

NANYANG TECHNOLOGICAL UNIVERSITY



# Teachable Agent for Improving Ikigai

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in partial fulfillment of the requirements for the degree of  
Doctor of Philosophy

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## Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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## Authorship Attribution Statement

This thesis contains material from 1 paper published in the following peer-reviewed journal and 1 paper accepted at conferences in which I am listed as an author.

Chapter 2 is published as [Ping Chen, Siyuan Liu, Xuehong Tao, Takayuki Ito. 2021. Meaning and Health: A Review on Ikigai. \*International Journal of Information Technology\* 27\(1\), 2021.](#)

The contributions of the co-authors are as follows:

- Prof Ito suggested the direction of this research.
- I wrote the manuscript. The manuscript was revised together with Dr. Siyuan Liu and Dr. Xuehong Tao.

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The contributions of the co-authors are as follows:

- Dr. Shen suggested the direction of this research.
- I wrote the manuscript. The manuscript was revised together with Dr. Xinjia Yu.
- I co-designed the agent architecture with Dr. Su Fang Lim.
- I co-designed the study with Dr. Xinjia Yu, conducted the user study, and analyzed the data.

Chapter 4 is accepted as [Ping Chen, Xinjia Yu, Su Fang Lim, and Zhiqi Shen. Enhancing the Well-Being of Seniors: A Teachable Agent for Ikigai. In \*International Journal of Crowd Science.\*](#)

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# Abstract

The global elderly population is projected to more than double by 2050, emphasizing the need for meaningful elderly care. We delved into “Ikigai”, a concept that originated in Japan, signifying an individual’s purpose and satisfaction in life. In this research, we aim to assess and enhance an individual’s Ikigai level. We introduce a knowledge graph-based survey system for dynamic Ikigai assessments, improving response reliability and reflecting Ikigai’s evolving essence. Additionally, we propose a supervised learning model that predicts Ikigai levels from user profiles to help continuous evaluation. For Ikigai enhancement, we propose a teachable agent for the elderly, aiming to stimulate cognitive abilities and heighten self-esteem. Additionally, a reinforcement learning-driven hobby recommender recommends potential Ikigai-boosting activities based on personal attributes. Through a phenomenographic analysis, we explore individual perceptions of these methods, revealing how technology can bolster life’s purpose and meaning. Our pioneering research uniquely fuses advanced techniques with Ikigai exploration.

# Acronyms

AI	Artificial intelligence
IADL	Instrumental activities of daily living
TA	Teachable agent
CAI systems	Computer Aided Instruction Systems
AIED	Artificial Intelligence in Education
ILEs	Intelligent Learning Environments
ITS	Intelligent Tutoring Systems
EnALI	Enhancing Agent-Learner Interaction
MTA	Motivated Teachable Agent
MCLS	Math Concept Learning System
RDF	Resource Description Framework
LPG	Labeled Property Graph
IRI	International Resource Identifiers
MLP	Multi-layer perception
TAI	Teachable agent for <i>ikigai</i>
RL	Reinforcement learning
FCM	Fuzzy Cognitive Map
PA	Pedagogical Agent

# Chapter 1

## Introduction

Currently, there is a significant demographic change globally. For the first time in human history, people aged 65 and above outnumbered children aged five and below worldwide, in 2018. Between 2019 and 2050, the global population of people aged 65 and above is expected to more than double, while the number of children under the age of five is expected to remain relatively stable [3]. Aging populations are a major trend affecting the global community.

The aging population brings about many problems. Aging is characterized biologically as a “time-dependent functional decline that affects most living organisms” [4]. Loss of physiological integrity brought on by this functional deterioration results in diseases like cardiovascular disease, cancer, diabetes, and neurological problems [4]. It was found that 50 percent of senior people have two chronic conditions and 80 percent have one or more [5]. In addition to higher rates of morbidity, mortality, and medical expenses, these disorders can occasionally cause significant disability.

As there are more people who live longer and are more likely to encounter health problems, the demand for public healthcare resources is increasing. At the same time, with an aging population, there are fewer taxpayers, which further burdens the healthcare and pension systems. As such, finding ways to help the elderly maintain their health condition is crucial.

With increasing life expectancy and an aging population, issues surrounding the quality of life, social engagement, and psychological well-being of the elderly have

become crucial societal concerns. It has necessitated the exploration of innovative approaches to ensure not just longevity, but also a life filled with joy, purpose, and satisfaction for the elderly.

In this pursuit, Ikigai, a notion that originated from Japan, may provide a profound framework for exploring a meaningful and fulfilling life. Ikigai is often referred to as “purpose in life” and “the sense that life is worth living”. Work, family, and friends are examples of sources of Ikigai. This concept is considered to be an important factor in improving one’s health and living a more satisfying life [6]. It is considered to be the most used index of well-being for Japanese studies about the elderly [6–9].

Having a stronger sense of Ikigai has numerous physical and mental benefits. It is linked to longevity [10–12], well-being, and enhanced overall quality of life [13]. Studies have demonstrated that the notion of Ikigai may be applicable to cultures outside Japan, and it has begun to attract increasing global attention [14–16].

In light of global demographics and the benefits Ikigai provides, it is compelling to consider how this concept can be applied to improving the well-being of the elderly. By extending the understanding of Ikigai beyond Japan, we could potentially improve the quality of life for aging societies around the world. By combining Ikigai principles with modern technologies such as artificial intelligence, we could develop innovative, scalable, and effective solutions aimed at promoting the well-being of our elderly. In order to ensure a meaningful and fulfilling life for the elderly, this research represents a crucial step in tackling the challenges presented by the aging global population.

