Survey on Social Simulation and Knowledge Extraction from Simulation Results - Application for Constructing Life Planning Support Frameworks -

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Abstract—**Asset formation for the retirement generation is a common issue around the world and has been widely discussed in various countries. We begin this paper by surveying the research on asset formation and life planning. Then, we show a data-driven life planning support framework based on social simulation. Based on the data and simulation results, this framework is intended to run simulations based on customer attribute data and to evaluate and validate measures for customers' retirement assets. The social simulation model is constructed based on finance theory. Machine learning methods are used for the analysis of customer features and evaluation of the policy measures. Moreover, the simulation results are represented by experience mapping techniques. The following are the key findings: our framework 1) allows for effective discussion of measures to avoid the depletion of retirement assets and 2) allows simulation results to be widely interpreted and shared not only by model developers and analysts but also by decision-makers and frontline personnel.**

Keywords- social simulation; knowledge extraction; financial retirement planning; experience mapping techniques

I. INTRODUCTION

In this paper, we first survey the research on asset formation and life planning. Then, we show a life planning support framework built based on data and social simulation. This paper extends our prior paper presented at eKNOW 2021 [1].

Asset formation for the retirement generation is a common issue around the world and has been widely discussed in various countries [1; 2]. As national, individual, and social measures, various measures are being discussed, such as raising the retirement age, establishing assets at a young age, and reducing spending. There has been little discussion, however, about asset withdrawal, and there is room to expand and modernize basic research and analysis to better consider current issues. To address this issue, it is important to have a simulation framework that enables effective discussion of measures to avoid depletion of retirement assets. In addition, it is desirable to have a method that allows simulation results to be widely interpreted and shared not only by model developers and analysts, but also by decision makers and those in charge in the field as shown in the survey section later.

Our framework is designed to run simulations based on data of customer attributes and to evaluate and validate measures for customers' retirement assets based on the data and simulation results. The social simulation model is built on finance theory [3]. Machine learning methods are also used for the analysis of customer characteristics and the evaluation of policy measures [4; 5]. Furthermore, we use experience mapping techniques to represent the simulation results extending prior research [6].

Here, this framework is intended to be used by financial planners and retail strategy planners who create life plans for their customers.

As a exemplification of the proposed framework, this paper presents a specific case study that focuses on customer asset formation and withdrawal for the retirement generation.

The structure of this paper is as follows: Section II introduces related work, Section III describes the proposed methodology, and Section IV explains the social simulation model we used. Section V provides applications, and in Section VI, we summarize the results.

II. RELATED WORK

In this section, we begin with a survey of asset formation and life planning (*A*). We begin by discussing portfolio selection theory among households, which is relevant to the issues addressed in this paper. Then, we examine surveys and research on asset formation and withdrawal in the postretirement period. Next, we introduce previous research on social simulation methods, the computer simulation methods used in this paper (*B*). There have been reports of research using social simulation to solve problems in social science. Finally, we mention the experience mapping techniques (*C*). The formal description of those techniques will be oriented in this paper for knowledge extraction from simulation results.

A. Asset Formation and Life Planning

1) Lifetime portfolio selection

Under several assumptions, the optimal ratio of risky asset holdings in the classical theory of household portfolio selection is determined by the expected rate of return on risky assets, the interest rate on safe assets, the variance of the rate of return on risky assets, and the relative risk aversion [7; 8]. On the other hand, it has been pointed out that many households do not hold any risky assets [9], suggesting the existence of mechanisms that cannot be explained by classical theory alone.

Bodie et al. [10] argued that the optimal risk asset ratio is high for young people with large human assets because they can cope with risks such as falling prices by increasing labor supply and working extra hours. Chen et al. [11] considered life insurance in addition to human asset allocation and investigated the optimal allocation of safe assets and life insurance when investment opportunities change over time.

On the other hand, empirical approaches suggest that households' investment in risky assets increases with age and then declines. Ameriks & Zeldes [12] showed that the allocation to equities over the life cycle follows a "mountainous" trend, using the United States (U.S.) as an example. This trend is common not only in the U.S. but also in other developed countries. In Japan, the stock allocation ratio peaks later than in the U.S. and Europe: 1) it reaches its maximum in the late 50s and 60s and 2) investment in stocks does not decrease substantially even after retirement. This implies that many Japanese households enter the stock market only after they get their retirement money [13].

2) Asset Formation and Withdrawal focused on Postretirement

Asset formation for the retirement generation is a common issue around the world [2] and has been widely discussed in various countries [14]. In the U.S., the empirical benchmark is a fixed withdrawal rate of 4% of initial assets [15]. On the contrary, some critics argue that a fixed withdrawal rate is inefficient [16] and that "rules" should be set to vary the withdrawal rate and amount [17; 18].

In Japan as well, various surveys, studies, and calculations have been conducted regarding the formation and withdrawal of assets after retirement [19; 20; 21]. The Financial System Council's estimate [20] calculated the required amount of funds to be withdrawn for an elderly couple and unemployed household in a simplified manner as follows:

Monthly net income and expenditure (−55,000 yen/month) × 30 years ≒ ⊿20 million yen

This estimation was easy to understand and drew national attention. On the other hand, it is based on the average household income and expenditure (deficit of approximately 55,000 yen per month) of an unemployed elderly couple whose only source of income is the pension and does not take into account each individual's income and expenditure situation and lifestyle. Other studies have focused on investment strategies in asset formation and estimated the probability of depletion using annual time series paths of asset prices by Monte Carlo simulation [21]. While this study takes into account the risky asset investment strategy as well as the macroenvironment (inflation rate), it does not explicitly address various individual characteristics. Furthermore, there is a study that simulates the future depletion rate of financial assets in real terms using macroeconomic data such as the amount of financial assets and disposable income of individuals [19]. While this study takes into account an individual's income and asset class, it does not address risky asset investment or inflation rates.

