Eliciting psychosocial factors using search query data to improve conceptual modeling: A case study of Japanese food supply chains during the COVID-19 pandemic

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Abstract

To effectively address environmental and social issues such as climate change and sustainability, it is necessary to build a conceptual model that allows stakeholders with different perceptions and values to reach a consensus and make decisions toward achieving the desired goals. The construction of conceptual models using participatory modeling methods involves exploring psychosocial factors that cause stakeholders to act, and physical variables such as people's activities and environmental events. However, many of these processes rely heavily on qualitative data obtained from interviews. This results in a lack of modeling transparency and excessive complexity. Psychosocial factors also tend to be treated as exogenous variables. In this study, we propose a participatory modeling method that uses qualitative interview data and quantifiable keyword search data to explore the psychosocial factors that should be incorporated into the conceptual model. These psychosocial factors are key components of stakeholders' mental models. This method identifies characteristic search queries by considering changes in the quantity and time series of search queries, and combines interview data and distinct search queries to create a causal loop diagram in collaboration with stakeholders. Incorporating psychosocial factors as endogenous variables into the conceptual model increases the model's reliability and enables an understanding of the potential for complex nonlinear dynamics across social and environmental dimensions. We examined the applicability of this process using a case study that explored changes in eating habits and intervention points in Tokyo before and after the COVID-19 pandemic.

Keywords

Search query data; participatory modeling; conceptual modeling; mental model; eating habits

1. Introduction

In recent years, research on decision making has gained increasing attention in environmental and social science fields related to sustainability. In these sustainability-related fields, stakeholders from different backgrounds and cultures come together across organizations to make decisions. However, the greater the differences among the stakeholders and decision makers in terms of their socioeconomic status, backgrounds, and values, the more they differ in their perceptions of the current system. This can lead to decision-making conflicts and reduce the effectiveness of the decision-making process. In addition, a decision-making process involving different perceptions of the current system can lead to problems whereby one stakeholder's decision can have

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Cite this article as:
Komaki, A., Sato, M., Nakajima, M., & Kohtake, N.
Eliciting psychosocial factors using search query data to improve conceptual modeling: A case study of Japanese food supply chains during the COVID-19 pandemic
Socio-Environmental Systems Modelling, vol. 7, 18751, 2025, doi:10.18174/sesmo.18751

Socio-Environmental Systems Modelling
An Open-Access Scholarly Journal
http://www.sesmo.org

unintended negative consequences for other stakeholders. It is generally acknowledged that better decisions are reached with less conflict and more chance of success when stakeholders, that is, those who will be bearing the consequences of the decision, drive the decision-making process.

A growing number of studies have employed collaborative learning approaches to develop conceptual models, aiming to build consensus among stakeholders from different backgrounds and cultures (Argent et al., 2016; Elsawah et al., 2017; Pluchinotta et al., 2021, 2022; Robinson, 2008). Conceptual models are designed to enhance understanding of the structure and behavior of a system. They also aim to incorporate mental models, which include psychosocial factors that influence stakeholders' perceptions and actions within that system. These mental models are crucial for understanding how stakeholders interpret and interact with the system. Effective conceptual models are robust and elegant, incorporating a limited number of variables that represent key aspects of stakeholders' mental models. These focused models are often more effective for conceptual modeling than models built with numerous complex variables (Argent et al., 2016; Asif et al., 2023). Participatory modeling approaches are primarily used to facilitate collaborative learning of these conceptual models among stakeholders.

While building conceptual models using participatory modeling is effective, incorporating information derived from mental models into the structure of conceptual models faces challenges. Traditional interview methods used to elicit mental models primarily yield qualitative data. Integrating this data into the quantitative structure of conceptual models is often difficult. These qualitative methods are subject to various biases and limitations, including the selection of interviewees, the framing of questions by interviewers, and time constraints. Consequently, the psychosocial factors represented in mental models are frequently treated as exogenous variables, thus limiting their integration into the core structure of conceptual models.

In this study, we focused on information-seeking behavior (Sarkar et al., 2020; Chang & Huang, 2020; Chisty et al., 2021) that expresses people's implicit needs and proposed a participatory modeling method that combines search query data and interview data to elicit the participants' mental models. We combined qualitative data from interviews with quantitative data from an analysis of search queries to generate causal loops among stakeholders. Then, we applied this method to a case study investigating the impact of the COVID-19 pandemic on the Japanese food supply chain and explored the conceptual models that must be considered to make the Japanese food supply chain sustainable in the future.

The rest of the paper is organized as follows. Section 2 presents a review of the existing literature on conceptual modeling and mental model extraction processes. Section 3 presents our proposed participatory modeling method using search query data, which is then applied in Section 4. More specifically, we apply this methodology to a case study involving changes in eating habits in Japan caused by the COVID-19 pandemic. Section 5 discusses how our proposed method contributes to the literature. Section 6 concludes and offers suggestions for future research.

2. Literature review

In environmental and social science fields related to sustainability, numerous studies have developed conceptual models as a basis for common understanding in decision making. This study focused on conceptual models created by stakeholders in a participatory manner. The following sections review the relationship between conceptual models and mental models, as well as methods for eliciting mental models, ranging from traditional approaches to emerging technologies.

2.1 Study area

In decision-making research within the environmental and social sciences, conceptual models and mental models play crucial roles. While they are conceptually interrelated, they possess distinct characteristics.

A mental model is an individual's internal representation of the real world, based on the person's experiences, knowledge, and values (Forrester, 1961, 1992; Jones et al., 2011). Doyle and Ford (1998) define a mental model as "a relatively enduring and accessible, but limited, internal conceptual representation of an external system" (p. 19). These models are subjective, may differ between individuals, and often have an implicit nature. Additionally, mental models contain psychosocial factors that drive decision making.

Conceptual models, by contrast, represent a shared understanding of a specific system or problem (Robinson, 2008). According to Gupta et al. (2012), a conceptual model is "a summary of the abstract state of knowledge about the structure and function of the system." Conceptual models are typically created through collaboration among multiple stakeholders, integrating individual mental models and forming a consensus (Etienne et al., 2011; Villamor et al., 2019).

In socio-environmental modeling, the process of constructing conceptual models is complex. Each stakeholder possesses their own mental model. Through participatory modeling, these individual mental models are shared. As Voinov et al. (2018) point out, the participatory modeling process is "a purposeful learning process for action that engages the implicit and explicit knowledge of stakeholders to create formalized and shared representations of reality (p. 233)." Finally, through discussion and consensus building, a conceptual model is formed.

In this process, individual mental models function as inputs for the conceptual model, and the final conceptual model represents the group's shared understanding. As Argent et al. (2016) emphasize, effective conceptual models need to be evaluated from the perspectives of "scope," "logic," "connections," "flow and sequence," and "limits, thresholds, and conditionals."

2.2 Methods for eliciting mental models in socio-environmental modeling

In socio-environmental modeling, the elicitation of mental models is a crucial step in constructing conceptual models. Traditional elicitation methods encompass various approaches.

Interviews are widely used to obtain detailed perspectives from individual stakeholders. Elsawah et al. (2017) highlight that interviews "provide a deep understanding of subjective views or mental models about how the system functions, with opportunities for clarification, follow-up questions, and feedback" (p. 132). They also note that, while interviews can be time-consuming, they help build rapport with stakeholders and offer a "safe" environment for less experienced modelers.