## 1.1 Background and Motivation

The world is witnessing an extraordinary and long-term shift in the age structure of the global population. Increasing life expectancy and declining birth rates are driving this shift. As a result, both the percentage of elderly people and the absolute number of elderly people in the population are rising steadily throughout the country. In 2020, there were 727 million people aged 65 and above. Over the next three decades, the global population of elderly people is expected to more than double, reaching 1.5 billion by 2050 [17]. According to epidemiological studies,

11% of the world's population is over 60, with a projected growth to 22% of the population by 2050 [18].

This demographic change brings with it numerous challenges. Countries with rapidly aging populations must devote more funds and resources to their healthcare systems because the demand for healthcare increases with age. Furthermore, with the decline in worker-to-pensioner ratios and an increase in the number of people spending more of their lives in retirement, the healthcare and pension systems are under increasing stress. Meanwhile, family structures are changing as people live longer and have fewer children, leading to reduced care options for the elderly.

These underline the urgent need to focus not only on the physical health of older adults but also on their psychological and emotional well-being. It is in this context that the traditional Japanese concept of Ikigai provides a potent and meaningful perspective. Ikigai is a complicated concept that encompasses many aspects and is centered on finding joy and fulfillment in life. Discovering and maintaining this sense of Ikigai can play a critical role in enhancing overall well-being and life satisfaction, including the elderly.

As individuals age, they often face significant life changes, including retirement, changing family dynamics, and physical health challenges. These transitions may lead to feelings of loss, emptiness, and a decline in mental well-being. By fostering a strong sense of purpose and satisfaction in life, Ikigai may provide the elderly with a resilient psychological framework to navigate the challenges of aging. Studies have found links between a higher sense of Ikigai and longevity, a lower risk of cardiovascular diseases, and a slower rate of age-related cognitive decline.

Therefore, the adoption and pursuit of Ikigai could be a powerful strategy to counter the potential psychological challenges posed by an aging population. It provides a pathway to stay engaged, find joy, and derive purpose in life, ultimately enhancing the quality of life for older adults. In a world where the elderly population is rapidly growing, integrating the principles of Ikigai into aging societies could be a significant step towards ensuring a healthier, happier, and more fulfilling later life for all.

There are, however, some challenges when it comes to dealing with one's Ikigai. Generally, Ikigai is considered a complex concept that encompasses many things, including the meaning of life, motivations, values, and much more [19, 20]. Because

of its complexity, assessing or improving one's Ikigai level can be a challenge in and of itself. Furthermore, Ikigai is a subjective concept that has a variety of sources varying from person to person, emphasizing the importance of personalization when it comes to Ikigai.

With the worldwide demographic landscape undergoing an extraordinary transformation, there are fewer younger populations who can provide care and support for the elderly. The role of intelligent technologies, especially in the form of intelligent agents, has gained significant attention. Conversational agents, powered by techniques like artificial intelligence, were designed to interact with humans in a way that is natural and intuitive, providing assistance, and companionship for the elderly. Teachable agents represent a specific type of intelligent agent that learns from its interactions with humans, mirroring the process of human learning and encouraging active engagement from the user.

The integration of such intelligent and teachable agents in the context of aging could offer compelling benefits. For instance, these agents could serve as companions for the elderly, helping to alleviate feelings of loneliness and isolation, while providing them with a sense of purpose and motivation. Furthermore, the interactive and adaptive nature of teachable agents allows for a better understanding of the elderly to achieve better personalization for support.

The intersection of these intelligent, teachable agents with the concept of Ikigai presents an innovative approach to enhancing the quality of life among the aging population. By leveraging intelligent agents to facilitate the elderly in their journey of discovering and sustaining their Ikigai, we can offer a novel pathway to psychological well-being. These agents could help the elderly explore their passions, find purpose in their daily activities, and maintain a strong sense of self-identity, which are crucial for fostering Ikigai. In this way, the marriage of intelligent technologies and the philosophy of Ikigai can potentially revolutionize our approach to aging, providing more enriching, fulfilling, and resilient pathways into the later stages of life.

## 1.2 Research Problems and Research Objectives

Researchers believe that Ikigai should be viewed as a composite construct that encompasses life's meaning, motivations, and values [19, 20]. Meanwhile, there is a need to consider personal variance since the concept is highly personal and subjective. Thus, the research seeks to address two problems related to the elderly's Ikigai, which are how to assess and improve the elderly's Ikigai.

The main objectives of this research thus aim to address the following specific challenges.

*Question 1: How can we continuously assess an elderly individual's Ikigai?*

Before we can effectively measure the Ikigai of elderly individuals, we must first gain a comprehensive understanding of existing Ikigai scales and measurements, as well as identify any potential limitations within these methods. Ikigai, by its nature, is a dynamic and fluid concept that can evolve over time. Therefore, the continuous and timely assessment of an individual's Ikigai level is critical. By implementing consistent evaluation, we can detect any fluctuations or drops in Ikigai levels and promptly initiate suitable interventions. There are two parts that are important in this research question, "continuously" and "assess".

- "Assess": Existing measures of Ikigai have certain limitations. While it's important to accurately assess an individual's Ikigai level, it is equally crucial to understand the underlying reasons for these specific levels. Uncovering the reasons behind high or low ratings on each item can provide richer insights and pave the way for more effective interventions.
- "Continuously": As Ikigai is a concept that is not static and can change in response to various personal and environmental factors, existing one-time measurement techniques may not fully capture this dynamic. In order to bridge this gap, a continuous assessment strategy is essential. The continuous assessment approach should not only capture Ikigai's changing nature, but also be able to detect subtle shifts in its level over time in order to bridge this gap.