Kikuchi and Takahashi constructed a social simulation model that expresses asset formation and withdrawal before and after retirement [3]. They presented a simulation of the customer's asset situation at a future point in time, taking into account asset succession and price fluctuations of risky assets based on individual questionnaire data concerning asset formation and withdrawal before and after retirement [4; 5]. In this paper, we construct a life planning support framework based on the simulation model.

B. Social Simulation Method

A social simulation is an approach in the social sciences that uses computer simulation to analyze social phenomena [22; 23]. In recent years, many studies have been grounded in real data in the field of social simulation [24; 25].

Yamada et al. [24] proposed a method that utilizes actual data and agent simulation to solve problems in business and industry. They classified various types of airport behavior using real-world data, and they used agent-based simulation to successfully reproduce congestion conditions when new equipment was installed at Fukuoka Airport in Japan [25]. Many such analyses have also been reported, e.g., corporate behavioral analysis via modeling based on finance theory [26; 27].

Detailed analyses such as Yamada et al.'s can facilitate onsite decision-making and are expected to greatly contribute to efficient decision-making in both social and economic activities. Understanding and interpreting the model structure and simulation results, on the other hand, are not limited to model developers and analysts but may be conducted widely by decision-makers and field staff related to management and administration. As a result, having a methodology for extracting knowledge and insights from simulation log data as well as a framework for sharing the extracted knowledge and insights among stakeholders is critical.

C. Experience Mapping Techniques

In the design of products and services, "design thinking" has been attracting attention [28; 29; 30]. As observational methods, experience mapping techniques such as persona–scenario technique [31], customer journey map [32], empathy map, and so on [33] are used to uncover users' latent needs.

It is believed that the use of the experience mapping techniques has the effect of standardizing the perceptions among stakeholders, such as developers and marketers of products and services. This method may be an effective means of facilitating communication among stakeholders, which is a problem in the analysis of social simulation results, as discussed in the previous section.

1) Persona–scenario technique

In the field of marketing, human–computer interaction, and interaction design, "persona" is widely used as a method to support customer-oriented product and service design [6; 31; 34]. Persona marketing refers to the creation of an image of a person based on clear and specific data about that real person. The use of personas leads to improving the quality of decision-making regarding the design of products and services.

Table I provides a sample of a persona comparison poster [34]. In this paper, referring to the previous literature [6], we analyze and write down the results of our social simulation in the form of the persona comparison poster.

TABLE I. EXAMPLE OF PERSONA COMPARISON POSTER [34]

Name	Tanner	Colbi	Austin	Preston
Age	9	7	12	3
Tagline	The tenacious tinkerer	The creative child	The active competitor	The precious preschooler
Personal Computer (PC) location	PC in family room only	Uses a PC in the family room and sometimes her brother's PC, when he lets her	Has a PC in his bedroom, rarely uses the PC in the family room	Uses the PC in the office with Mom
Internet Connection	Dial-up	Broadband	Broadband	Dial-up
PC/Internet Activity	Gaming, web surfing, some school work/re-search	Chatting with friends, surfing the web, school work/research, arts/crafts	Gaming, web surfing, tracking sports schedules, tracking favorite athletes, some school work/re-search	Educational games and light entertainment deemed worthy by Mom

2) *Other experience mapping techniques*

Other experience mapping techniques include empathy map, customer journey map, service blueprint, and so on [33] (Fig. 1). The customer journey map [32] is the most basic and widely used visual description method in service design, and it is used in this paper. We write down the results of our social simulation in the form of a customer journey map, as we did with the previous persona–scenario technique.

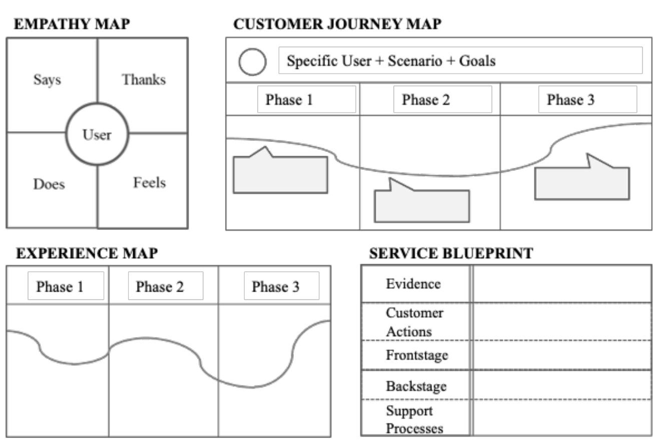

Figure 1. Various experience mapping techniques [33]

III. METHODOLOGY

In this section, we outline our proposed life planning support framework for retirees based on data and social simulation. This framework is based on our previous studies [3; 4; 5; 6].

A. *Outline*

Our framework is designed to run simulations based on real data of customer attributes and to evaluate measures for customers' retirement assets based on the data and simulation results. Fig. 2 depicts an overview of the proposed framework, which corresponds to the concept of cyber-physical systems. Our framework consists of the following two procedures:

1) Data augmentation by social simulation: Real data and simulation logs/paths are integrated and treated as augmented customer attribute data (See I in Fig. 2).