Surveys are useful for gathering information from a broader group of stakeholders. Smith et al. (2022) demonstrated this by conducting structured intercept interviews, a method that involves briefly approaching individuals in a public setting to conduct face-to-face surveys at the point of experience, using a mobile app in urban blue spaces. This method allowed efficient collection of data from people using paths along a canal, providing insights into factors influencing space utilization.

Group model building (GMB) (Purwanto et al., 2019; Scott et al., 2016) is a participatory method that facilitates dialogue among stakeholders and helps form a common understanding. Voinov and Bousquet (2010) describe GMB as a process originating from the Netherlands, initially developed for business applications, later adopted for various applications such as natural resource management. They explain that GMB "involves a group of people, stakeholders, in one or more sessions to build the conceptual model" and is "considered as a process of building mutual understanding, defining terms and notions, and sharing experiences" (p. 1269). The method often employs visual tools like Causal Loop Diagrams (CLDs) and may be extended using systems dynamics tools (Stave, 2010). CLDs are one way to represent conceptual models and visually represent relationships between variables in a system; they provide a framework for seeing interrelationships and patterns of change rather than isolated elements (Bosch & Nguyen, 2015). For example, arrows show causal relationships, with "S" (same) or "O" (opposite) indicating whether variables move in the same or opposite directions. The delay symbol (||) represents a time lag between cause and effect in the system. CLDs, then, are useful for understanding system dynamics, building consensus among stakeholders, and identifying leverage points (Bosch & Nguyen, 2015).

However, while these methods are helpful in revealing individual mental models and integrating them to construct conceptual models, they have limitations. As Pluchinotta et al. (2022) point out, these techniques face "the difficulty of eliciting stakeholders' system boundary perceptions." For instance, it can be challenging to capture implicit knowledge or values that are not explicitly expressed.

To address these limitations, new methods have been proposed. For example, Luštický and Štumpf (2021) and Saaty (2008) used multi-criteria decision analysis to identify leverage points of tourism destination competitiveness. Smith et al. (2022) utilized social network analysis to analyze factors influencing the use of urban blue spaces. These methods attempt to structure and quantify mental models. Furthermore, studies are emerging, such as that conducted by Huang et al. (2022), that explore people's values using social media data. These new approaches aim to address aspects that traditional methods struggle to capture.

The present study proposes a new approach using search behavior data to complement existing methods, aiming for more comprehensive mental model elicitation. This approach sought to capture what Sarkar et al. (2020) describe as "people's implicit information needs."

2.3 Eliciting mental models using search query data

Many studies have explored the potential of search behavior data for understanding people's mental models and decision-making processes (Choi & Varian, 2012; Marchionini, 2006; Sarkar et al., 2020; Wilson, 1999). Search engines have become a primary source of information for many individuals, making search query data a valuable resource for inferring people's intentions, concerns, and knowledge structures (Choi & Varian, 2012).

The use of search query data has shown promise in various fields, particularly in predicting and monitoring health-related trends. For instance, Ginsberg et al. (2009) demonstrated that search query trends could be used to detect influenza epidemics in near real-time. Similarly, Kurian et al. (2020) utilized Google Trends data to analyze public interest and concerns related to COVID-19 across different states in the United States.

In the context of mental model elicitation, search behavior data offer several advantages. They provide a non-intrusive method of capturing people's implicit needs and interests, which may not be easily articulated in interviews or surveys (Sarkar et al., 2020). Furthermore, the temporal nature of search data allows researchers to track changes in mental models over time, potentially revealing shifts in perceptions and priorities during significant events or crises.

However, the integration of search behavior data into participatory modeling approaches for mental model elicitation is still in its early stages. There is a need for methodologies that can effectively combine the quantitative insights from search data with the qualitative depth of traditional elicitation methods (Marchionini, 2006; Sarkar et al., 2020). Such integration could provide a more comprehensive understanding of stakeholders' mental models, particularly in complex socio-environmental systems where perceptions and behaviors evolve rapidly.

3. Participatory modeling method using search query data

This chapter presents a novel participatory modeling method that integrates search query data with stakeholder interview data. This method aims to elicit mental models of stakeholders in systems where consensus is required and to explore the mental models that should be incorporated into conceptual models.

3.1 Overview of the method

The primary objective of this method is to combine qualitative data from interviews with quantitative data acquired from an analysis of search query data to generate a causal loop in conjunction with the participants. This approach allows for the incorporation of people's hidden implicit needs that are difficult to elicit from interviews alone. Indeed, search queries reflect information-seeking behavior that often precedes action (Chang & Huang, 2020; Sarkar et al., 2020).

The method consists of four main steps (see Figure 1):

1. Identifying physical events: In this step, interviews are conducted with stakeholders to identify physical events, and core system variables are selected for shared understanding.
2. Finding characteristic search query data: In this step, representative search queries are extracted using database search tools, focusing on the time period and location of interest.
3. Sharing the causal structure: In this step, CLDs are created with stakeholders, based on both the selected system variables and the search query data.

4. Clustering search queries and naming categories: In the final step, system variables and related search queries are connected with lines, and the psychosocial factors they have triggered are inferred as category names.

These steps are designed to be implemented through a series of workshops involving various stakeholders, which facilitates a collaborative learning process about the system in question.

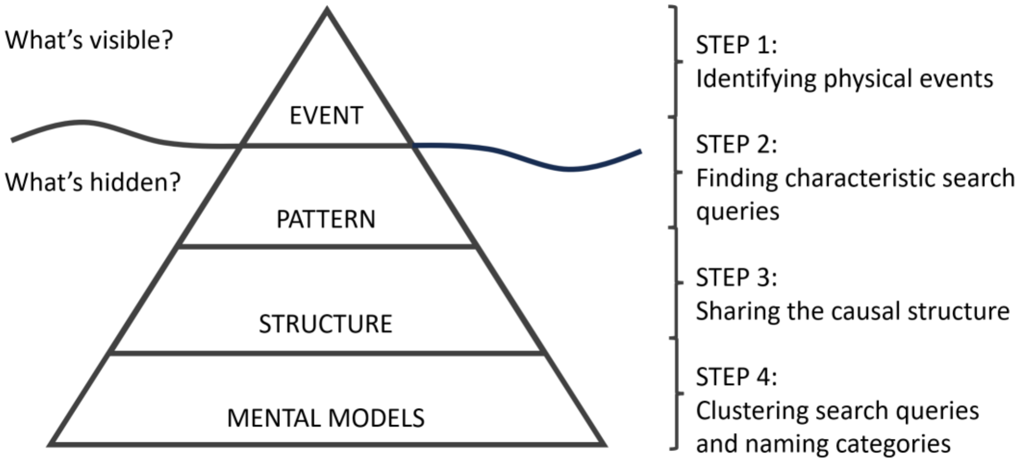

Figure 1: Participatory modeling method using search query data.

3.2 Detailed steps of the method

Each of the four steps, as mentioned above, are implemented through a four-stage workshop involving various stakeholders. Participants include stakeholders and experts with diverse backgrounds related to the research theme. Through the process, psychosocial factors are identified that are key components of stakeholders' mental models and that, importantly, influence their actions.

