXTRACTION USING PLSA

The results for five latent classes corresponding to males and females over 60 are shown in Figs. [4](#page-14-0) to [8](#page-18-0) and Figs. [9](#page-19-0) to [13,](#page-23-0) respectively. In each figure, the component factors $w \in C_w^{(k)}$ related to one latent class $C^{(k)}$ are plotted as a bar chart based on the descending order of $P(w|z_k)$, which corresponds to the contribution of *w* in $C_w^{(k)}$, with an enlarged display of top 30 plots. At the same time, a bar chart corresponding to the partial extraction of at most 10 factors related to driving only is also displayed. These factors appearing in (1) and (2) of Figs. [4](#page-14-0) to [13](#page-23-0) are listed in text format in Appendix [C.](#page-42-0)

C. PREPARATION FOR ADDITIONAL ANALYSIS USING T-SNE

Based on the PLSA results, we focus here on cases where differences appear in other attributes that we want to focus on, even if they belong to the same latent class. Specifically, we focus on cognitive function (MMSE) as a representative health item and define

• "MMSE_slope_good": a binary variable representing subjects who drive every day and have non-negative four-year slopes for MMSE over 2016–2019

and

• "MMSE slope bad": a binary variable representing subjects who drive every day and have negative four-year slopes for MMSE over 2016–2019

TABLE 7. Number of subjects corresponding to ''MMSE_slope_good'' and ''MMSE_slope_bad'' in each latent class, where the upper and lower tables are for males and females over 60, respectively.

as two different target variables that consider driving and MMSE maintenance simultaneously. Then, if we count the number of subjects corresponding to ''MMSE_slope_good'' and ''MMSE_slope_bad'' in each latent class, we obtain the results shown in Table [7.](#page-12-0) In particular, we can find a small number of subjects corresponding to each of the target variables in latent classes $C^{(3)}$ and $C^{(5)}$ for males over 60, and in latent classes $C^{(1)}$ and $C^{(4)}$ for females over 60, respectively. Therefore, we characterize those differences through an additional analysis using t-SNE according to the following approach.

First, in each of the above latent classes $C^{(k)}$, we restrict the set of subjects $C_d^{(k)}$ $\frac{d^{(k)}}{dt}$ to be analyzed to a subset

$$
C_{d'}^{(k)} = \left\{ d' \in C_d^{(k)} | \text{A subject } d' \text{ drives every day.} \right\}
$$

$$
= \left\{ d'_1, \dots, d'_{N_k} \right\} \text{ with } N_k = \left| C_{d'}^{(k)} \right| \tag{4}
$$

consisting only of those who drive every day. Next, for each binary variable $w = A_i \in C_w^{(k)}$, we also restrict the *N*-dimensional one-hot vector

$$
\boldsymbol{a}_{i}^{(k)} = [n(d_1, A_i), \dots, n(d_N, A_i)]^T \in \{0, 1\}^N \qquad (5)
$$

corresponding to A_i to an N_k -dimensional partial one-hot vector

$$
\boldsymbol{a}'_i^{(k)} = \left[n\left(d'_{1}, A_i\right), \ldots, n\left(d'_{N_k}, A_i\right) \right]^T \in \{0, 1\}^{N_k}, \quad (6)
$$

where the symbol T denotes the transposition. Then, since $N_k \leq \left| C_d^{(k)} \right|$ \mid $\begin{bmatrix} a^{(k)} \\ d \end{bmatrix}$, there is a possibility to be formed as $\mathbf{a'}_i^{(k)} =$ **0** (the zero vector) for some $\mathbf{a'}_i^{(k)}$ $i^{(k)}$. Therefore, we process to remove those zero vectors and let

$$
C_{w'}^{(k)} = \left\{ w' \in C_w^{(k)} \mid [n(d'_1, w'), \dots, n(d'_{N_k}, w')]^T \neq 0 \right\}
$$

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FIGURE 2. Examples of preliminary analysis results with scatter plots for all males and females over 20 in 2018, stratified by ''Driving frequency'', ''Driving time'', ''Transmission: Automatic (AT) or Manual (MT)'', and ''Likes or dislikes about driving'', respectively (on the left side, horizontal axis: age, vertical axis: CESD-20 score; on the right side, horizontal axis: age, vertical axis: GLFS-25 score).

FIGURE 3. Examples of preliminary analysis results with scatter plots for all males and females over 20 in 2018, stratified by ten latent classes based on PLSA with *K* = 10 (on the left side, horizontal axis: age, vertical axis: CESD-20 score; on the right side, horizontal axis: age, vertical axis: GLFS-25 score).