2) Knowledge extraction: From the above-augmented data, knowledge about the sustainability of assets for each customer is extracted using machine learning methods and experience mapping techniques (See II in Fig. 2).

In detail, the real data is a large survey data containing various attributes of customers (Section V-A). In this paper, we use cross-sectional data from individual questionnaires. Then, the social simulation model is constructed based on finance theory [36; 37] (Section IV). The model addresses asset formation in retirement, taking into account asset succession and risky asset price fluctuations. Based on the model, simulations are run to perform what-if analysis of the customer's asset's sustainability (Section V-D). The proportion of asset depletion in future, as obtained from the simulation results, is treated as augmented data for the original questionnaire data. Moreover, machine learning methods [38; 39] are used for the analysis of customer features (Section V-C) and evaluation of the policy measures (Section V-E). Finally, the results are represented using experience mapping techniques [34; 32] (Section V-F and G).

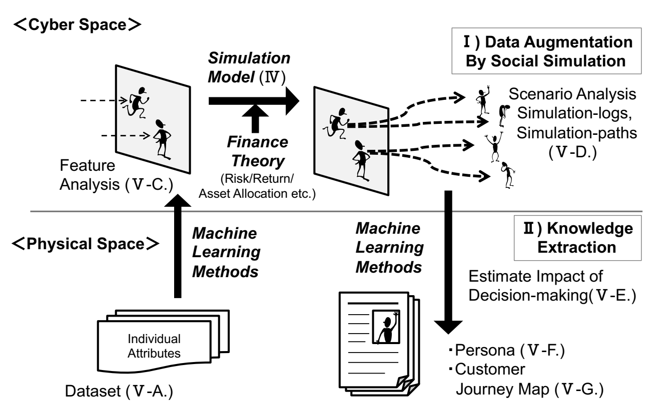

Figure 2. Basic Architecture of the proposed Life Planning Support framework

Here, this framework is intended to be used by financial planners and retail strategy planners who create life plans for their customers.

B. The Usefulness of the Proposed Framework

a) Perspectives on the advanced analysis of the sustainability of personal assets:

Regarding asset depletion, many studies have analyzed macrostatistical data, e.g., the amount of financial assets and disposable income [19]. Furthermore, based on market data, the effect of price fluctuations on owned assets and asset depletion has been examined [21]. However, previous studies only used actual data to express some of the characteristics of individuals. In short, traditional analysis has frequently focused on people with specific characteristics to simulate asset depletion scenarios. Additionally, in those studies, ad hoc analysis was required for each person to examine possible measures to be taken.

On the other hand, the proposed framework is capable of handling various attributes of individuals. Individual investment preferences and the amount of assets they will inherit in the future, for example, have rarely been addressed in previous studies. In addition, our framework can comprehensively and semiautomatically specify potential life planning measures for each customer. The framework will allow for effective discussion of measures to avoid the depletion of retirement assets.

b) Perspectives on visualization of simulation results

As mentioned in Section II-B, it is important to have a methodology for extracting knowledge and insights from simulation log data and a framework for sharing the extracted knowledge and insights among stakeholders.

In the proposed method, simulation paths and logs, which are simulation results, are classified using machine learning methods and then visualized using experience mapping methods. By describing the results using those methods, a) the results can be compared in a graphical format, and b) the perspectives of customers and users can be expressed. This will allow the results to be widely interpreted and shared, not just by model developers and analysts, but also by decision-makers and frontline personnel. Furthermore, it has the potential to improve communication among stakeholders during the analysis and sharing of simulation results.

C. Limitation of the Proposed Framework

One of the limitations of this analysis is that there is arbitrariness on the part of the modeler as to which attributes of the targeted individuals are reflected in the simulation model. Furthermore, in the process of extracting knowledge from simulation results, the analyst's discretion in selecting which results to focus on and describe formally may exist. Of course, the social simulation model used must be an accurate representation of the real world.

IV. Social Simulation Model

In this section, we describe the social simulation model used in this paper. This model is based on our previous studies [3; 4; 5].

A. Outline

As an example of the proposed framework, we show a simulation of the customer's asset situation at a future point in time, taking into account asset succession and price fluctuations of risky assets based on individual questionnaire data concerning asset formation and withdrawal in old age.

We constructed a computer simulation model that expresses asset formation and withdrawal before and after retirement (Fig. 3).

Each actor in the model has a specific asset balance at a certain age. According to the actor's status, each actor has both regular income and expenditure (cash inflow and outflow) and unexpected income and expenditure (depending on life events) (before and after retirement). Each actor's characteristics are expressed statistically. In addition, by manipulating the attributes of the actors, what-if analysis can be performed to examine responses to the implementation of a particular policy or decision-making.

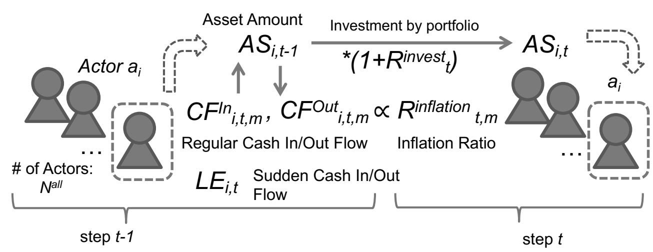

Figure 3. Conceptual diagram of a simulation model

The assets held by each actor include cash, deposits, and risk assets. Risk assets are fully invested in a portfolio of traditional assets and provide returns according to the risk of the portfolio. Furthermore, regular income and expenditure are adjusted to account for inflation. The external environment is comprised of the portfolio's risk–return profile, the inflation rate, and the variance of each, as described further below.