Developing strategies to enhance the elderly's Ikigai level requires a thorough understanding of their Ikigai level, which is closely related to accurate assessment

and effective intervention. Thus, the first goal of this thesis is to develop dynamic and continuous methods for assessing Ikigai levels. Ikigai's dynamic nature, which may change over time due to varying life circumstances and internal psychological changes, is the primary intention behind this focus. As a result of capturing these changes, we are able to provide a more accurate, nuanced, and individualized understanding of the purpose and satisfaction of elderly individuals. The continuous assessment process can also enable timely interventions. When an individual's Ikigai level declines, steps can be taken to address it immediately, avoiding prolonged periods of distress or dissatisfaction. As a result of such a refined understanding of Ikigai, the various factors that may influence Ikigai levels among the elderly can be identified, which can range from personal health status to social engagement.

*Question 2: How can we enhance an elderly individual's Ikigai level?*

Since Ikigai is associated with a host of benefits, we need to explore methods for enhancing this sense of life's worthiness, especially in the elderly population. This exploration holds a great deal of importance, as it has the potential to improve their well-being and longevity. However, a one-size-fits-all approach may not be feasible, due to Ikigai's intricate complexity. The Ikigai concept encompasses multiple aspects, each contributing to its uniqueness.

Taking a targeted approach can be potentially helpful in dealing with this complexity. By focusing on specific aspects of Ikigai - such as self-esteem or purpose in life - we can improve these aspects. Besides offering a manageable and systematic exploration of Ikigai enhancement, such targeted efforts would also address the varied needs of the elderly.

It is also important to recognize the highly individual nature of Ikigai at the same time. Ikigai is not a uniform concept, but rather a deeply individual one that differs greatly based on each individual's unique life experiences, values, and motivations. In order to enhance Ikigai, a personalized approach is necessary. In order to tailor our interventions to align with the specific needs, and context of each individual, we need to understand each person's unique situation and their Ikigai level.

It is a complex challenge to boost Ikigai levels among the elderly, which requires thoughtful, targeted, and personalized approaches. This thesis thus aims to develop these personalized, multifaceted interventions, and study their efficacy.

## Research Objectives

The main objective of this research is to design and develop ways to assess and enhance the elderly's Ikigai. Since teachable agents, with their unique feature of being able to continuously learn from users, demonstrate a great potential for personalization and continuous assessment. Meanwhile, they have been proven to be able to enhance one's self-esteem and stimulate a sense of responsibility and motivation during the "learning-by-teaching" process, and these are two important aspects of Ikigai. As such, teachable agents are chosen to be a possible approach to achieving this objective. Therefore, in this thesis, we focus on designing and developing a teachable agent for assessing the elderly's Ikigai with the ultimate goal of improving Ikigai among the elderly population. To accomplish this primary objective, the research is guided by the following specific objectives:

This research is primarily aimed at designing and implementing innovative ways to enhance and evaluate Ikigai among older adults. It is based on the understanding that Ikigai, or a sense of purpose, can have a significant impact on one's well-being and quality of life in the later years. It is likely that the elderly will experience unique challenges as they transition into this phase of life, resulting in a decrease in their Ikigai. Thus, our primary objective is to create tools that facilitate and sustain this essential aspect of life, thereby promoting health and happiness.

A promising avenue we are exploring is the unique capabilities of teachable agents. These agents can learn continuously from their interactions with users, offering significant potential for personalized assessments and in-time intervention. A feature like this is especially critical in relation to something as personalized and dynamic as Ikigai since every individual's Ikigai is unique and variable. With the help of teachable agents, we aim to create a tool that can adapt to the nuances of individual Ikigai based on the dynamic learning capabilities of these agents. Additionally, teachable agents have demonstrated their effectiveness in enhancing self-esteem, responsibility, and motivation through the "learning-by-teaching" process. As these are crucial aspects of Ikigai, teachable agents can inherently foster Ikigai through their interactions with users. Teachable agents are ideal candidates for achieving our research objective because they can assess and enhance Ikigai simultaneously.

As a result, this thesis focuses on creating, and developing a teachable agent that can be used to assess and foster Ikigai among the elderly. By actively improving

Ikigai, we hope to promote healthier, more satisfying, and fulfilled lives within this population rather than just measuring it. Our research strategy is based on a series of specific objectives that will help us achieve this ambitious goal. It is these objectives that will guide our design of the teachable agent, and direct our methodologies. The specific objectives are as the following:

- To construct an Ikigai knowledge graph that dynamically generates questions to better assess and understand one’s Ikigai.
- To develop machine learning algorithms that predict one’s Ikigai based on his/her profile which can be used for easier continuous assessment.
- To design a teachable agent that engages the elderly in activities aimed at improving their Ikigai.
- To create a recommendation system that suggests hobbies and activities that may enhance an individual’s Ikigai.

### 1.3 Research Contributions

The significance of this research is underscored by its potential to address crucial challenges related to the well-being of the rapidly growing elderly population. This is achieved through the intersection of the traditional Japanese philosophy of Ikigai and cutting-edge artificial intelligence technology. By facilitating the exploration and enhancement of their Ikigai—a concept tied closely to personal fulfillment, it cultivates a robust sense of purpose and satisfaction. This may subsequently mitigate feelings of isolation and depression, both prevalent issues among the elderly, leading to an improvement in their psychological well-being. The main contributions of this research include four aspects:

- *Introduction of the Ikigai Knowledge Graph.* The research pioneers the creation of a dynamic questionnaire system, powered by knowledge graphs, to better understand the complex construct of Ikigai and automate Ikigai assessment. This system helps understand the complex construct of Ikigai, a Japanese concept related to personal fulfillment and purpose in life. By doing so, it offers invaluable insights into the factors that contribute to either low

or high levels of Ikigai. To our knowledge, this is the first attempt at creating a knowledge graph specifically aimed at understanding and enhancing Ikigai.