This section provides a comprehensive explanation of each step in the participatory modeling method using search query data. These steps are designed to be applicable across various contexts and research areas.

STEP 1: Identifying physical events
This initial step focuses on engaging stakeholders to identify physical events related to the theme or problem and to determine core system variables. Facilitators conduct semi-structured interviews, either in groups or individually, depending on the participants' circumstances. These interviews are aimed at eliciting stakeholders' perceptions of changes over time in a given theme or problem, its various elements, and the relationships among those elements.

On the basis of the gathered information, facilitators organize the potential physical events recognized by stakeholders and extract system variables that will form the foundation for shared understanding. To align stakeholders' perceptions of these events, the team collaboratively collects quantitative data from sources such as government statistics, open data, and analytical reports. Through facilitated dialogue, core system variables are then selected. Following existing research (Schaffernicht, 2017), the number of selected variables is typically limited to 15–20 per stakeholder group. These variables are categorized into endogenous variables (which stakeholders can directly manipulate) and exogenous variables (which cannot be directly manipulated). To enhance the identification and visualization of system variables in causal loops, the System Design Canvas (Komaki et al., 2021) is utilized, which effectively illustrates relationships and promotes a deeper understanding of system dynamics.

STEP 2: Finding characteristic search queries
In this step, patterns in search behavior are investigated using keyword search analysis techniques. In this approach, the concept of public attention is applied to search query data, focusing on two main patterns of search volume trends: pulse-type and sequential-type.

The pulse-type pattern aligns with the “issue-attention cycle” theory proposed by Downs (1972), which describes how public attention to a specific issue rises sharply and then gradually declines. This pattern is characterized by a sudden spike in search volume followed by a rapid decrease (Figure 2), often observed with keywords related to sudden events or short-lived trends.

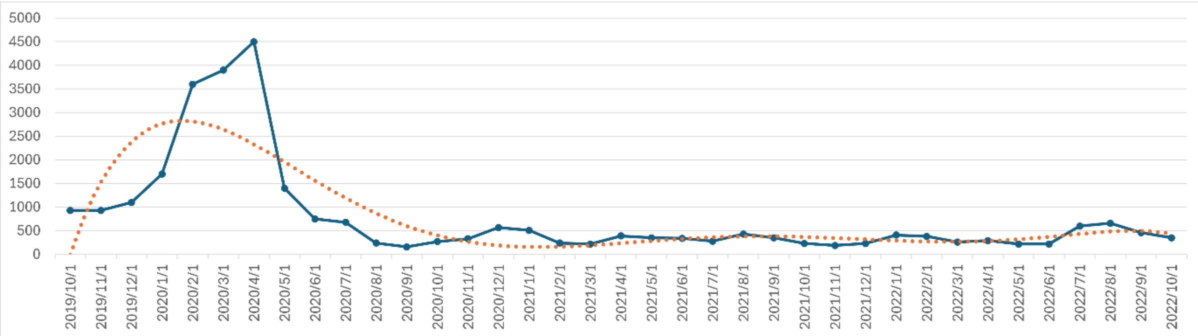

Figure 2: Example of a pulse-type search query (“Enhance immunity”) obtained from DS.INSIGHT. The vertical axis indicates the number of unique users in Japan who searched for the keyword. The red dotted line is a polynomial curve that approximates the data. Note that these keywords are English translations of the original Japanese search queries analyzed in the study.

The sequential-type pattern corresponds to the “punctuated equilibrium model” discussed by Holt and Barkemeyer (2012) in the context of media coverage of sustainability issues. This pattern shows a gradual increase or decrease in search frequency over time (Figure 3), reflecting a more sustained change in public interest or awareness.

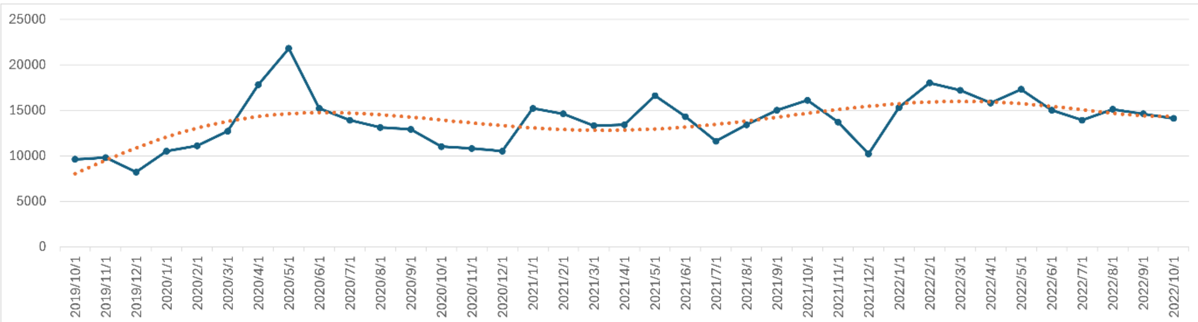

Figure 3: Example of a sequential-type search query (“What is a quick dinner to make?”) obtained from DS.INSIGHT. The vertical axis indicates the number of unique users in Japan who searched for the keyword. The red dotted line is a polynomial curve that approximates the data. Note that these keywords are English translations of the original Japanese search queries analyzed in the study.

We chose to focus on these two patterns because they represent distinct ways in which public attention and interest evolve. The pulse-type pattern helps identify issues that generate sudden, intense interest but may not sustain long-term attention. The sequential-type pattern, by contrast, allows tracking of more gradual shifts in public consciousness or ongoing concerns.

To extract representative search queries, database search tools that can analyze search trends over specific time periods and locations are used. Then, the extracted keywords are classified into pulse-type (Figure 2) or sequential-type (Figure 3) according to their search volume trends, and considering factors such as the speed of change, duration of interest, and overall pattern of the search volume curve.

STEP 3: Sharing the causal structure

In this step, facilitators use the GMB method to collaboratively create CLDs with stakeholders. Both the system variables identified in Step 1 and the search queries gathered in Step 2 serve as inputs for developing these diagrams. As shown in Figure 4, system variables are connected with causal links, and "S" (same direction) or "O" (opposite direction) is noted near the arrows to create causal loops. When there is a time lag between cause and effect in the system, a delay symbol (||) is added.