B. Actor

Let A be the set of actors and let $\#A = N^{all}$. Actor a_i has the following attributes in step t of the simulation and inflation scenario m: age $age_{i,t}$, retirement age $age_i^{retired}$, cash and deposit balance $CA_{i,t}$, risk asset balance $RA_{i,t}$, cash inflow $CF^{In}_{i,t,m}$, cash outflow $CF^{Out}_{i,t,m}$, cash flow from life event $LE_{i,t}$, and total asset balance $AS_{i,t} = CA_{i,t} + RA_{i,t}$.

$$A = \{a_i = (i, age_{i,t}, age_i^{retired}, CA_{i,t}, RA_{i,t}, CF^{In}_{i,t,m}, CF^{Out}_{i,t,m}, AS_{i,t}, LE_{i,t})\}$$

Here, age is expressed as follows.

$$age_i \in \{age_{i,0}, age_{i,0} + 1, \ldots, age_i^{retired}, \ldots\}$$

Then, the simulation time step, a single step represents one year in real-time.

C. External Environment

The return and inflation rate of portfolio j are generated in time series by Monte Carlo simulation as follows, where the number of trials is K.

The portfolio return (annual) is expressed as

$$R^{invest}_t = X_{1,t}\,\sigma + \mu.$$

The inflation rate (annual) is given as

$$R^{inflation}_{t,m} = (\rho X_{1,t} + \sqrt{(1-\rho^2)}\, X_{2,t})\, \sigma^{inflation} + \mu^{inflation}_m.$$

Here, σ is the risk of portfolio, μ is the expected return rate of portfolio, $\sigma^{inflation}$ is the standard deviation of the inflation rate, $\mu^{inflation}_m$ is the expected inflation rate at scenario m, ρ is a correlation coefficient between portfolio and the inflation rate. $X_1, X_2 \sim N(0,1)$, and $cov\,[X_1, X_2] = 0$.

The cumulative value IRC of the inflation rate referred to as cumulative inflation rate, is expressed as

$$IRC_{t,m} = IRC_{t-1,m}(1 + R^{inflation}_{t,m}),\ IRC_{0,m} = 1.$$

D. Cash Inflow/Outflow

Retirement cash inflows and outflows CF in step t are determined by considering the asset class to which actor i belongs and the cumulative inflation rate as follows:

$$CF^{In}_{i,t,m} = CF^{In}_{i,0,m}\,(1 + IRC_{t,m}),$$
$$CF^{Out}_{i,t,m} = CF^{Out}_{i,0,m}\,(1 + IRC_{t,m})$$

To keep the estimated possibility of withdrawal conservative, the net cash flow before retirement is set to zero.

E. Asset Formation and Withdrawal Rules

The cash and deposit balance and risk asset balance in each simulation step are varied according to the following rules. This expresses the preferential withdrawal of highly liquid cash and deposits at the asset withdrawal stage.

if $CA_{i,t} + CF^{In}_{i,t,m} - CF^{Out}_{i,t,m} >= 0$

then

$CA_{i,t+1} = CA_{i,t} + CF^{In}_{i,t,m} - CF^{Out}_{i,t,m} + LE_{i,t}$

$RA_{i,t+1} = RA_{i,t}\,(1 + R^{invest}_t)$

else

$CA_{i,t+1} = CA_{i,t} + LE_{i,t}$

$RA_{i,t+1} = RA_{i,t}\,(1 + R^{invest}_t) + CF^{In}_{i,t,m} - CF^{Out}_{i,t,m}$

F. Asset Depletion Rate

For the K trials, the number of times the asset balance becomes negative at age τ and inflation scenario m is denoted $K^{shortage}$, and the asset depletion rate, hereafter referred to as the depletion rate, is expressed as

$$R_{i,m,\tau}{}^{shortage} = K_{i,m,\tau}{}^{shortage}/K.$$

V. APPLICATIONS

In this section, we show applications of our framework.

A. Dataset: Individual Attributes

We use the individual questionnaire data from the "Awareness Survey on Life in Old Age for Before and After Retirement Generations" conducted by the MUFG Financial Education Institute [40]. The survey was aimed at men and women aged 50 and up. The survey area was Japan, and there were 6,192 valid responses. This questionnaire thoroughly investigated each individual's asset status (current asset balance and expected income/expenditure in old age), planned asset inheritance amount, investment stance, and outlook for old age, and so on.

The basic statistics of the questionnaire on age, current asset balance, asset balance to be inherited, and percentage of risky assets held are shown in Table II [5].

TABLE II. BASIC STATISTICS OF QUESTIONNAIRE (abstract)

Statistics	Question matters (extract)			
	Age	Asset Balance Current	Asset Balance to be Inherited	Risk Asset Holding Ratio
Mode	70	30-50 m yen	0 m yen	0%
Median	64.5	15-20 m yen	0 m yen	0%
Max	91	100- m yen	100- m yen	90%-
Min	50	0-1 m yen	0 m yen	0%
First Quartile	57	7-8 m yen	0 m yen	0%
Third Quartile	71	30-50 m yen	0 m yen	20-30%
# of Samples	6,192	6,192	5,342	6,068

B. Model Implementation and Simulation Environment

The social simulation model presented in Section IV was implemented using the python language; the versions of python and jupyter notebook are 3.8.5 and 6.1.4, respectively. The simulation environment was MacBook Air (13-inch, 2017), processor: Intel Core i7 2.2GHz dual core, memory: 8GB 1600 MHz DDR3, OS: macOS Big Sur ver 11.4.