(2) Partial extraction of at most 10 factors related to driving only

FIGURE 4. Results for the latent class $C^{(1)}$ (for males over 60). (1) Enlarged display of top 30 factors $w\in C^{(1)}_w$ based on descending order of P (w $|z_1$). (2) Partial extraction of at most 10 factors related to driving only.

$$
= \left\{ w_1', \ldots, w_{M_k}' \right\} \text{ with } M_k = \left| C_{w'}^{(k)} \right| \tag{7}
$$

be the set of binary variables to be analyzed. That is, the data $X^{(k)}$ to be input to t-SNE is given as an $N_k \times (M_k + L_k)$

FIGURE 5. Results for the latent class $C^{(2)}$ (for males over 60). (1) Enlarged display of top 30 factors $w\in C^{(2)}_w$ based on descending order of *P* (*w*|*z*2). (2) Partial extraction of at most 10 factors related to driving only.

matrix

$$
X^{(k)} = \left[x_1^{(k)}, \dots, x_{M_k}^{(k)}, s_1^{(k)}, \dots, s_{L_k}^{(k)} \right]
$$
 (8)

that integrates M_k one-hot vectors

 (k_k)

$$
\mathbf{x}_{i}^{(k)} = [n (d'_{1}, w'_{i}), \dots, n (d'_{N_{k}}, w'_{i})]^{T}
$$

\n
$$
\in \{0, 1\}^{N_{k}} (i = 1, \dots, M_{k})
$$
 (9)

(2) Partial extraction of at most 10 factors related to driving only

FIGURE 6. Results for the latent class $C^{(3)}$ (for males over 60). (1) Enlarged display of top 30 factors $w\in C^{(3)}_w$ based on descending order of P (w $|z_3$). (2) Partial extraction of at most 10 factors related to driving only.

(2) Partial extraction of at most 10 factors related to driving only

FIGURE 7. Results for the latent class $C^{(4)}$ (for males over 60). (1) Enlarged display of top 30 factors $w\in C^{(4)}_w$ based on descending order of P ($w\,|z_4$). (2) Partial extraction of at most 10 factors related to driving only.

FIGURE 8. Results for the latent class $C^{(5)}$ (for males over 60). (1) Enlarged display of top 30 factors $w\in C^{(5)}_w$ based on descending order of P (w $|z_5$). (2) Partial extraction of at most 10 factors related to driving only.

FIGURE 9. Results for the latent class $C^{(1)}$ (for females over 60). (1) Enlarged display of top 30 factors $w\in C^{(1)}_w$ based on descending order of *P* (*w*|*z*1). (2) Partial extraction of at most 10 factors related to driving only.

corresponding to the component factors, and several other one-hot vectors

$$
\mathbf{s}_{j}^{(k)} \in \{0, 1\}^{N_k} \ (j = 1, \dots, L_k) \tag{10}
$$

corresponding to the defined target variables. Furthermore, in order to take the Kansei (sensitivity) factor into account actively, we set the number of target variables to $L_k \in$ {2, 3} by including not only ''MMSE_slope_good'' and ''MMSE_slope_bad'' but also a binary variable

FIGURE 10. Results for the latent class $C^{(2)}$ (for females over 60). (1) Enlarged display of top 30 factors $w \in C^{(2)}_w$ based on descending order of *P* (*w*|*z*2). (2) Partial extraction of at most 10 factors related to driving only.

• Y19Car<Driving questionnaire> Likes or dislikes about driving _''Like''

representing the subjects corresponding to ''I like driving'' (corresponding to *A*⁹⁹⁷ for males over 60 and *A*¹⁰⁴⁷ for

(2) Partial extraction of at most 10 factors related to driving only

FIGURE 11. Results for the latent class $C^{(3)}$ (for females over 60). (1) Enlarged display of top 30 factors $w\in C^{(3)}_w$ based on descending order of P ($w\ket{z_3}$). (2) Partial extraction of at most 10 factors related to driving only.

(2) Partial extraction of at most 10 factors related to driving only

FIGURE 12. Results for the latent class $C^{(4)}$ (for females over 60). (1) Enlarged display of top 30 factors $w\in C^{(4)}_w$ based on descending order of P ($w\,|z_4$). (2) Partial extraction of at most 10 factors related to driving only.

FIGURE 13. Results for the latent class $C^{(5)}$ (for females over 60). (1) Enlarged display of top 30 factors $w\in C^{(5)}_w$ based on descending order of P (w $|z_5$). (2) Partial extraction of at most 10 factors related to driving only.

FIGURE 14. Characterization results for component factors and target variables corresponding to the latent class *C* (3) (for males over 60): The original on the left and the same on the right with target variables highlighted.

FIGURE 15. Characterization results for component factors and target variables corresponding to the latent class *C* (5) (for males over 60): The original on the left and the same on the right with target variables highlighted.

females over 60) as one of the target variables (related factors) if it is a variable not belonging as a component factor and not forming a zero vector.