- *Development of a Teachable Agent for Ikigai Improvement.* In another novel approach, we explore the application of teachable agents within the context of aging. Teachable agents are typically used in educational settings, but our research diverges from this norm. We develop a teachable agent with the specific aim of motivating elderly individuals to enhance their Ikigai, providing a fresh perspective in the field of gerontechnology. This approach is the first of its kind in utilizing a teachable agent to enhance one's Ikigai and overall well-being.
- *Use of Machine Learning to Predict and Enhance Ikigai.* As part of our research, we also adopt machine learning methodologies to predict and enhance Ikigai levels, a new frontier. It is an exciting and pioneering effort that utilizes cutting-edge technology in the field of Ikigai and individuals' mental well-being.
- *Adoption of a Phenomenographic Approach.* To fully understand the varying ways individuals interact with our proposed approaches, our research adopts a phenomenographic approach during user studies. This involves understanding the various ways individuals experience a phenomenon and how they make sense of their experiences. The results derived from this approach offer valuable insights and lay the groundwork for future research, potentially influencing how we approach the study of Ikigai and its enhancement.

The proposed knowledge graph-based assessment system and the machine learning models for predicting one's Ikigai level and recommending hobbies based on user profile can be embedded into the teachable agent. Taken as a whole, this research possesses the capacity to effect considerable contributions to the domains of gerontechnology and artificial intelligence. Most importantly, it holds promise for substantial improvements to the lives of the aging population.

## 1.4 Thesis Structure

This thesis is systematically organized as follows:

Chapter 2 provides an in-depth examination of the existing body of literature related to Ikigai, teachable agents, knowledge graphs, and machine learning, specifically within the sphere of well-being. In addition, an in-depth exploration of phenomenography, which is a qualitative research method that contributes valuable insight into the understanding of different human experiences, was done. By surveying these relevant academic disciplines, we establish the theoretical foundation that informs and guides the diverse methodologies and investigations undertaken in this study.

Chapter 3 introduces the methodologies proposed to determine an individual's level of Ikigai. It delves into the design and development of a knowledge graph centered around the concept of Ikigai and probes the dynamic process of question generation used to assess a person's sense of life fulfillment and purpose. In addition, this chapter outlines the machine learning techniques employed to predict an individual's level of Ikigai based on their provided profile.

Chapter 4 investigates potential methods to augment a person's Ikigai level. A teachable agent is proposed to enhance elderly individuals' Ikigai while fostering an understanding of health-related concepts. This chapter also details a reinforcement learning-based hobby recommendation system. User studies are conducted to validate the effectiveness of both of these proposed methodologies.

Chapter 5 serves as the conclusion of the thesis, encapsulating the significant contributions made by the research and discussing potential directions for future work.

By leveraging an interdisciplinary and integrative approach, this thesis contributes a unique perspective to the intersection of personal well-being, artificial intelligence, and gerontology. It paves the way for future research in the arena of AI-driven wellness interventions, setting the stage for potential advancements in how we approach aging, well-being, and the integration of AI technologies.

# Chapter 2

## Literature Review

In this chapter, we delve deep into the theoretical landscape that shapes our research, scrutinizing a multitude of academic works to establish the academic framework for our study.

This chapter starts with an exploration of Ikigai. Unraveling this Japanese notion, we engage with a wealth of literature to understand its concept, its impact on physical and mental health, especially among the elderly, and the current challenges.

Then the realm of teachable agents was reviewed. As we traverse through a myriad of developments and studies, we aim to understand the potential of these agents in facilitating personalized learning experiences. The goal is to understand their current applications and possible future directions, with a keen eye on their potential role in assessing and enhancing an individual's Ikigai level.

Following this, knowledge graphs and machine learning in mental well-being were examined. We delve into the applications of knowledge graphs in different domains. Concurrently, we explored the potential applications of machine learning, particularly in relation to well-being, to uncover ways in which it could be instrumental in predicting and improving Ikigai.

Lastly, phenomenography, a qualitative research method known for its effectiveness in deciphering different ways in which people experience a phenomenon, was reviewed. By reviewing a wide range of academic works, we aim to comprehend how this method can guide us in understanding the unique experiences of our study participants.

In this extensive review of literature, we intend to bring together diverse pieces of the academic puzzle in order to gain a more comprehensive understanding of the areas of this research.

## 2.1 Ikigai

<sup>1</sup>In this chapter, we review two key concepts in this research. Firstly, the notion of Ikigai, its importance, and current challenges. We then review the development and applications of teachable agents and their linkage with Ikigai. Knowledge graphs and machine learning in predictive well-being are also reviewed. The interplay of the concepts is also discussed.

In this chapter, we carefully dissect two primary concepts integral to our research. The first area of focus is Ikigai, a concept deeply ingrained in Japanese culture and philosophy that signifies a 'reason for being'. This principle carries significant weight, particularly in relation to individual purpose and satisfaction. We take a close look at the core elements of Ikigai, its unique importance, particularly within the context of aging populations, and the associated challenges it currently faces.

Following our examination of Ikigai, we turn our attention to the evolution and applications of teachable agents. These agents, designed to learn from users through interaction, carry substantial potential within the educational field, and may be helpful in the wellness sphere. The relationship between teachable agents and Ikigai is of particular interest, considering the unique feature of such agents to learn from individuals, and thus may be potentially helpful in identifying and enhancing people's Ikigai, thereby improving overall well-being.