C. Feature Analysis of Individual Questionnaire Data

Based on the above individual questionnaire data, we established several patterns of "possible person attributes" through segmentation by feature analysis [4; 5].

TABLE III. QUESTIONNAIRE ITEMS USED FOR FEATURE ANALYSIS

Item	Question matters
Attributes	Age, Sex, Household composition, etc.
Financial Statue	Stock data: Asset Balance(Current), Asset Balance(to be Inherited), etc. Flow data: Regular Cash In/Out Flow, etc.
Risk Preference	Investment Experience, Risk Asset Holding Ratio, etc.

For the individual data, the following items were targeted (Table III), and clustering was performed using the k-means method [38]. The number of clusters was set to five in this case based on the results of the elbow chart and silhouette analysis, which are frequently used to determine the number of clusters. There were 4,592 samples available for all items in the data.

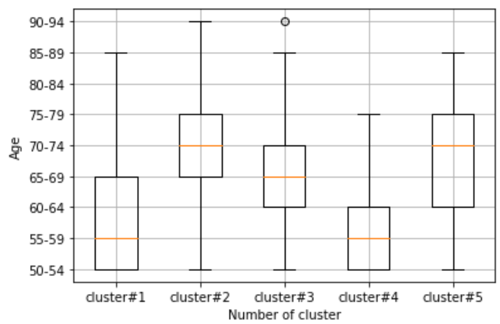

Figure 4. (a) Distribution of Age Groups for Each Cluster

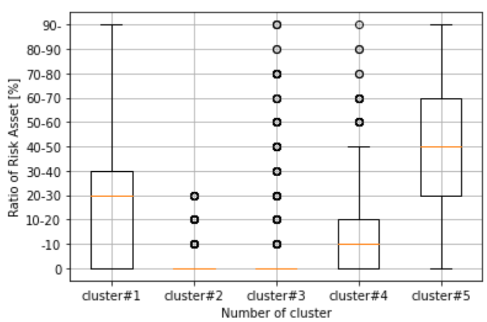

Figure 4. (b) Distribution of Risk Assets Holding Ratio for Each Cluster

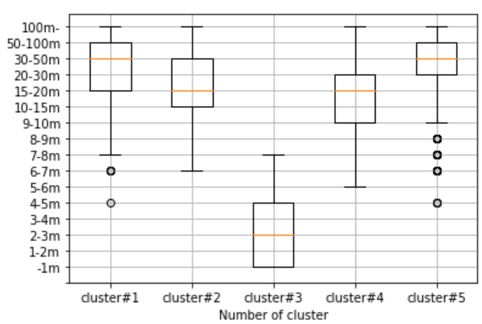

Figure 4. (c) Distribution of Current Financial Asset Balances for Each Cluster

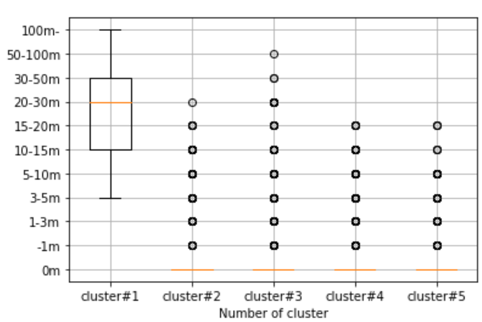

Figure 4. (d) Distribution of Financial Assets to be Inherited for Each Cluster

From the obtained clustering results (clusters #1–#5), Figs. 4(a)–4(d) show the distribution of the answers to typical questionnaire items for each cluster as a box plot.

The median age group *age* was 55–59 years for clusters #1 and #4, 65–69 years for cluster #3, and 70–74 years for clusters #2 and #5, as shown in Fig. 4(a).

The median holding ratio of risk assets R^{risk} was 0% for clusters #2 and #3, 0%–10% for cluster #4, 20%–30% for cluster #1, and 40%–50% for cluster #5, as shown in Fig. 4(b).

The median current balances of financial assets FA^{now} was 2–3 million yen for cluster #3, 15–20 million yen for clusters #2 and #4, and 30–50 million yen for clusters #1 and #5, as shown in Fig. 4(c).

The median balance of financial assets to be succeeded FA^{future} was zero for clusters #2–#5 and 20–30 million yen for cluster #1, as shown in Fig. 4(d).

Risk asset holding ratio, i.e., investment preferences of individuals and the amount of assets they will inherit in the future have rarely been addressed in previous studies. So, our proposed framework is capable of handling various attributes of individuals.

D. Asset Formation Simulation: Depletion Rate Based on Individual Questionnaire Data

Using the social simulation model referred to in Section IV, we performed computer simulations of asset formation and withdrawal based on the cluster set described in the previous section (Table IV). Then, we estimated the asset depletion status of representative people who were typified by the individual questionnaire data [4; 5].

Here, the annual income and expenditure CF^{net} for each asset class was set from macro statistics data [41] according to the current balance of financial assets. The correspondence with the model described in Section IV is expressed as follows.

$$N^{all} = 5 \text{ (cluster\#1–\#5)},\quad CA_{i,0} = FA^{now}_i * (1 - R^{risk}_i),\quad RA_{i,0} = FA^{now}_i * R^{risk}_i,\quad CF^{Out}_{i,0,m} - CF^{In}_{i,0,m} = CF^{net}_i$$

TABLE IV. Setting Attributes for Each Cluster

# of cluster	Attributes			
	age	FA^{now}	FA^{future}	R^{risk}
#4	57	17.5 m yen	none	5%
#1	57	40.0 m yen	25.0 m yen	25%
#3	67	2.5 m yen	none	0%
#2	72	17.5 m yen	none	0%
#5	72	40.0 m yen	none	45%

We also define the parameters as follows: $age_i^{retired} = 60$, the actor's age at which a life event occurs: $age_{i,t'} = 70$, $LE_{i,t'} = FA^{future}_i * R^{future}$. Here R^{future} is the ratio of asset succession (representing the ratio of the actual balance of financial assets to be succeeded). And t' is the age at which a life event (asset succession) occurs. In this paper, the above parameters are called “Case of Making Basic Decisions.”