D. ADDITIONAL ANALYSIS RESULTS USING T-SNE

According to the approach described in the previous section, Figs. [14](#page-24-1) and [15](#page-24-2) and Figs. [16](#page-25-0) and [17](#page-25-1) show the results of characterizing similarities among component factors and target variables for the latent classes $C^{(3)}$ and $C^{(5)}$ for males over 60 and $C^{(1)}$ and $C^{(4)}$ for females over 60, respectively. In particular, on the right side of each figure, the standing positions of the two target variables ''MMSE_slope_good'' and ''MMSE_slope_bad'' are clearly highlighted with their rough circular neighborhoods.

FIGURE 16. Characterization results for component factors and target variables corresponding to the latent class $\mathcal{C}^{(1)}$ (for females over 60): The original on the left and the same on the right with target variables highlighted.

FIGURE 17. Characterization results for component factors and target variables corresponding to the latent class $\mathcal{C}^{(4)}$ (for females over 60): The original on the left and the same on the right with target variables highlighted.

IV. DISCUSSION AND LIMITATIONS

A. INTERPRETATION AND DISCUSSION FOR PLSA RESULTS Looking over the component factors of each latent class obtained by PLSA, we can interpret that $C^{(1)}$, $C^{(2)}$, $C^{(3)}$ and $C^{(4)}$ are broadly classified as relatively high health classes and $C^{(5)}$ as a relatively low health class, for both males over 60 and females over 60. More specifically, we can interpret the results as follows.

1) THE CASE OF MALES OVER 60

• The latent class $C^{(1)}$ can be interpreted as a relatively high health class that has the most principal feature with artery occlusion diagnosed as normal in 2019, and also has many items diagnosed as normal on the blood examination. Focusing on features with respect to driving, subjects who drive every day appear relatively in $C^{(1)}$.

TABLE 8. Top 30 factors in ascending order of the 2-dimensional compressed Euclidean distance for each of ''MMSE_slope_good'' (see upper table) and "MMSE_slope_bad" (see lower table), corresponding to the latent class $\mathcal{C}^{(3)}$ (for males over 60).

A350	Y16 <personal form="" record=""> Sitting trunk flexion [cm] ">=30.4 and <42.6"</personal>	2.223559195	1.905122595
A760	Slope <personal form="" record=""> Maximal walking speed of 10 meters [sec] $">= (Min)$-</personal>	1.81123405	2.040137589
	0.49 and ≤ 0.07 "		
A39	Y19 <personal form="" record=""> Maximal walking speed of 10 meters [sec] ">=(Min)2.3</personal>	1.711822066	2.719474472
	and \leq 3.96"		
A360	Y16 <personal form="" record="">TUG test [sec] ">=5.24 and <7.38"</personal>	2.752655201	2.923058996
A353	Y16 <personal form="" record=""> Whole body reaction time [msec] ">=409.6 and <539.2"</personal>	3.003024769	3.202881288
A257	Y17 <personal form="" record=""> Maximal walking speed of 10 meters [sec]</personal>	2.253038878	3.307620531
	" $>=(Min)2.25$ and <3.58 "		
A750	Slope <personal form="" record="">TUG test [sec] ">=-0.8 and <-0.19"</personal>	2.754775964	3.44657456
A249	Y17 <personal form="" record=""> TUG test [sec] $">= (Min)3.04$ and <4.5"</personal>	2.695725716	3.750880318
A281	Y17 <vision test=""> Distance vision (Left eye) $[-]$ ">=1"</vision>	2.876800409	3.776172219
A689	Y16 <health questionnaire=""> SF-36$v2$ score (0-100 points) [-] : GH $v>=50$ and <60v</health>	3.473962427	4.15151389
A337	Y16 <personal form="" record=""> Grip strength (Right hand) [kg] ">=28.8 and <40.2"</personal>	3.39980788	4.293833932
A997	Y19Car <driving questionnaire=""> Likes or dislikes about driving "Like"</driving>	3.552268929	4.610708248
A726	Slope <personal form="" record=""> Grip strength (Right hand) [kg] $">=-4.4$ and <-0.6"</personal>	4.064653815	4.681423358

TABLE 8. (Continued.) Top 30 factors in ascending order of the 2-dimensional compressed Euclidean distance for each of "MMSE_slope_good" (see upper table) and "MMSE_slope_bad" (see lower table), corresponding to the latent class $\cal C^{(3)}$ (for males over 60).