Our study further incorporates an analysis of knowledge graphs, and machine learning, specifically within the context of predictive wellness. Knowledge graphs have the capacity to integrate and visually present a wealth of interconnected information, which allows for flexibility. Machine learning, with its capabilities for uncovering underlying patterns, can offer actionable insights about individual wellness.

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<sup>1</sup>The work in this section has been published as Ping Chen, Siyuan Liu, Xuehong Tao, Takayuki Ito. 2021. Meaning and Health: A Review on Ikigai. *International Journal of Information Technology* 27(1), 2021.

Finally, an integral component of this review is an in-depth discussion on how these diverse concepts interact. We examine how the nuances of Ikigai, the dynamic learning capacity of teachable agents, the interconnected data of knowledge graphs, and the predictive prowess of machine learning converge. Understanding the synergies and tensions between these aspects is crucial, as it enables us to further develop an integrative approach that can be effectively implemented to enhance personal wellbeing and extend the beneficial impact of our research.

### 2.1.1 Concept of Ikigai

Ikigai is a complicated concept that encompasses aspects like “purpose in life” and “life satisfaction”. Japan’s most authoritative dictionary describes it as “joy and a sense of well-being from being alive” and “realizing the value of being alive” [21].

The term Ikigai consists of two parts, “*iki*” which represents “life” and “*gai*” which represents “to be worthwhile” [22]. The etymology of this word suggests that it originally denoted the meaning or significance of human life, as well as the social value of a person’s life [23].

As one of the earliest Ikigai theorists, in the late 1950s, Dr. Kamiya treated leprosy patients during the period when the disease was considered fatal. As she discovered, some people can maintain their optimism even in adversity, while others cannot. According to her, “Ikigai” distinguishes between patients who have hope and those who don’t. It was through Ikigai that patients managed to retain hope and meaning in their lives. She introduced this term to the public because of its uniqueness, which makes it difficult for other languages to fully explain [24]. It is a form of striving to find a deeper meaning instead of avoiding a challenge [24].

As a concept deeply embedded in Japanese philosophy and day-to-day life, Ikigai is often hard to translate or define in English. Many refer to Ikigai as “purpose in life”, “the sense that life is worth living” or “a reason for living” [7, 25–28]. In Western cultures, an explanatory model of Ikigai takes the form of a Venn Diagram as shown in Figure 2.1, illustrating its convergence of four fundamental components: “what you love”, “what you are good at”, “what the world needs”, and “what you can be paid for” [22, 29]. It is said that Ikigai falls at the intersection of passion, vocation, mission, and profession - a state of harmonious fulfillment. Nevertheless,



FIGURE 2.1: A Venn diagram that illustrates Ikigai

this interpretation has drawn criticism, as it tends to narrowly associate Ikigai with financial gains and work. In order to attain Ikigai, one's passion or mission must necessarily align with skills or services that are compensable. This perspective fails to encompass a comprehensive, deeply understood understanding of Ikigai in Japan, where it was born. In the Japanese context, Ikigai is seen as a broader concept, deeply interwoven into some things in daily life regardless of a person's professional identity. It is understood that Ikigai can be expressed in hobbies, family bonds, or simple everyday pleasures that give individuals joy and satisfaction. The results of a 2010 survey conducted by Japan's Central Research Services<sup>2</sup> indicate that only 30% of respondents attribute Ikigai to their work. The majority of participants, however, attribute Ikigai to leisurely activities and hobbies. In addition to family relationships and the joy gained from spending time with pets, other aspects of their personal lives contributed to their sense of Ikigai. This shows that, in its most authentic form, Ikigai is a deeply personal, multifaceted phenomenon that

<sup>2</sup><https://www.crs.or.jp/backno/No636/6362.htm>

encompasses much more than achieving professional accomplishments or gaining financial success.

Research suggests that Ikigai should be seen as a composite construct that encompasses life's meaning, motivations, and values [19, 20], despite the fact that multiple translations exist, such as those that refer to the process of "realizing" or "gaining joy from" the purpose [30]. It has been suggested that ikigai is similar to eudaimonic wellbeing [31], which is a state of well-being and functioning.

There are seven needs associated with Ikigai, according to Kamiya [24]: a fulfilling existence, a need for growth and change, a need for future perspectives, a need for responses, a need for freedom, a need for self-actualization, and a need for significance. Besides these seven needs, some people may have additional needs, and the strength and combination of those needs will vary by individual. There may be interconnected needs: some may merge with others. A single Ikigai item may satisfy a multitude of needs. She also noted that Ikigai is a phenomenon that occurs in everyday life [24]. In her view, people can attain Ikigai by satisfying three psychological needs: life satisfaction, change, and an optimistic future. In her view, life satisfaction refers to feeling satisfied with how one is progressing in one's life; people need change to feel personal growth and avoid stagnation; a bright future represents a hope that the future will be drastically different from their (negative) present circumstances.

Mogi [32] believes that Ikigai is more quality-oriented rather than success-focused. It is more associated with intrinsic joy and curiosity-based motivation, where the activity is a reward in and of itself.

There is a lot of debate over which kind of Ikigai is best for each individual, according to Matthews [33]. Some claim that Ikigai can be found in pursuing one's own personal dream, thereby describing it as a form of self-realization, whereas others associate Ikigai with a sense of oneness, arguing that true purpose in life is found through commitments to a group like family. As a philosophical notion, Ikigai outlines many areas that foster a sense of autonomy and self-awareness, two of which are considered crucial to determining one's life's meaning.