Other parameter settings, e.g., the portfolio’s risk–return profile and inflation rate, are shown in Table V. Note that the risk–return of the portfolio was set assuming a portfolio comprising foreign stocks and bonds [3]. The expected inflation rates were according to three patterns, i.e., (1) no inflation (0%), (2) moderate inflation (actual results for the past 30 years in Japan [42]: 0.53%), and (3) 2% inflation (monetary easing target). Here, the standard deviation of the inflation rate was the same as pattern (2), which is the actual result for the past 30 years in Japan.

TABLE V. Parameter Settings: Case of Making Basic Decisions

Item	Value
Curbing of Expenditure	Without
$age^{retired}$	60
R^{future}	100%
μ_j, σj	(6.37%, 18.0%)
$\mu_{inflation}$	{ 0.0%, 0.53%, 2.0%}
$\sigma_{inflation}$	1.26%
K	10,000

The depletion rate at age 90 and age 100 by cluster and inflation scenario is shown in Table VI [4].

TABLE VI. SIMULATION RESULT: DEPLETION RATES IN CASE OF MAKING BASIC DECISIONS

# of cluster	Depletion rates by inflation scenario					
	(1) No inflation		(2) Moderate inflation		(3) 2% inflation	
	Age: 90 (%)	Age: 100 (%)	Age: 90 (%)	Age: 100 (%)	Age: 90 (%)	Age: 100 (%)
#4	34	75	60	86	93	98
#1	0	0	0	0	0	0
#3	100	100	100	100	100	100
#2	0	34	0	94	0	100
#5	0	0	0	1	0	5

The depletion rate of cluster #4 increases according to the high inflation scenario, and the depletion rate of cluster #1 is zero in all scenarios. However, keep in mind that the simulation was based on the assumption that financial assets are inherited expectedly. In all scenarios, the depletion rate of cluster #3 was 100%. Cluster #2, similar to cluster #4, exhibits a high depletion rate in a high inflation scenario. Asset depletion was observed with a low probability in the limited case of high inflation at the age of 100 for cluster #5.

E. Estimate of Impact of Various Decisions on Depletion Rates

We conducted a what-if analysis in which the actors made various decisions to control asset depletion. By calculating feature importance using machine learning methods, we examined the effectiveness of these decisions [4].

We analyzed decisions that have a large effect on the depletion rate for the clusters set shown in Table IV. We considered the following decisions: 1) portfolio’s risk–return profile, 2) retirement age, 3) curbing of expenditure, and 4) asset succession.

- *What-if analysis and calculating feature importance*

The parameter settings are shown in Table VII. Here, the assumed decision-making patterns are as follows. The annual income and expenditure CF^{net} by asset class has two patterns, i.e., with and without curbing of expenditure. The retirement ages are 60, 65, and 70 years. There are three asset succession patterns, i.e., 100%, 50%, and 0%, and four portfolio risk setting patterns, i.e., 18%, 12%, 6%, and 0% (returns are set according to the corresponding figures, i.e., 6.37%, 4.68% 2.87%, and 0.01%; see reference [3]). For each cluster set, 72 decision-making patterns were generated. Note that the other parameters were the same as those shown in Table V. In this paper, the above parameters are called “Case of Making Various Decisions.”

TABLE VII. Parameter Settings: Case of Making Various Decisions

Item	Value
Curbing of Expenditure	{Without, With}
$age^{retired}$	{60, 65, 70}
R^{future}	{100%, 50%, 0%}
μ_j, σj	{(6.37%, 18.0%), (4.68%, 12.0%), (2.87%, 6.0%), (0.01%, 0.0%)}
$\mu_{inflation}$	{ 0.0%, 0.53%, 2.0%}
$\sigma_{inflation}$	1.26%
K	10,000

Here, we focus on the status of asset depletion and nondepletion at the specific age for each cluster. The importance of variables that classify depletion and nondepletion for each cluster was calculated using the random forest method [39] (Fig. 5).

For cluster #4, the importance of the portfolio risk setting was relatively high. Cluster #1 showed the highest importance in order of asset succession ratio, portfolio risk settings, and curbing of expenditure. For clusters #3 and #2, the importance of curbing expenditure was extremely high. In addition, cluster #5 had the highest importance in order of portfolio risk setting and curbing of expenditure.