- The latent class $C^{(2)}$ can be interpreted as a relatively high health class that has the most principal feature with high SF-36v2 scores (especially Quality of Life related to Role Emotional) in 2017, and also has many items with high levels on the health questionnaire. Focusing on features with respect to driving, subjects who drive for the purpose of shopping appear relatively in $C^{(2)}$.
- The latent class $C^{(3)}$ can be interpreted as a relatively high health class that has the most principal feature with nutrition diagnosed as normal in 2016, and also has many items diagnosed as normal on the blood examination. Focusing on features with respect to driving, subjects who drive for the purpose of going for the leisure appear relatively in $C^{(3)}$.
- The latent class $C^{(4)}$ can be interpreted as a relatively high health class that has the most principal feature with osteoporosis diagnosed as normal in 2016, and also has subjects with high visual acuity (distance vision) or standard body fat percentage. Focusing on features with respect to driving, subjects who drive 3–4 days a week appear relatively in $C^{(4)}$.
- The latent class $C^{(5)}$ can be interpreted as a relatively low health class that has the most principal feature with atherosclerosis diagnosed as abnormal in 2017, and also has subjects with low visual acuity (distance vision) or high body fat percentage. Focusing on features with respect to driving, subjects who drive both AT and MT cars appear relatively in $C^{(5)}$. $C^{(5)}$ may also include a minority of subjects who drive reluctantly for the purpose of going to the hospital.

2) THE CASE OF FEMALES OVER 60

• The latent class $C^{(1)}$ can be interpreted as a relatively high health class that has the most principal feature with nutrition diagnosed as normal in 2019, and also has many items diagnosed as normal on the blood examination. Focusing on features with respect to driving, subjects who drive every day appear relatively in $C^{(1)}$.

- The latent class $C^{(2)}$ can be interpreted as a relatively high health class that has the most principal feature with high GLFS-25 scores in 2017, and also has many items with high levels on the health questionnaire. Focusing on features with respect to driving, subjects who can relate to the excitement for the sense of speed appear relatively in $C^{(2)}$.
- The latent class $C^{(3)}$ can be interpreted as a relatively high health class that has the most principal feature with lipid diagnosed as normal in 2018, and also has many items diagnosed as normal on the blood examination. Focusing on features with respect to driving, subjects who drive for the purpose of commuting appear relatively in $C^{(3)}$.
- The latent class $C^{(4)}$ can be interpreted as a relatively high health class that has the most principal feature with nutrition diagnosed as normal in 2017, and also has many items diagnosed as normal on the blood examination (but with high body fat percentage). Focusing on features with respect to driving, subjects who drive both AT and MT cars appear relatively in $C^{(4)}$.
- The latent class $C^{(5)}$ can be interpreted as a relatively low health class that has the most principal feature with high body fat percentage in 2018, and also has relatively low SF-36v2 scores and declining grip strength. Focusing on features with respect to driving, subjects who do not drive appear relatively in $C^{(5)}$. $C^{(5)}$ may also include a minority of subjects who drive reluctantly for the purpose of going to the hospital.

Based on the above interpretations, we can consider that there is support for a relatively positive relationship between driving and health for both males and females over 60.

B. INTERPRETATION AND DISCUSSION FOR T-SNE **RESULTS**

Based on the t-SNE results, in order to characterize ''MMSE_slope_good'' and ''MMSE_slope_bad'' in

TABLE 9. Top 30 factors in ascending order of the 2-dimensional compressed Euclidean distance for each of ''MMSE_slope_good'' (see upper table) and "MMSE_slope_bad" (see lower table), corresponding to the latent class $\mathit{C}^{\left(5\right)}$ (for males over 60).

A341	Y16 <personal form="" record=""> Grip strength (Right hand) [kg] ">=(Min)6 and <17.4"</personal>	16.61888639	2.51853447
A345	Y16 <personal form="" record=""> Grip strength (Left hand) [kg] $">=12.6$ and <24.2"</personal>	16.61811288	2.518545674
A20	Y19 <personal form="" record=""> Whole body reaction time [msec] ">=913.6 and \leq (Max)1142"</personal>	13.67813537	2.64066257
A744	Slope <personal form="" record=""> Whole body reaction time [msec] ">=234.9 and \leq=(Max)324.5"</personal>	13.67797418	2.641611516
A3	Y19 <personal form="" record=""> Age [years old] "80-89"</personal>	17.1290507	2.92717643
A1001	Y19Car <driving questionnaire=""> Moments when you feel better while driving "When hearing the sound of the engine running"</driving>	12.67829095	2.971022735
A43	Y19 <cognitive function=""> MMSE score (0-30 points) [-] _"1"</cognitive>	17.13440544	3.115779573
A564	Y18 <health questionnaire=""> SF-36v2 score (0-100 points) [-] : BP ">=70 and < 80"</health>	13.92618841	3.3104195
A977	Slope <health questionnaire=""> SF-36v2 score (0-100 points) [-] : RE $">=7.5$ and <22.5"</health>	11.27555345	3.374877722
A971	Slope <health questionnaire=""> SF-36v2 score (0-100 points) $[-]$: SF $">=5$ and 15"</health>	15.36134399	3.399541855
A122	Y18 <personal form="" record=""> Grip strength (Right hand) [kg] ">=18.4 and < 28.8"</personal>	16.14427203	3.405733065
A847	Slope <blood examination=""> Uric acid [mg/dL] (for gout diagnosis) _">=(Min)- 1.23 and \leq 0.8"</blood>	11.28613196	3.483246233
A455	Y18 <health questionnaire=""> CESD-20 score (0-60 points) [-] ">=41 and <= 50"</health>	13.31170694	3.766904634
A93	Y19 <blood examination=""> White blood cell count [/µL] (for immunodiagnosis) "Abnormal"</blood>	12.96220716	3.934885101
A126	Y18 <personal form="" record=""> Grip strength (Left hand) [kg] ">=13.8 and <25.6"</personal>	18.1170232	3.952968246
A204	Y18 <blood examination=""> Hemoglobin [g/dL] (for anemia diagnosis) "Abnormal"</blood>	11.1101406	3.970169329
A95	Y19 <blood examination=""> Hemoglobin [g/dL] (for anemia diagnosis) "Abnormal"</blood>	11.14537756	3.985373693
A915	Slope <pulmonary (spirometry)="" function="" testing=""> FEV1.0%G [%] (for obstructive pulmonary disease diagnosis) ">=1.58 and <3.75"</pulmonary>	18.09133234	4.048145704