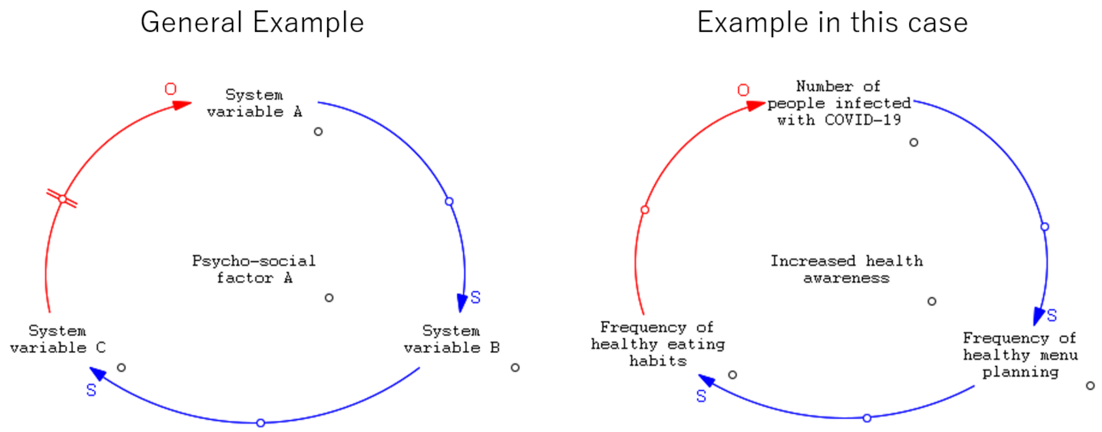

Figure 4: How to write causal loops and psychosocial factors: The left side illustrates that psychosocial factor A drives the feedback loop created by System variables A, B, and C. The right side demonstrates a feedback loop driven by increased health awareness. As shown in Figure 4, this psychosocial factor drives a feedback loop that includes the number of COVID-19 infections, frequency of healthy menu planning, and healthy eating habits. "S" near the arrows indicates "Same direction," while "O" indicates "Opposite direction." These notations represent the nature of causal relationships between variables. The delay symbol "||" represents a time lag between cause and effect in the system.

CLD workshops can be conducted either in person or online, depending on the circumstances. A variety of digital tools are available for constructing causal loops, including system dynamics software such as Vensim® (Garcia, 2018) and online data visualization platforms like Kumu (https://kumu.io/). The choice of tools should depend on participants' familiarity with the technology and the complexity of the model being developed.

Throughout the workshops, stakeholders work together to map out relationships between variables, constructing a shared visual representation of the system's structure. This collaborative effort helps to uncover hidden feedback loops, delays, and other system dynamics that may not be obvious at first glance. The resulting CLD serves as a shared conceptual model of the system, promoting mutual understanding among stakeholders.

STEP 4. Clustering search queries and naming categories

In this step, connections are established between system variables and relevant search queries, and related keywords are clustered into meaningful categories (see Figure 5). These connections were collaboratively drawn through facilitated discussions in the workshops, in which participants interpreted which search queries people were likely to have used when experiencing or responding to those physical events. Context, timing, and thematic relevance were considered during this process. It is essential to recognize how real-world stakeholders' awareness and interests shape physical events and to derive appropriate category names. In this study, these categories are defined as psychosocial factors.

Pluchinotta et al. (2022) emphasize the importance of classifying system variables identified in participatory workshops into meaningful themes. This helps clarify stakeholders' mental models and supports decision making through systemic insights. In this study, we developed psychosocial factors that drive causal loops by organizing not only system variables but also search queries. The organization was based on thematic similarity and relevance, as identified through stakeholder discussions. Keywords with similar meanings or associated with similar behaviors were grouped together into categories, which were then interpreted and named as psychosocial factors.

This process fosters a deeper understanding of system dynamics, helping stakeholders identify common behavioral drivers within the system. By clarifying the role of psychosocial factors in the causal loops, the overall behavior of the system becomes more comprehensible. As shown in Figure 4, the psychosocial factors driving the causal loops are placed at the center of the corresponding CLDs.

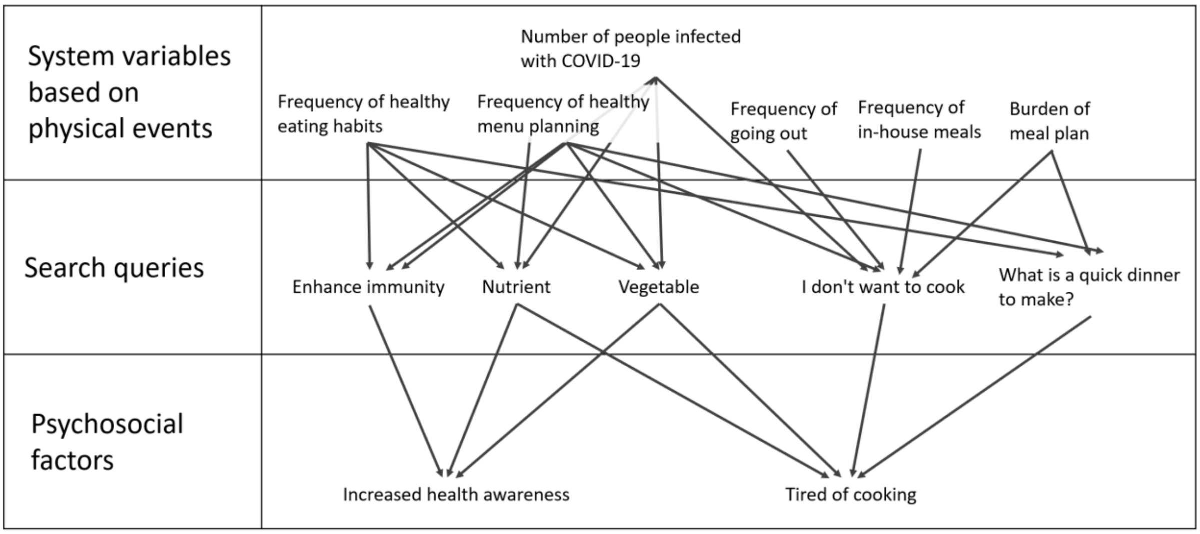

Figure 5: Derivation of psychosocial factors.

4. Case study: dietary habits during COVID-19 in Japan

4.1 Research background

4.1.1. Outreach and education

Japanese dietary habits is characterized by its nutritional balance and use of diverse ingredients. Notably, the average daily vegetable consumption is relatively high at about 280.5 grams, with an emphasis on seasonal produce (Ministry of Health, Labour and Welfare, 2019). However, recent trends in eating out and lifestyle changes have led to a decline in vegetable intake among younger generations, presenting a challenge.

Meanwhile, food waste is also a serious issue in Japan. Addressing food waste at the retail and consumer levels is a critical issue aligned with the Sustainable Development Goals (SDGs). According to data from the United Nations Food and Agriculture Organization, one-third of the world's food (approximately 1.3 billion tons) is wasted annually (Food and Agriculture Organization of the United Nations, 2019). In Japan, approximately 25 million tons of food waste is generated annually, of which edible food waste (food loss) is estimated to be about 5.7 million tons (Ministry of Agriculture, Forestry and Fisheries, 2021). The Japanese food supply chain is known for its meticulous attention to quality and safety, ensuring timely delivery and product consistency. However, these high standards, including strict expiration labeling and cosmetic criteria, can unintentionally contribute to increased food waste.

4.1.2. Impact of the COVID-19 pandemic

The COVID-19 pandemic has significantly affected the food supply chain and eating habits in Japan. Measures aimed at preventing the spread of COVID-19, such as school closures, restrictions on going out, and reduced restaurant opening hours, excluded some types of foods from the food supply chain. These foods were often discarded unless they could be diverted for other uses.

Consumer behavior also changed dramatically (Sato et al., 2023). There were instances of panic buying or hoarding following the declaration of a state of emergency, leading to food waste. However, as the situation progressed, many consumers became more cautious, reducing their food waste and, consequently, economic loss.