According to Kumano [34], Ikigai is about life affirmation, goals/dreams, the meaning of life, the meaning of existence, fulfillment, and commitment. Among these

aspects, commitment makes Ikigai distinctive to subjective well-being and psychological well-being [34]. As Kumano [19] suggests, Ikigai can be predicted by absorption in pleasant, present life conditions, acceptance and coping with unfavorable, past circumstances, meaning-making, and awareness of future goals. Ikigai and subjective well-being are commonly associated with personal satisfaction with one's current and past lives, but Ikigai also encompasses one's perception of his or her future and social interaction [35]. Similarly, Mori [36] proposed that the level of Ikigai is influenced by one's "vertical connections", or the consistency or lack thereof in oneself across the past, present, and future. According to Mori, the higher the level of consistency, the greater the level of Ikigai.

Shirai et al. [37] describe Ikigai as a concept that encompasses both happiness and life satisfaction as well as evaluation of meaning in life, self-esteem, and self-efficacy.

## 2.1.2 Importance of Ikigai

Ikigai is associated with various health benefits for both physical and mental health. Research shows that it may be applicable to non-Japanese cultures [38]. Thus, maintaining a high level of Ikigai is beneficial for the elderly for them to enjoy healthy lives. However, as people age, they may lose the sense of Ikigai.

### 2.1.2.1 Health Benefits

#### Physical Health

A sense of purpose, or an Ikigai, has been thought to be a key to longevity [10–12]. Ikigai can be a modifiable health practice that prevents middle-aged and older persons from decaying in higher-level functional abilities [39].

A strong sense of Ikigai has been associated with a reduced risk of all-cause mortality [8, 40–42]. People with a strong sense of Ikigai have a lower risk of cardiovascular diseases and stroke [8, 42, 43] and are less likely die from cardiovascular diseases [43, 44]. In addition, they have a significantly lower risk for external-cause mortality [42].

A strong sense of Ikigai can prevent functional impairment. Mori et al. [7] found that people with a stronger sense of Ikigai are more mobile and perform more instrumental activities of daily living (IADL).

In the systematic review by Roepke et al. [45], stronger senses of meaning were associated with better physical health as well as behavioral characteristics that decreased the risk of negative health outcomes and increased the likelihood of positive health outcomes. In their review, some people regarded Ikigai as an aspect of meaning in life, while others did not. Those who had found meaning reaped a slew of benefits, including a faster recovery after knee surgery [46] and a lower risk of disability in old age [47].

### **Mental health**

It has been shown that a strong sense of Ikigai improves one's well-being or quality of life [13].

Without meaning and purpose in life, people may feel empty and anxious, which adversely affects one's subjective well-being [24, 48]. In addition to helping people cope with stress effectively [49–52], Ikigai also helps them better integrate difficult psychological situations from their past, present, and future with less conflict and uncertainty. There is also evidence that it has protective effects on stress, depression, anxiety, and other mental illnesses [53, 54]. The feeling of Ikigai is associated with less depression and increased social support among people with a stronger sense of Ikigai [7]. It has also been linked with a slower rate of cognitive decline and a lower risk of psychological problems [40].

According to Maki [55], Ikigai interventions can be used to prevent dementia, a disease that primarily affects older adults, by preventing primary (intervene before adverse health effects occur), secondary (delay the disease's development), and tertiary (slow or stop disease progression). Having Ikigai is an important factor in dementia prevention, according to empirical evidence [55]. As dementia diagnosis is often accompanied by negative emotions, which may contribute to dementia progression [56], maintaining one's sense of identity unchanged before and after the onset of dementia may help to overcome the critical transitional stage [56]. In the context of tertiary prevention, Ikigai support is essential for rehabilitation [57].

### 2.1.2.2 Ikigai and Aging

Ikigai is argued to be the most used index of well-being in Japanese studies about the elderly [6–9]. To help the elderly achieve better health and live more fulfilling lives, the Japanese government implemented the Active 80 Health Plan, which promotes a healthy lifestyle and a sense of Ikigai [6].

However, according to the White Paper on the National Lifestyle released by the Cabinet Office of Japan in 2007, the elderly tend to lose the feeling of Ikigai after retirement. Nakanishi et al. [58] classify four sources of Ikigai from the perspective of the elderly, namely work, learning, civic or religious activities involvement, and participation in group recreational activities. As people age, they may experience loss of Ikigai due to reasons like retirement, loss of functional abilities, and loss of loved ones. Hasegawa and Gashu [59] state that most people are inclined to suffer from one or more of the four categories of loss that impact Ikigai: 1) health, 2) economic base, 3) social relationships, and 4) life purpose. Research also shows that many people lose Ikigai as they age, and there are significant individual variances in the decline of Ikigai [60].

### 2.1.3 Current Challenges

Ikigai, an intricate concept that encompasses various elements, poses distinct challenges. This multifaceted nature can complicate the process of holistically evaluating an individual's level of Ikigai. It can be arduous to pinpoint the precise interplay of factors that culminate in a high or low level of Ikigai, given that an individual's diminished sense of Ikigai could be attributed to any combination of these factors.

This complexity is further compounded when attempting to enhance a person's Ikigai. The challenge lies not only in identifying which aspect is lacking or needs improvement but also in devising effective strategies to bolster the individual's connection with these aspects. This process is far from straightforward and requires careful, often trial-and-error, exploration to identify the most successful interventions.

Furthermore, the highly personal and subjective nature of Ikigai introduces an additional layer of complexity. As it is inextricably linked with an individual's life

experiences, values, and perspectives, interpretations of Ikigai can vary dramatically from person to person. Therefore, an approach that might help one individual connect with their Ikigai may not resonate with another. This necessitates a personalized approach when dealing with Ikigai, with strategies and interventions tailored to each person's unique circumstances and interpretation of their life's purpose.