TABLE 9. (Continued.) Top 30 factors in ascending order of the 2-dimensional compressed Euclidean distance for each of ''MMSE_slope_good'' (see upper table) and ''MMSE_slope_bad'' (see lower table), corresponding to the latent class *C* (5) (for males over 60).

particular, the top 30 factors in ascending order of the 2 dimensional compressed Euclidean distance to them are shown in Tables [8](#page-26-0) to [11.](#page-32-0) In each table, the factors in the highlighted (light blue) cells in the upper table are characterized as clearly closer distances for ''MMSE_slope_good'', while the factors in the highlighted (light blue) cells in the lower table are characterized as clearly closer distances for ''MMSE_slope_bad''. Considering the interpretations of the PLSA results described in the previous section, we can see that the factors characterizing ''MMSE_slope_good'' and ''MMSE_slope_bad'' are not well differentiated in the relatively high health latent classes (i.e., $C^{(3)}$ for males over 60 and $C^{(1)}$ and $C^{(4)}$ for females over 60). Conversely, we can see that they are clearly differentiated in the relatively low health latent class (i.e., $C^{(5)}$ for males over 60). In particular, we can see that the related factor corresponding to ''I like driving'', which is included as a driving item taking the Kansei (sensitivity) into account, emerges as a high ranking factor that characterizes ''MMSE_slope_good''. This can be interpreted to mean that even if health declines are similar, those who like driving may have less MMSE decline than those who do not. As a natural reason, for those who like driving, we can consider that the high maintenance of cognitive function (MMSE) may be occurred because they enjoy driving, have a wider range of activities, and increase the possibility of multitasking through choosing to drive themselves rather than alternative transportation.

C. SIGNIFICANCE OF THE RESULTS OF THIS STUDY

The results of this study suggest that cognitive decline is more likely to be suppressed in the elderly who like to drive, and that they are more likely to continue social participation and improve their quality of life through driving, leading to self-actualization and community revitalization. In other words, we believe that we have suggested that it is important to design automobiles that allow the elderly to enjoy safe, secure, and comfortable transportation according to their health status, and to create opportunities for them to come to like driving through public health transportation policies that should be tailored to individuals to promote their health, taking into account the balance between the convenience of automobiles and their effects on health.

On the other hand, we cannot rule out the possibility that factors not included in this dataset, such as differences in diet, medical history, exercise habits, and residential area, as well as factors extracted from actual driving behavior rather than from questionnaires, may be confounding factors with large contributions in some of the latent classes. Therefore, we believe that it is important to integrate such factors into the analysis in order to further increase the confidence for the latent classes.

D. LIMITATIONS OF THIS STUDY

In this study, the number of latent classes in PLSA has determined based on preliminary analysis and interpretability.

TABLE 10. Top 30 factors in ascending order of the 2-dimensional compressed Euclidean distance for each of ''MMSE_slope_good'' (see upper table) and "MMSE_slope_bad" (see lower table), corresponding to the latent class $\overline{C^{(1)}}$ (for females over 60).