The impact of COVID-19 on the supply chain for some types of food has continued past the end of the pandemic. This prolonged effect necessitates a reevaluation of the food supply chain's sustainability and resilience in Japan.

4.2 Research design

This case study aimed to explore the changes in the eating habits of consumers caused by the COVID-19 pandemic in urban centers in Japan. Our primary focus was on understanding the systems related to eating habits and food consumption; we specifically examined the changes that occurred during the first and second waves of the COVID-19 pandemic in 2020.

Our main research question was: “What were the changes in food awareness and behavior in the first and second waves of the COVID-19 pandemic in 2020?”

To address this question, we established the following objectives:

1. Identify key stakeholders in the food supply chain affected by the pandemic.
2. Elicit mental models of key stakeholders and create conceptual models of food-related behaviors.
3. Explore potential intervention points to enhance healthy and sustainable eating habits for Japan’s future.

To ensure a comprehensive understanding of the food supply chain, we identified and recruited three main types of stakeholders:

1. Food-conscious consumers living in the Tokyo metropolitan area, who are attentive to health, nutrition, and the environmental impact of their food choices
2. Representatives from major supermarket chains
3. Representatives from major restaurant chains

Participants were selected using a snowball sampling method (Reed et al., 2009). This method involves asking initial participants to recommend other potential participants who meet the criteria for the study. This approach was particularly useful in identifying food-conscious consumers and reaching out to industry representatives.

Faculty members and doctoral students from Keio University and Tokyo University of Agriculture facilitated this study, all of whom possessed basic knowledge of CLDs and system dynamics. Table 1 provides information about the participants involved in each step of the participatory modeling method implemented in this study. Steps 2, 3, and 4 are listed together because they involved the same participants.

Table 1: Types and numbers of workshop participants in each step.

	Stakeholder group	Type of participants	Number of people	Total participants
Step 1	Food-conscious consumers	Working people living in Tokyo	7	10
		University professor	1	
		Facilitators	2	
	Retailers	Supermarket workers	2	6
		Part-time employee at a convenience store	1	
		University professor	1	
		Facilitators	2	
	Restaurant operators	Food Consultant	1	8
		Manager of a major diner	2	
		Part-time employees in restaurants	2	
		University professor	1	
		Facilitators	2	
Step 2 Step 3 Step 4	Food-conscious consumers	Working people living in Tokyo	1	3
		University professor	1	
		Facilitators	1	
	Retailers	Supermarket workers	1	4
		University professor	1	
		Facilitators	2	
	Restaurant operators	Manager of a major diner	2	5
		University professor	1	
		Facilitators	2	

4.3 Application of the method

This section describes the application of our participatory modeling method to the case study of food lifestyle behavior during the COVID-19 pandemic in Japan. We followed the four-step process outlined in Section 3, and adapted it to the specific context of our research.

Step 1: Identifying physical events
We conducted semi-structured interviews separately for three stakeholder groups: Food-conscious consumers, with a total of ten participants; Retailers, with six participants; and Restaurant operators, with eight participants. The interviews were conducted online, owing to COVID-19 restrictions, with each session lasting approximately 2 hours. In some cases, when participants could not be scheduled for group sessions, individual interviews were conducted to accommodate their availability.

During these interviews, participants shared their experiences and observations related to food consumption and supply chain changes during the pandemic. On the basis of the gathered information, we organized the potential physical events recognized by stakeholders and, to align their perceptions, collaboratively collected quantitative data from sources such as the household surveys disclosed by the Japanese government (Statistics Bureau of Japan, 2020) and the survey on changes in the dietary habits of Japanese people disclosed by the Ministry of Agriculture, Forestry and Fisheries (2021).

Through dialogue with stakeholders, we selected core system variables for shared understanding from the pool of shared physical events. The number of selected system variables was limited to 15–20 per stakeholder group, as suggested by existing research (Schaffernicht, 2017). These variables were categorized into endogenous variables, which stakeholders can directly manipulate, and exogenous variables, which cannot be directly manipulated. Table 2 presents a partial list of variables identified by each stakeholder group.

Table 2: Variables identified in the case study.

Stakeholder Group	Endogenous variables	Exogenous variables
Food-conscious consumers	-	Number of people infected with COVID-19
	Frequency of going out	-
	Frequency of shopping	-
	Frequency of in-house Meals	-
	Number of meals out	-
	-	Burden of meal planning
Retailers	-	Total supermarket sales
	-	Physical store sales
	-	Online store sales
	Purchase of popular brands	-
	Types of small-portion foods and meal kits	-
	-	Customer satisfaction
Restaurant operators	Assortment of takeout and delivery businesses	-
	Measures to increase sales per customer	-
	-	Restaurant sales
	-	Hours of operation
	Fixed-cost reduction measures	-
	Inventory	
	-	Number of customers in the restaurant
	-	Number of customers for takeout and delivery

Step 2: Finding characteristic search queries
In this step, we used the Yahoo! DS.INSIGHT search database (Nomura et al., 2021) to analyze people's search behavior patterns during the COVID-19 pandemic. We chose this tool because it is widely used in Japan: about 80% of Japanese internet users of all ages using Yahoo! as their search engine. DS.INSIGHT provides services that can analyze user search data, location information, and demographic data, making it particularly suitable for our research purposes.

We specified the period from October 2019 to October 2022 and extracted representative search queries that showed changes starting in April 2020, when the state of emergency was declared in Japan. Figure 2 shows the search volume trend for "Enhance immunity," a representative pulse-type search query that generated a rapid increase in searches when COVID-19 began to spread rapidly throughout Japan in early 2020. Figure 3 also shows the trend in variations in the search volume for, "What is a quick dinner to make?," a sequential-type search term for which the number of searches increased gradually as a result of the COVID-19 pandemic. Note that these keywords are English translations of the original Japanese search queries analyzed in the study. We spent approximately 2–3 hours searching for such characteristic search queries with each stakeholder group.

Yahoo! DS.INSIGHT is a paid software program, and through collaborative work between stakeholders and Keio University students who had the license, we identified representative search queries and classified them into pulse-type (i.e., search frequency jumps rapidly over a short period) and sequential-type (i.e., search frequency gradually increases or decreases). Table 3 presents some examples of characteristic search queries identified with each stakeholder group, along with their wave type and search volume range.

Table 3: Examples of extracted search queries.

Stakeholder Group	Characteristic search queries	Wave type	Minimum search volume	Maximum search volume
Food-conscious consumers	Refraining from going out	Pulse	0	110,000
	Food loss	Pulse	530	40,700
	Vegetable	Pulse	6,500	20,000
	If you have trouble making a dinner menu	Sequential	7,200	21,800
Retailers	Meal kit	Sequential	1,600	10,500
	Online supermarket	Sequential	14,500	115,000
	Home cooking	Pulse	560	14,400
	Supermarket congestion	Pulse	0	91,500
Restaurant operators	Short business hours	Pulse	0	11,900
	Catering	Pulse	5,200	32,000
	Home-delivery boxed lunch	Pulse	8,400	22,900
	Menu	Sequential	3,000	19,000

Step 3: Sharing the causal structure
Facilitators used tools like Miro and Vensim® to construct CLDs with stakeholders, following the GMB method. Using system variables associated with the physical events identified in Step 1 and incorporating search queries from Step 2, they visualized relationships between variables for over approximately 6–7 hours spread across several days. The aim of this step was to reveal feedback loops, delays, and other system dynamics that are not immediately apparent.