In a broader context, these challenges also highlight the need for further research and exploration within both academic and practical applications of Ikigai. As a relatively new concept in the field of wellness outside Japan, it remains to be seen how its potential can be fully harnessed in a consistent and effective manner.

## 2.2 Teachable Agents

Teachable agents (TAs) are pedagogical agents inspired by the “learning-by-teaching” theory which produced the protégé effect [61]. When students are asked to teach others, they display greater capability in comprehending learning materials, become more conscious of their learning process, and put forth more effort in the learning process, as compared to students learning for their own benefit. In a famous experiment, Bargh and Schul [62] found that people who prepared to teach others about paragraph comprehension had better results on quizzes than those who prepared to do the comprehension themselves. A similar situation was reported by Gaustard [63], where tutors benefited equally or more than tutees.

### 2.2.1 Development of Teachable Agents

The emergence and development of teachable agents is a fascinating journey that lies at the intersection of computer science, cognitive science, and pedagogical theory. The initial development of these agents was rooted in the broader history of using computers as tools to aid instruction, a practice dating back to Pressey's 1925 Computer Aided Instruction Systems (CAI systems) [64].

Early iterations of computer-aided instruction involved rather rigid systems that required students to repeatedly memorize material, which was often a demotivating experience [65]. However, the realization of these limitations spurred significant

advances, such as the development of Artificial Intelligence in Education (AIED) and Intelligent Learning Environments (ILEs). Here, the use of AI in Computer Aided Instruction Systems enhanced the interaction experience between users and the system, paving the way for a more dynamic learning experience [66].

The emergence of teachable agents marks a distinct shift in this trajectory. These agents are designed to learn from the user, providing an interactive and personalized learning environment. Notably, the development of these agents has roots in the “learning-by-teaching” pedagogy, where the learner assumes the role of the teacher, enhancing their own understanding of the subject matter. Incorporating this methodology into Intelligent Tutoring Systems (ITS) allowed the creation of multiple agent roles within the learning environment, such as teachers and learning companions [67].

One of the first prominent teachable agents was the “Betty” system, designed for science learning by teams at Stanford University’s “AAA lab” and Vanderbilt University’s “Teachable Agent Group” [68, 69]. Students teach Betty by creating and modifying concept maps, thereby visually representing relationships between concepts and reasoning mechanisms [70]. This setup not only enhances student comprehension but also allows them to evaluate Betty’s learning progress based on her problem-solving explanations. Intriguingly, this method introduced the “Protégé Effect” [61] - students feeling responsible for their teachable agent and, in turn, investing more effort into learning.

Following Betty, another notable teachable agent, “SimStudent”, was developed at Carnegie University with the primary goal of facilitating the creation of cognitive tutors. These tutors, effectively functioning as learning-by-tutoring systems, emulate the classroom instructional environment for subjects like mathematics [71]. The integration of SimStudent into the Artificial Peer Learning environment (APLUS) allowed students to tutor the AI, effectively simulating the learning-by-teaching pedagogy [71].

The subsequent progression of teachable agents has extended towards studying cognitive, affective, and social aspects of student-agent interactions [72]. Modern systems integrate personality traits and conversational ability, as showcased in a teachable agent system developed by Sjöden et al. [73]. Using the Enhancing Agent-Learner Interaction (EnALI) framework [74], they equipped a teachable

agent with enhanced social and conversational abilities. The study of this system underscored the significance of agent context, user knowledge, and communication styles in determining effective learning outcomes [73]. Thus, the evolution of teachable agents represents a key stride in the development of personalized, effective learning tools.

### 2.2.2 Benefits of TA

Previous research has demonstrated that when asked to tutor another student, students learn a subject more effectively. Traditionally, this entailed devoting effort to setting up peer tutoring arrangements for students. However, it is difficult to collect detailed records of interactions between tutors and tutees during a study. Education experts around the globe then attempted to solve the problem using technology. Computer-generated students, known as teachable agents, who require human teachers to instruct them in everything were developed. These teachable agents don't feel humiliated or angry when they don't know something, in contrast to actual students. They respond consistently to effective instruction without making careless or random errors, and their influence on learning can be properly recorded and measured. SimStudent [75], is an example TA that was designed for this purpose.

Additionally, teachable agents enable students to better their learning, explore, and solve problems for themselves [68]. The possibility exists for TAs to improve students' capacity for knowledge reflection and self-explanation [76]. Students who are given the opportunity to teach are forced to consider the underlying ideas and connections of a subject in order to assess what another student already understands and to further their own comprehension. TAs also encourage taking ownership of learning and assist students in restructuring and reorganizing their knowledge [77]. Students gave their TAs social status by attributing to them responsible behavior and mental states. Additionally, they were more inclined to accept mistakes by expressing negative emotions and attributing failures to certain factors. Having a TA may foster a sense of responsibility that inspires learning, creates a setting where knowledge may be improved through revision, and shields students' egos from the psychological effects of failure.

## 2.2.3 Types of Teachable Agents

Due to the benefits brought about by the TAs, much has been done in the area. To create TAs, three major techniques have been used, namely, knowledge-sharing, knowledge-tracing, and knowledge-learning.

### 2.2.3.1 Knowledge-sharing Teachable Agents

Knowledge-sharing TAs use the knowledge (e.g., a concept map) that students share to solve problems. Students directly teach such agents by delivering shared knowledge. All interactions between students and TAs, for example, teaching, reasoning, and answering are delivered in a visible, explicit, and unambiguous form through shared knowledge representation [78].