Therefore, it is difficult to completely remove arbitrariness, and there is a limit in universality that can be widely deployed unless a more objective method of determination is taken into account. In addition, even though it is possible in the case of document analysis to validate latent classes by separately setting up other documents that contain a limited number of words and common topics, because the target of analysis in this study is humans, the difficulty of completely covering attribute differences, such as unlimited individual and regional differences, makes it impossible to set up a separate population for validation, which limits the analysis to an understanding of the current situation. Furthermore, note that the above analysis by t-SNE is only a characterization of a small number of subjects. Therefore, it is a limitation of this study that it is impossible to say whether the above findings represent general features or not, while it is certainly possible to facilitate knowledge discovery without wasting a small number of subjects. In other words, in order to avoid simply ignoring subjects corresponding to singular values or outliers for which statistical significance is impossible to discuss, t-SNE can be a useful approach if we limit its use to actively extracting hypotheses specific to minority events, which are difficult to capture with classical statistics, by locally characterizing target variables as much as possible in terms of which factors appear in closest proximity.

As mentioned above, including in the introduction, both PLSA and t-SNE have unique advantages in terms of ease of understanding and characterizing the current state of the data, and it would be difficult to replicate them using other methods. On the other hand, as something that cannot be understood by PLSA in the first place, we cannot find a parent-child relationship to whether people drive because they are healthy, or whether they are healthy because they drive. Therefore, we believe that such findings may be found complementary by utilizing a Bayesian network, for example, together with a data set that can track changes over time for a longer period of time.

V. CONCLUSION

In this study, to facilitate knowledge discovery about the relationship between driving and health among the elderly, we have analyzed large-scale data obtained from a set of health and driving surveys using the machine learning methods PLSA and t-SNE for males and females over 60. The PLSA results show that there are broad categories of latent classes that can be interpreted as having a generally high or low level of health. In particular, a relatively positive

TABLE 11. Top 30 factors in ascending order of the 2-dimensional compressed Euclidean distance for each of ''MMSE_slope_good'' (see upper table) and "MMSE_slope_bad" (see lower table), corresponding to the latent class $\overline{C^{(4)}}$ (for females over 60).

"MMSE_slope	A flag variable representing subjects who drive every day and have a non-negative	0	2.383599945
good"	MMSE slope for 4 years $(2016-2019)$		
A369	Y16 <cognitive function=""> MMSE score (0-30 points) [-] "2"</cognitive>	0.000491672	2.383618621
A329	Y17 <heel bone="" density="" test="">T-score derived from OSI [-] (for osteoporosis</heel>	1.379916785	2.51596913
	diagnosis) "Abnormal"		
A198	$Y18$ <blood examination=""> Hemoglobin [g/dL] (for anemia diagnosis) "Abnormal"</blood>	3.829541164	2.912351789
A299	Y17 <blood examination=""> Creatinine [mg/dL] (for kidney diagnosis) "Abnormal"</blood>	4.952151346	2.947806606
A707	Y16 <health questionnaire=""> SF-36y2 score (0-100 points) [-] : RP $">=70$ and <80"</health>	0.713313291	2.976768398
A1070	Y19Car <driving questionnaire=""> Scenes where you have felt better while driving</driving>	3.020868491	3.034915438
	"None"		
A963	Slope <pulmonary (spirometry)="" function="" testing=""> $FEV1.0\%G$ [%] (for obstructive</pulmonary>	5.43481484	3.081396834
	pulmonary disease diagnosis) " \geq =1.51 and <6.77"		
A810	Slope <cognitive function=""> MMSE score (0-30 points) $[-1$ ">=0.1 and <0.3"</cognitive>	0.827016039	3.187840189
A537	Y19 <health questionnaire=""> SF-36$v2$ score (0-100 points) [-1: SF $v=60$ and <70$v=60$</health>	1.129453493	3.290428257
A708	Y16 <health questionnaire=""> SF-36$v2$ score (0-100 points) [-]: RP $">=80$ and <90"</health>	5.442325467	3.295596216
A490	Y19 <health questionnaire=""> SF-36v2 score (0-100 points) [-] : PF $">=40$ and <50"</health>	1.476945995	3.295720326
A931	Slope <blood examination=""> Fischer's ratio $[-]$ (for amino acid diagnosis) ">=-0.19</blood>	4.208461526	3.356408379
	and ≤ 0.1 "		

TABLE 11. (Continued.) Top 30 factors in ascending order of the 2-dimensional compressed Euclidean distance for each of ''MMSE_slope_good'' (see upper table) and "MMSE_slope_bad" (see lower table), corresponding to the latent class $C^{(\bf 4)}$ (for females over 60).

relationship is found between driving and health. In addition, the t-SNE results show that the factors characterizing subjects who drive every day but maintain or decrease cognitive function (MMSE) are more clearly differentiated in the relatively low health class. In particular, ''I like driving'' is found to be a notable related factor characterizing the high maintenance of cognitive function. This finding has been effectively obtained because of a detailed analysis while handling items that take the Kansei (sensitivity) into account. Our future works include examining fewer qualitative decision rules for the number of latent classes, clarifying more detailed dependencies between driving and health based on changes over time, and increasing confidence in our findings on the overall features and specific characteristics between driving and health by measuring and integrating data on actual driving behavior, not just on questionnaires. In order to strongly promote healthy longevity in the future, we believe that it is an important theme to provide cars that stimulate the Kansei (sensitivity) and make driving enjoyable, while facilitating knowledge discovery through integrated data analysis that incorporates further relevant factors and longer-term data.