Step 4: Clustering search queries and naming categories
In this final step, we connected physical events identified in Step 1 with search queries found in Step 2 using lines, and divided related and similar groups of search queries into named categories. These category names were defined as psychosocial factors related to stakeholders' mental models. This process involved mixed groups of stakeholders and was conducted over multiple sessions, totaling approximately 4-5 hours of discussion.

Through dialogue with stakeholders, facilitators examined the consistency between psychosocial factors and loops in the CLDs. Table 4 presents examples summarizing the relationships between psychosocial factors, search queries, and physical events for each stakeholder. This step facilitated consensus building among participants and helped create a shared understanding of the underlying mental models of the system.

4.4 Analysis of conceptual models of eating habits in Japan during COVID-19

Here, we review the conceptual models of eating habits in Japan during the COVID-19 pandemic that were agreed upon through participatory modeling. These conceptual models represent the mental models of different stakeholder groups. Using participatory modeling, we identified four causal loops each, with psychosocial factors, for food-conscious consumers and food retailers, and five causal loops with psychosocial factors for restaurant operators.

The conceptual model for food-conscious consumers consisted of four causal loops: two balancing causal loops driven by the psychosocial factors, “Self-restraint in eating out” and “Increased health awareness,” and two reinforcing causal loops driven by separate psychosocial factors, “Using up foodstuffs” and “Tired of cooking.” During the COVID-19 pandemic, the most prominent issue for this stakeholder group was the number of COVID-19 infections, and these four causal loops were acting to decrease the number of COVID-19 infections (see Figure 6). For example, the psychosocial factor, “Increased health awareness” among food-conscious consumers influenced and drove the entire causal loop involving “Frequency of healthy menu planning,” “Frequency of healthy eating habits,” and “Number of people infected with COVID-19.” We also confirmed that the psychosocial factor, “Increased health awareness,” was related to the psychosocial factor, “Using up foodstuffs,” which reflected a desire to use up ingredients in the refrigerator.

Table 4: Examples of relationships between psychosocial factors, related search queries, and physical events for each stakeholder group.

Stakeholder Group	Psychosocial factors	Related search queries	Related physical events
Food-conscious consumers	Increased health awareness	“Enhance immunity”; “Nutrient”; “Vegetables”	“Frequency of healthy menu planning”; “Frequency of healthy eating habits”; “Number of people infected with COVID-19”
	Self-restraint in eating out	“Refraining from going out”	“Number of people infected with COVID-19”; “Frequency of going out”; “Number of meals out”
Retailers	Stay-at-home demand	“Online supermarket”; “Nest-dweller consumption”; “Home cooking”	“Total supermarket sales”; “Purchase of popular brands”; “Customer satisfaction”; “Physical store sales”; “Online store sales”
	Logistics shortage	“Supermarket shortage”; “Sold out”; “Supermarket buying up of goods”	“Total supermarket sales”; “Logistics burden”
Restaurant operators	Inability to increase the number of customers in restaurant	“Short business hours”; “Reduced business hours”	“Restaurant sales”; “Number of employees including part-timers”; “Number of customers in the restaurant”
	Increase off-premise sales	“Catering”; “Home-delivery boxed lunch”	“Restaurant sales”; “Assortment of takeout and delivery businesses”; “Number of customers for takeout and delivery”

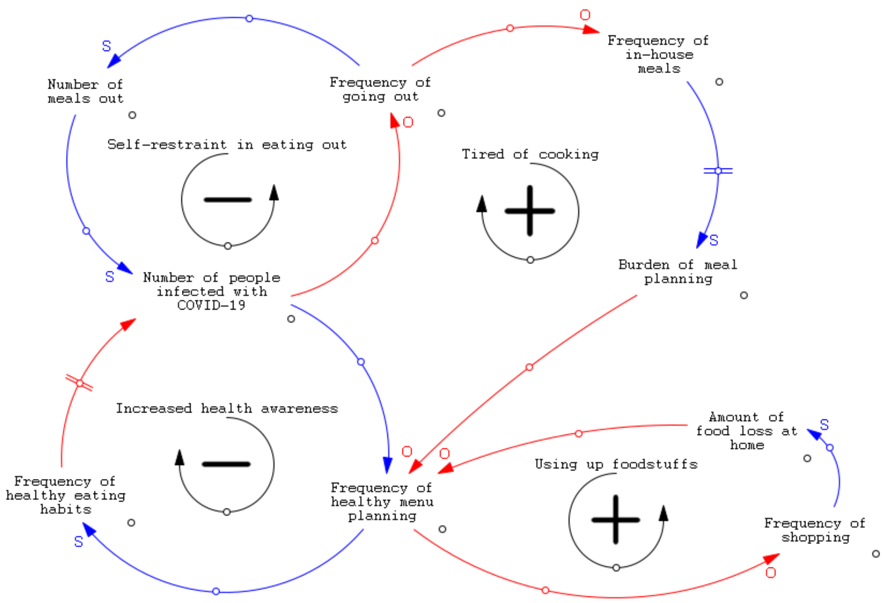

Figure 6: Causal loops perceived by food-conscious consumers. “S” near the arrows indicates “Same direction,” while “O” indicates “Opposite direction.” These notations represent the nature of causal relationships between variables. The delay symbol “||” represents a time lag between cause and effect in the system.

The conceptual model for food-conscious consumers also included two delay points. One was between “Frequency of in-house meals” and “Burden of meal planning,” and the other was between “Frequency of healthy eating habits” and “Number of people infected with COVID-19.” These were within the causal loop driven by the psychosocial factor, “Tired of cooking,” which was related to negative emotions associated with the workload of cooking at home. The “Tired of cooking” factor was classified as a sequential pattern when analyzing the search query data, and we concluded that it represented a gradual increase in negative emotions toward the workload of cooking at home.

The conceptual model for food retailers reflected an increase in the psychosocial factor, “Stay-at-home demand” (see Figure 7). In Japan, owing to the spread of COVID-19 in April 2020, many people refrained from going out, leading to an unprecedented increase in consumer behavior that emphasized “Spending time comfortably at home.” This consumer behavior was referred to as “Stay-at-home demand,” particularly in urban areas of Japan. In the conceptual model, the psychosocial factor, “Stay-at-home demand,” was shown to influence and drive the causal loop that increased “Purchase of popular brands,” enhanced “Customer Satisfaction,” boosted “Online store sales” and “Physical Store Sales,” and ultimately increased “Total supermarket sales.” However, logistics systems in Japan’s urban centers soon failed to keep up with this trend, and food retailers began to develop an awareness of “Logistics Shortage.” Looking at the search queries related to “Stay-at-home demand” and “Logistics Shortage,” we found that they were often of the pulse type, and we reached a consensus that these were a function of awareness that increased rapidly immediately after the onset of COVID-19.