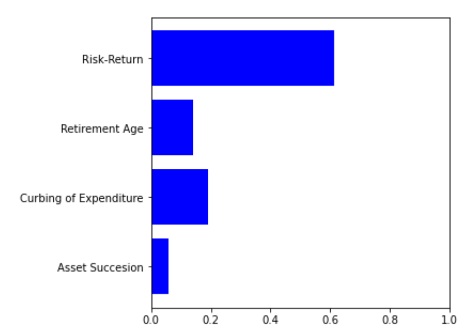

Figure 5. (a) Variable Importance for Each Cluster (#4)

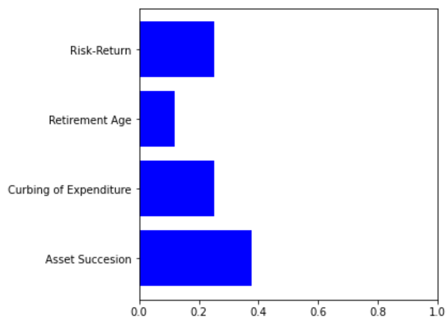

Figure 5. (b) Variable Importance for Each Cluster (#1)

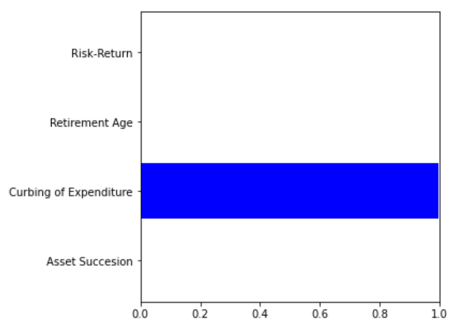

Figure 5. (c) Variable Importance for Each Cluster (#3)

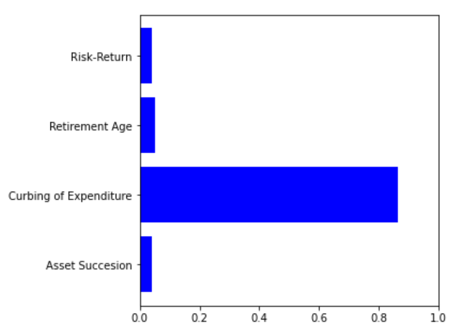

Figure 5. (d) Variable Importance for Each Cluster (#2)

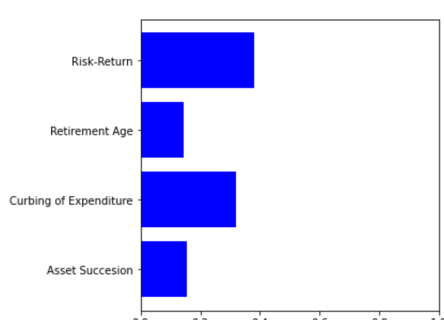

Figure 5. (e) Variable Importance for Each Cluster (#5)

- *Possible Effective Decisions for Each Cluster*

Next, from the results shown in Table VII and Fig. 5, we considered measures each individual can take to reduce the depletion rate (Table VIII).

Cluster #4: High depletion rate in the high inflation scenario. Appropriate risk-taking for inflation hedging and increasing retirement age could be effective measures [Fig. 5(a)].

Cluster #1: The depletion rate is low in all scenarios. However, this simulation assumed that financial assets are inherited as expected. Regarding variable importance, the ratio of asset succession was the highest [Fig. 5(b)], and appropriate and steady asset succession is important.

Cluster #3: The depletion rate was extremely high in all scenarios. Note that curbing expenditure was the only option among the decisions compared in this paper [Fig. 5(c)]. For cluster #3, drastic measures are required, e.g., curbing expenditure and expanding social security.

Cluster #2: The depletion rate was high in the moderate and high inflation scenario at age 100. Here, curbing expenditure is considered an effective action [Fig. 5(d)].

Cluster #5: Here, the depletion rate was high in a limited scenario. As a countermeasure, it is conceivable to take appropriate risks [Fig. 5(e)]. This cluster showed a high proportion of risk assets (Table IV), and it is important to avoid excessive risk to prevent price fluctuations (decreases) of the held risk assets.

Table VIII summarizes examples of actions each cluster could take to reduce the depletion rate. In addition to the results of the previous section (Table VI), our framework is capable of comprehensively and semiautomatically specifying possible life planning measures for each customer [4].

TABLE VIII. ASSUMED COUNTERMEASURES FOR EACH CLUSTER

# of cluster	Countermeasures (example)
#4	Appropriate risk taking for inflation hedging, increase retirement age
#1	Appropriate and steady asset succession
#3	Curbing expenditure, expanding social security
#2	Curbing expenditure
#5	Avoid excessive risk to prevent price fluctuations

F. Knowledge Extraction Using Experience Mapping Techniques: Persona–scenario Technique

From this section onward, the above simulation results are formally described using the experience mapping techniques. First, we use the persona–scenario technique [6; 34].

Table IX describes the contents of Tables IV, VI, and VIII. in the form of a persona comparison poster. Here, we exemplify Table IX (a) showing the moderate inflation scenario and Table IX (b) showing the 2% inflation scenario.

From the original questionnaire, attributes "Age group," "Current balances of financial assets," "Holding ratio of risk assets," and "Financial assets to be succeeded" were selected and entered as the attributes obtained by feature analysis. Furthermore, the statuses "Depletion rate at age 90" and "Depletion rate at age 100" were chosen and entered from the simulation results. In addition, effective measures to reduce the rate of depletion are described for each cluster.

The benefit of using the persona–scenario method for formal description is that it allows you to see and compare the differences in attributes and states between clusters for each simulation scenario. This limits the ability of stakeholders other than modelers and analysts to interpret simulation results.