APPENDIX

A. OVERVIEW OF PLSA

In this appendix, we give an overview of PLSA [\[17\]. L](#page-44-16)et the data

$$
A = \begin{bmatrix} n(d_1, w_1) & \cdots & n(d_1, w_M) \\ \vdots & \ddots & \vdots \\ n(d_N, w_1) & \cdots & n(d_N, w_M) \end{bmatrix}
$$
 (11)

consist of an $N \times M$ matrix based on the co-occurrence frequency $n(d, w) \in \{0, 1, 2, \ldots\}$ for pairs of documents (corresponding to samples representing subjects in this study) $d \in D = \{d_1, \ldots, d_N\}$ and words (corresponding to factors representing survey items in this study) *w* ∈ $W = \{w_1, \ldots, w_M\}$, associated with topics (latent variables) $z \in Z = \{z_1, \ldots, z_K\}$. Denote the probability that each document d is chosen as $P(d)$, the conditional probability that each topic *z* is chosen given document *d* as $P(z|d)$, and the conditional probability that each word *w* is chosen given topic *z* as $P(w|z)$. Then, the simultaneous probability $P(d, w)$ of each document *d* and word *w* is denoted by

$$
P(d, w) = P(d) P(w|d) = P(d) \sum_{z \in Z} P(w|z) P(z|d). (12)
$$

This can be rewritten as

$$
P(d, w) = \sum_{z \in Z} P(z) P(d|z) P(w|z).
$$
 (13)

Using this, the parameters $P(d|z)$, $P(w|z)$ and $P(z)$ are obtained by maximizing the log-likelihood function

$$
L = \sum_{d \in D, w \in W} n(d, w) \log P(d, w) \tag{14}
$$

according to the following EM algorithm.

1) INITIALIZATION $(t = 0)$

The initial values of $P(d|z)$, $P(w|z)$ and $P(z)$ are generated by uniform random numbers.

2) E-STEP
$$
(t \geq 0)
$$

$$
P(z|d, w) = \frac{P(z) P(d|z) P(w|z)}{\sum_{z' \in Z} P(z') P(d|z') P(w|z')}.
$$
 (15)

3) M-STEP (*t* ≥ 0)

$$
P(d|z) = \frac{\sum_{w \in W} n(d, w) P(z|d, w)}{\sum_{d' \in D, w \in W} n(d', w) P(z|d', w)},
$$

\n
$$
P(w|z) = \frac{\sum_{d \in D} n(d, w) P(z|d, w)}{\sum_{d \in D, w' \in W} n(d, w') P(z|d, w')},
$$

\n
$$
P(z) = \frac{\sum_{d \in D, w \in W} n(d, w) P(z|d, w)}{\sum_{d \in D, w \in W} n(d, w)}.
$$
 (16)

TABLE 12. List of factors $w \in C^{(1)}_w$ $w \in C^{(1)}_w$ $w \in C^{(1)}_w$ corresponding to (1) and [\(2\)](#page-9-2) in Fig. [4.](#page-14-0)

TABLE 13. List of factors $w \in C^{(2)}_w$ $w \in C^{(2)}_w$ $w \in C^{(2)}_w$ corresponding to [\(1\)](#page-9-1) and (2) in Fig. [5.](#page-15-0)

TABLE 14. List of factors $w \in C^{(3)}_w$ corresponding to [\(1\)](#page-9-1) and [\(2\)](#page-9-2) in Fig. [6.](#page-16-0)

4) TERMINATION CONDITION $(t \geq 1)$

Compute the log-likelihood function $L = L[t]$ and the error rate $E = |(L[t] - L[t-1]) / L[t]| (t \ge 1)$ for the iteration number $t = 0, 1, 2, \ldots$ of E-step and M-step. Under a sufficiently small threshold $\varepsilon > 0$, if $E \leq \varepsilon$ then terminate, otherwise repeat E-step and M-step.

B. OVERVIEW OF T-SNE

In this appendix, we give an overview of t-SNE [\[18\]. S](#page-44-17)uppose we have the data

$$
X = [x_1, \ldots, x_m]
$$
 (17)

consisting of an $n \times m$ matrix with *mn*-dimensional (highdimensional) vectors $x_i = [x_{i1}, ..., x_{in}]^T$ (*i* = 1, ..., *m*).