Other notable points in the food retailers’ conceptual model included the identification of two psychosocial factors: “Appropriate portions of food,” which aimed to contribute to reducing the burden of home cooking for consumers, and “Operational efficiency,” which aimed to reduce the workload of employees. Causal loops driven by these factors were confirmed. When examining the search queries related to these two psychosocial factors with stakeholders, we found that they were of the sequential type, reaching a common understanding that awareness gradually increased.

We also reviewed the conceptual model of restaurant operators, who, like food retailers, raised sales-related issues (see Figure 8). Restaurant operators were the stakeholders most affected by COVID-19, with restaurant operating hours restricted from April 2020 as a result of the government’s state of emergency declaration, which led to a dramatic decrease in the number of dining customers. This conceptual model showed that restaurant operators increased their awareness of “Off-premise sales,” strengthened their takeout and delivery business activities, thereby increasing the number of these customers in an attempt to increase restaurant sales. A critical psychosocial factor of "Declining hospitality" also emerged. The causal loop strengthened where restaurant sales decreased, cost-cutting measures for restaurant operations were intensified, and employee workload increased. The psychosocial factor, "Declining hospitality," was confirmed to be of the sequential type when looking at search queries, indicating that it gradually increased. Restaurants were subject to many external constraints, such as government-imposed restrictions and disruptions to global supply chains in response to the COVID-19 pandemic. As a result, their model became more complex than those of food-conscious consumers and food retailers.

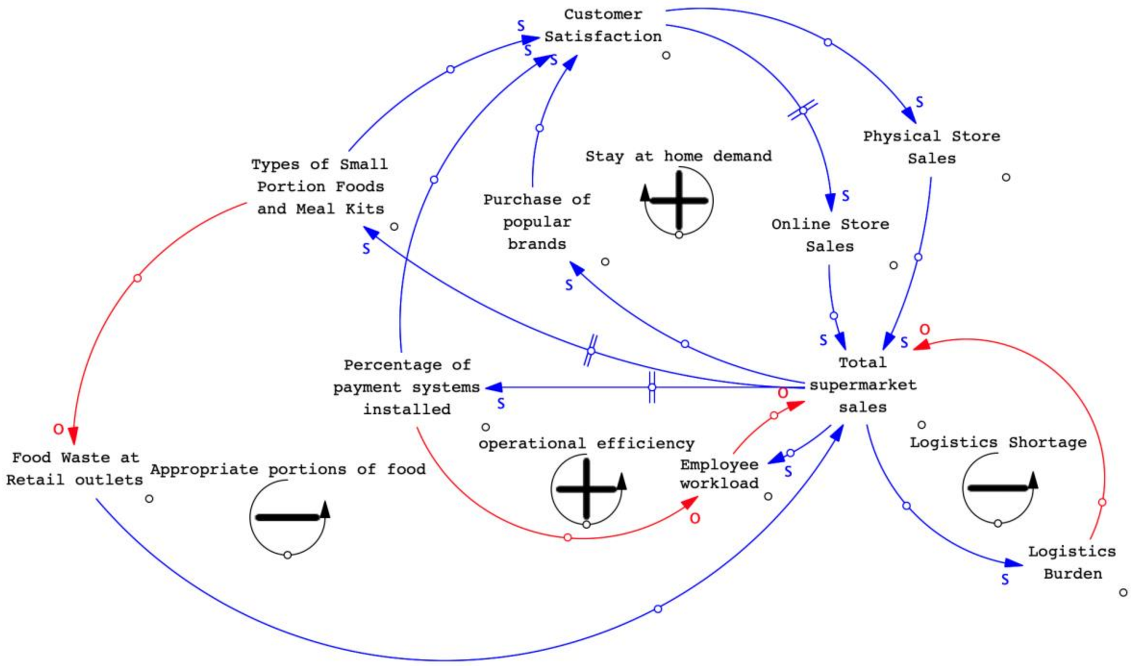

Figure 7: Causal loops perceived by food retailers. "S" near the arrows indicates "Same direction," while "O" indicates "Opposite direction." These notations represent the nature of causal relationships between variables. The delay symbol "||" represents a time lag between cause and effect in the system.

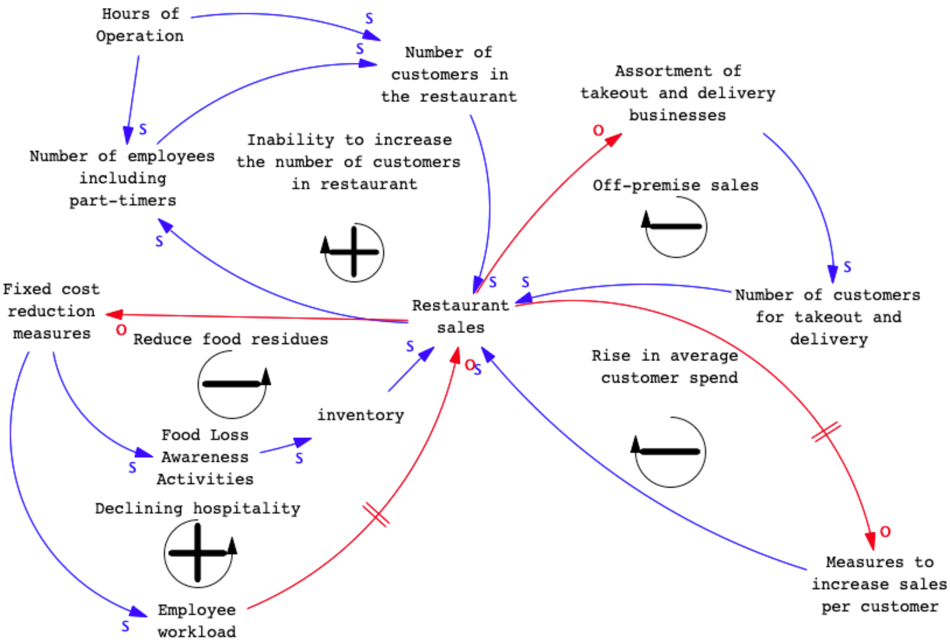

Figure 8: Causal loops perceived by restaurant operators. "S" near the arrows indicates "Same direction," while "O" indicates "Opposite direction." These notations represent the nature of causal relationships between variables. The delay symbol "||" represents a time lag between cause and effect in the system.

5. Discussion

In this study, we proposed a method to identify psychosocial factors that influence stakeholders' perceptions and actions within a system where consensus is required, and to incorporate these factors into conceptual models. These psychosocial factors are key components of stakeholders' mental models. Our proposed method enables the identification of these psychosocial factors and their effective integration into conceptual models by combining system variables identified through stakeholder interviews with quantitative data from search query analysis. Numerous studies using causal loops and system dynamics have attempted to visualize conceptual models that represent stakeholders' understanding of a system. However, most studies have only used qualitative coding based on interview data to identify the system variables and psychosocial factors that make up these conceptual models. This has led to difficulties in the scientific reproducibility of the elicited conceptual models. To address this challenge, our study included the use of search query data to improve the transparency and reproducibility of the conceptual model construction process.