TABLE IX. (a) PERSONA COMPARISON POSTER: MODERATE INFLATION SCENARIO

Cluster #	#4	#1	#3	#2	#5
Age group	55–59	55–59	65–69	70–74	70–74
Current balances of financial assets	15–20 m yen	30–50 m yen	2–3 m yen	15–20 m yen	30–50 m yen
Holding ratio of risk assets	0%–10%	20%–30%	0%	0%	40%–50%
Financial assets to be succeeded	0 m yen	20–30 m yen	0 m yen	0 m yen	0 m yen
Depletion rate at age 90	60%	0%	100%	0%	0%
Depletion rate at age 100	86%	0%	100%	94%	1%

TABLE IX. (b) PERSONA COMPARISON POSTER: 2% INFLATION SCENARIO

Cluster #	#4	#1	#3	#2	#5
Age group	55–59	55–59	65–69	70–74	70–74
Current balances of financial assets	15–20 m yen	30–50 m yen	2–3 m yen	15–20 m yen	30–50 m yen
Holding ratio of risk assets	0%–10%	20%–30%	0%	0%	40%–50%
Financial assets to be succeeded	0 m yen	20–30 m yen	0 m yen	0 m yen	0 m yen
Depletion rate at age 90	93%	0%	100%	0%	0%
Depletion rate at age 100	98%	0%	100%	100%	5%

G. Knowledge Extraction Using Experience Mapping Techniques: Customer Journey Map

This section provides a formal description of the simulation results using the customer journey map. Figure 6 describes the contents of Tables IV, VI, and VIII in the form of the customer journey map [32]. Here, the cases of both clusters # 4 and # 1 are illustrated.

The attributes obtained by feature analysis from the original questionnaire are described in the "User profile" section. In addition, the "Scenario and Goal" section describes simulation scenarios and results (future state for each cluster). Furthermore, the entire period was divided into four phases based on the state of the actors in the simulation. Following that, we included a summary of the changes in the balance of assets held as well as the status of actors in each phase.

The state of the actor is described in the balloon in the figure and is based on the simulation result. Discussions between stakeholders, on the other hand, can be used to describe the thoughts and feelings of expected customers and users. Thus, the formal description of simulation results using a customer journey map has the advantage of allowing the customer or user's perspective to be expressed as well.

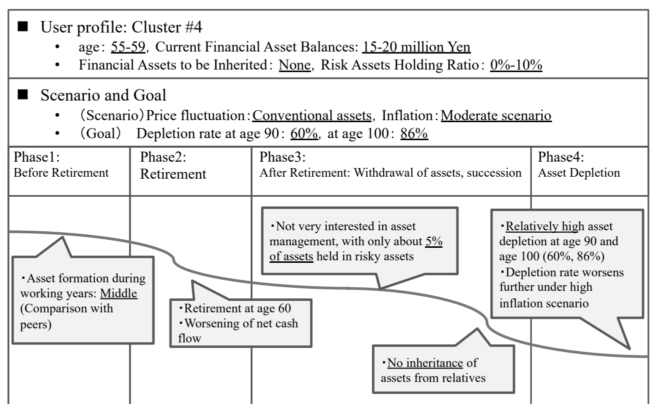

Figure 6. (a) Customer Journey Map: Cluster #4

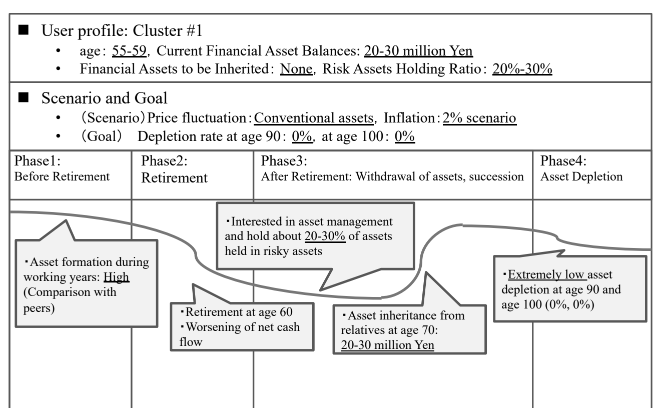

Figure 6. (b) Customer Journey Map: Cluster #1

VI. Concluding Remarks

In this paper, we first surveyed the research on asset formation and life planning. Then, we showed a life planning support framework built based on data and social simulation.

This framework was designed to run simulations based on data of customer attributes and to evaluate and validate measures for customers' retirement assets based on the data and simulation results. The social simulation model was built using finance theory. Machine learning is also used for customer feature analysis (k-means method) and policy measure evaluation (random forest method). Furthermore, the simulation results were represented using experience mapping techniques (persona-scenario technique and customer journey map).

As a exemplification of the proposed framework, we showed a specific case study that focuses on customer asset formation and withdrawal for the retirement generation. As the data source of customer attributes, we used large-scale individual questionnaire data.

The main findings are as follows: 1) our framework could effectively discuss measures to avoid the depletion of retirement assets. In addition, our framework is capable of dealing with a wide range of individual characteristics (Fig. 4) and specifying comprehensively and semiautomatically possible life planning measures for each customer (Tables VI and VIII). 2) Using our framework, simulation results can be widely interpreted and shared not only by model developers and analysts but also by decision-makers and the frontline personnel. By describing the simulation results using experience mapping techniques, a) the results could be compared in an overview (Table IX), and b) the viewpoints of customers and users can be expressed (Fig. 6).

Limitation of the proposed framework are: 1) there is arbitrariness on the part of the modeler as to which attributes of the targeted individuals are reflected in the simulation model, 2) in the process of extracting knowledge from simulation results, the analyst's discretion in selecting which results to focus on and describe formally may exist, 3) the social simulation model used must be an accurate representation of the real world.

By using the proposal system, financial planners and retail strategic planners could obtain knowledge feedback directly related to life planning. It is expected that financial institutions will also be able to provide detailed advice and counsel.

Future work would be to examine formal description methods for interpreting and sharing simulation results.

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