TABLE 15. List of factors $w \in C^{(4)}_w$ corresponding to [\(1\)](#page-9-1) and [\(2\)](#page-9-2) in Fig. [7.](#page-17-0)

Consider embedding each x_i as a dimension-compressed vector $y_i = [y_{i1}, \dots, y_{in'}]^T$ in an *n*'-dimensional (lowdimensional) space through a transformation into the conditional probabilities representing certain similarities based on the Euclidean distances among x_i ($i = 1, \ldots, m$).

Using a Gaussian distribution, in the high-dimensional space, define the conditional probability $p_{j|i}$ and the simultaneous probability *pij* by

$$
p_{j|i} = \frac{\exp(-\|x_i - x_k\|^2 / 2\sigma_i^2)}{\sum_{k \neq i} \exp(-\|x_i - x_k\|^2 / 2\sigma_i^2)},
$$

$$
p_{ij} = \frac{p_{j|i} + p_{i|j}}{2n},\tag{18}
$$

where $p_{i|i} = 0$ and $p_{ii} = 0$. The value of each σ_i , which corresponds to the standard deviation of the Gaussian distribution, is obtained through a binary search to fit the following predefined perplexity:

$$
perplexity = Perp (Pi) = 2H(Pi),
$$
 (19)

where

$$
H(P_i) = -\sum_j p_{j|i} \log_2 p_{j|i} \tag{20}
$$

TABLE 16. List of factors $w \in C_w^{(5)}$ corresponding to [\(1\)](#page-9-1) and [\(2\)](#page-9-2) in Fig. [8.](#page-18-0)

TABLE 17. List of factors $w \in C^{(1)}_w$ $w \in C^{(1)}_w$ $w \in C^{(1)}_w$ corresponding to (1) and [\(2\)](#page-9-2) in Fig. [9.](#page-19-0)

TABLE 18. List of factors $w \in C_w^{(2)}$ $w \in C_w^{(2)}$ $w \in C_w^{(2)}$ corresponding to [\(1\)](#page-9-1) and (2) in Fig. [10.](#page-20-0)

is the Shannon entropy. In addition, using a Student t-distribution with one degree of freedom, in the lowdimensional space, define the simultaneous probability *qij* by

$$
q_{ij} = \frac{\left(1 + \|\mathbf{y}_i - \mathbf{y}_j\|^2\right)^{-1}}{\sum_{k \neq l} \left(1 + \|\mathbf{y}_k - \mathbf{y}_l\|^2\right)^{-1}},\tag{21}
$$

where q_{ii} = 0. Using the Kullback–Leibler divergence, define the cost function *C* by

$$
C = KL (P||Q) = \sum_{i \neq j} p_{ij} \log \frac{p_{ij}}{q_{ij}}.
$$
 (22)

TABLE 19. List of factors $w \in C_w^{(3)}$ corresponding to [\(1\)](#page-9-1) and [\(2\)](#page-9-2) in Fig. [11.](#page-21-0)

Then, each y_i that minimizes C is obtained by using a gradient descent method. That is, for each iteration $t = 2, 3, \ldots, t_{\text{max}}$, compute the gradient

$$
\frac{\partial C}{\partial y_i} = 4 \sum_j (p_{ij} - q_{ij}) (y_i - y_j) (1 + ||y_i - y_j||^2)^{-1}
$$
 (23)

and update the *t*-th solution
$$
Y^{(t)} = [y_1, ..., y_m]
$$

with

$$
Y^{(t)} = Y^{(t-1)} + \eta \frac{\partial C}{\partial Y^{(t-1)}} + \alpha \left(t \right) \left(Y^{(t-1)} - Y^{(t-2)} \right), \tag{24}
$$

TABLE 20. List of factors $w \in C_w^{(4)}$ corresponding to [\(1\)](#page-9-1) and [\(2\)](#page-9-2) in Fig. [12.](#page-22-0)

where t_{max} , η and $\alpha(t)$ represent the predefined values named the maximum number of iterations, the learning rate and the momentum, respectively. The initial value $Y^{(1)} = Y^{(0)}$ is generated by a normal random number with a mean 0 and a standard deviation 10−⁴ .

C. COMPONENT FACTORS APPEARING IN [\(1\)](#page-9-1) AND [\(2\)](#page-9-2) OF FIGS. [4](#page-14-0) TO [13](#page-23-0)

In this appendix, we list component factors (binary variables) appearing in [\(1\)](#page-9-1) and [\(2\)](#page-9-2) of Figs. [4](#page-14-0) to [13](#page-23-0) as Tables [12](#page-34-0) to [21](#page-43-0) in text format, respectively.

TABLE 21. List of factors $w \in C_w^{(5)}$ corresponding to [\(1\)](#page-9-1) and [\(2\)](#page-9-2) in Fig. [13.](#page-23-0)

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