The uniqueness of our proposed method lies in combining qualitative data from interviews with quantitative data from search query analysis to generate causal loops in collaboration with participants. Search query data are particularly important because it reflects people's implicit needs and interests that are often difficult to capture in interviews. Previous studies have used search queries to analyze sensitive topics such as predicting disease outbreaks (Ginsberg et al., 2009; Kurian et al., 2020). Our method applies this approach to the analysis of socio-environmental systems. By linking interview data with information-seeking behavior, this method can identify psychosocial factors that reflect not only expressed opinions but also implicit needs. Furthermore, it complements the sample size limitations often faced in participatory modeling with broader search data, and enables a more accurate assessment of the importance of psychosocial factors through analysis of search query volume and frequency changes. This approach allows for the construction of more comprehensive and reliable conceptual models, leading to a deeper understanding of the complex dynamics in socio-environmental systems.

We classified search query trends into pulse-type and sequential-type patterns. This classification draws on literature in public attention and media studies, particularly Downs' (1972) "issue-attention cycle" theory and Holt and Barkemeyer's (2012) "punctuated equilibrium model." Pulse-type patterns reflect how public attention to a specific issue rises sharply and then gradually declines, often associated with sudden events or short-lived trends. Sequential-type patterns, by contrast, represent more sustained changes in public interest or awareness. This classification method allowed stakeholders involved in participatory modeling to easily identify both rapid changes and gradual shifts in the system. Notably, sequential-type patterns were crucial for understanding the sustained impact of psychosocial factors and long-term changes. This approach proved effective in building a shared understanding of the system among stakeholders and capturing different ways in which public attention and interest evolve.

The use of common search query data that could be referenced by participants in the participatory modeling group increased the transparency and reliability of the data and contributed to the development of a mental model that could be shared in the group without being biased by individual opinions. System dynamics is highly dependent on quantitative and qualitative data that enable the drawing of feedback loops that characterize complex systems (Mirchi et al., 2012). Previous studies that acquired data through repeated interviews have experienced problems with data transparency because the data acquisition process is often a black box. The proposed method, which retrieves search queries from search engines widely used by stakeholders, was more persuasive to participants because of the reproducibility of the data.

Psychosocial factors, moreover, were incorporated into the conceptual model in an effort to promote consensus building among stakeholders. Psychosocial factors are related to human values, which are triggers for actions taken by stakeholders in relation to the system. Previous studies have also emphasized that modeling requires making assumptions and choices aligned with human values (Mayer et al., 2017). When seeking intervention points in a system with stakeholders, it is difficult to adjust the parameters of each individual variable, but a common understanding of the fundamental human values held by each stakeholder is useful in facilitating consensus building.

Some limitations exist with respect to the applicability of our proposed method. Because it requires a search engine that is routinely used by the target stakeholders, it is necessary to identify search queries using search engines that are frequently used by these groups. It is important to note that numerous search engines exist, and their use varies depending on the country, organization, and age of the target stakeholder. In this case study, we used data obtained from Yahoo!, which is popular with Japanese people of all age groups. In some cases, an appropriate search engine might not be available, in which case this method cannot be applied. There are also limitations on the types of themes for which consensus building can be achieved. While it is readily achievable in relation to themes about major social and environmental changes such as the COVID-19 pandemic, it might be more difficult to obtain in relation to events described as “daily ripples” because their characteristics are less likely to be clearly expressed in search queries. In the case of the COVID-19 pandemic, the period during which it impacted Japan was clear, and thus it was easy to capture the characteristics of people’s search trends. Another limitation concerns the time commitment required from participants. In this study, Steps 3 and 4 of the participatory modeling process required approximately 10–12 hours, spread across multiple sessions. This time requirement may limit the method’s applicability in contexts where stakeholders have limited availability.

It is also important to note that commercial enterprise-driven data such as those used in this case study are always subject to sampling bias, unlike official government statistics. The sample size, data acquisition methods, and data cleansing techniques are not necessarily transparent. However, data based on search queries contain information about people’s intentions and implicit needs that often cannot be captured through questionnaires and interviews. High-frequency time-series data are also available. Thus, in this study, we combined interview-based data with search query data. Further research is needed on how to combine qualitative and quantitative data.

The participants in this study reported that the four participatory modeling steps provided new insights in their use of previous search query trends, rather than the usual interview process. They noted that search query trends are useful in identifying a person’s implicit needs because they might have forgotten about issues that are raised in interviews. Some concern was expressed that Step 4, which clusters search queries and identifies various categories, requires the facilitator to have sufficient experience in understanding the degree to which physical events and search queries need to be interconnected.

Experts and stakeholders commented that the results from the application of this methodology to the case of changes in eating habits in Japan during the COVID-19 pandemic provided an understanding of the mental models and structures that people will invoke when considering eating habits in Japan in the future. The case study we conducted used a limited set of stakeholders: a large restaurant chain, a large supermarket, and food-conscious consumers. These stakeholders were selected because they are indispensable food-related stakeholders. Researchers familiar with the food industry in Japan were included in the discussions to enable the finalization of a causal loop that could be agreed upon from an expert perspective. The experts commented that the mental models of the three stakeholders and the physical events shown in the causal loop diagrams have not been well-researched in Japan, and thus the results of this study make a valuable contribution. Compared with the results of overseas studies on eating habits (Iranmanesh et al., 2022; Lamy et al., 2022; Qian et al., 2020), the mental model of consumers who want to use up the food they already have and the mental model of retailers who want to provide the right amount of food to consumers are unique to Japan. Participatory modeling showed that behaviors aimed at raising health awareness to reduce the spread of COVID-19 and using up existing foodstuffs, although seemingly unrelated, are actually closely related within the participants’ mental models. Participants involved in the modeling emphasized that the consumers’ mental models of “Increased health awareness” and “Using up foodstuffs” are important intervention points that must be reinforced when considering sustainable Japanese food habits in the future, and that these mental models are essential for consensus building. Thus, future research should include the creation of scenarios involving retailers and restaurant operators aimed at strengthening these mental models of consumers.

6. Conclusions

In environmental and social science fields related to sustainability, there are increasing opportunities for decision making among stakeholders with different perceptions and values. However, if stakeholders view the system from too narrow a perspective, they are unable to detect events that occur outside of the system they perceive, which can lead to unintended negative consequences. While a growing number of studies have used a participatory modeling approach in which stakeholders with different backgrounds and mental models engage in collaborative learning about the system to build a common conceptual model, the majority of these studies have relied on qualitative coding based on data obtained through interviews. In this study, we propose a novel participatory modeling method that combines qualitative data from interviews and quantitative data from the analysis of search queries to generate causal loops with stakeholders who need to reach consensus. Our proposed method extracted psychosocial factors to be incorporated into the conceptual model by considering the variables obtained from the interviews and classifying related search queries into pulse and sequential types on the basis of their volume and change trends. Search queries tap into people's hidden implicit needs that are difficult to elicit from interviews because people use search engines and engage in information-seeking behavior to obtain information before they take action. This participatory modeling method facilitates stakeholders' understanding of the conceptual model. The effectiveness of this method was shown by conducting a case study that examined changes in eating habits in Japan during the COVID-19 pandemic.

Acknowledgements

This work was supported by the Keio University Doctorate Student Grant-in-Aid Program from the Ushioda Memorial Fund. The authors are grateful to the workshop participants. The University Strategic Research Project of Tokyo University of Agriculture supported this research from 2022 to 2023.

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