Betty's Brain is an example of a knowledge-sharing TA. Betty's Brain system is a teachable agent learning environment in which students read articles and then use concept maps to teach, query, and quiz a virtual agent, Betty, casual linkages in science [68, 79]. The concept map consists of nodes that represent concepts, and links that represent relationships between nodes. A relation is a unidirectional link that connects two concepts. Concept maps aid in categorizing groups of objects and expressing interactions between them. They also serve as a means of expressing knowledge hierarchies and causal relationships [80]. To teach Betty, students can make use of three types of links, namely, causal, hierarchical, and descriptive. A causal link describes how a change in the originating node impacts the destination node in an active relationship. In addition, increase (“++”) and decrease (“--”) labels are also used to qualify causal relationships. For example, “Fish eat Plants”, and the word “eat” suggests a decreasing relationship. Students can use a hierarchical link to create class structures to organize domain knowledge. For example, “Fish is a type of Animal”. Students can use a descriptive link to include remarks or intriguing aspects about an object in their concept map. For example, “Fish live by Rocks”. There are two mechanisms in the query mode: a reasoning mechanism and an explanation mechanism. Betty's reasoning mechanism allows her to analyze the knowledge that the student has taught her in order to answer questions. Betty can use the explanation mechanism to provide a detailed explanation of how she arrived at her answer. Betty and the student are informed about whether Betty's answers are correct or incorrect in the quiz mode, by the

teaching expert. Meanwhile, the teaching professional provides hints to assist the student in debugging the concept map. Betty's Brain is intended to assist students in developing structured knowledge networks, taking responsibility for and making decisions about their learning, and developing reflection or meta-cognitive abilities [68], all of which will help them prepare for future learning.

Motivated Teachable Agent (MTA) and Persuasive Teachable Agent (PTA) proposed by Zhao *et al.* [78] and Lim *et al.* [81], respectively, can be another examples of knowledge-sharing TA. MTA can reason and determine for itself on the selection for the next goal and actions to take, and it can follow its intrinsic motivation and connect with students by pursuing its own agenda by executing a hierarchy of goals. On the other hand, the PTA utilizes persuasion theory to strategically enhance students' learning attitudes. They are embedded into a 3D virtual environment where primary and secondary students are required to teach it about science knowledge like transportation in plants. Using osmosis as an example, students create a concept map by dragging and dropping concepts and relations to create a concept map for the TAs. Based on the concept map, the agents derive logic rules and attempts to enter the root of a banana tree using the concept map. Furthermore, the PTA sends tailored messages that cultivate a positive attitude towards learning.

### 2.2.3.2 Knowledge-tracing Teachable Agents

Another genre of TA makes use of the knowledge-tracing technique that is used by Cognitive Tutors to identify students' competency [82]. Cognitive Tutors are an intelligent tutoring system developed by Carnegie Learning based on John Anderson's adaptive control of thought theory of cognition. Cognitive Tutors utilize the cognitive model which has two purposes. To begin, the model observes student behavior in order to determine a student's problem-solving method. Model tracing is the technique through which it accomplishes this. Second, each action taken by the student is linked to one or more abilities, which are references to the cognitive model's knowledge components. Individual student's performance on these abilities is tracked over time and presented in a "skillometer" for students to see. This technique is referred to as knowledge tracing. Via model tracing and knowledge tracing, Cognitive Tutors evaluate students' learning progress, direct students down the correct path to problem solutions, and provide feedback.

Knowledge-tracing TAs are designed with a set of knowledge that must be acquired. To provide the agent with a limited ability to solve problems, some of the knowledge is set as inactive at first. As the student tutors the agent, the model tracer detects the knowledge that was taught and activates the knowledge that has been taught such that the agent can apply it to solve future problems.

For students to understand arithmetic concepts, Pareto et al. developed a knowledge-tracing TA and a Teachable Agent Arithmetic Game [83, 84]. All of the games in the learning environment are digital card and board games for two players. Students can play the games themselves, teach an agent to play, or watch the agent play. During teaching, the agent and the student “work together” as one of the players. A student can teach by two means. First, by showing the agent how to play. One can also allow the agent to make an attempt to play the game based on its knowledge, and then make the choice about whether or not the agent’s choice is accepted. If the agent’s choice is rejected, the student is required to show how he/she plays. The agent learns in two ways. It can learn by watching the student play and by asking questions. The agent is also capable of playing without assistance from the student. It has no prior knowledge and can only ‘guess’ at first. It then plays according to its present level of knowledge, which is determined by how much and how well it has been taught. Students may observe how much the agent understands in comparison to an “expert player” by the knowledge meters displayed. The agent does not play optimally if it has not become an “expert player”. The system achieves this by only allowing the agent to “see” the knowledge with a certain probability. When all knowledge is seen, the agent is able to make optimal choices.

Lenat and Durlach [85] developed BELLA, the sixth-grade mathematics learning-by-teaching system. BELLA already knows the sixth-grade math curriculum; all it does is run an avatar named Elle who appears to be struggling in the subject and has an even worse understanding of pre-algebra than the student. When a student, who plays the tutor’s role, interacts with Elle, BELLA observes and learns more about the student every time he/she corrects Elle, as well as from his/her silence and inaction. This aids BELLA in determining pedagogically beneficial modifications to make in Elle’s mental model, which subsequently affects Elle’s behavior in the future. From the student’s perspective, it seems as if he/she is teaching Elle. In circumstances where BELLA is unfamiliar with some aspects of

the current student's profile, it makes Elle make those mistakes. If the student corrects Elle, BELLA learns something new about the student. In the meantime, this provides the student with a slight boost in self-esteem [85].

### 2.2.3.3 Knowledge-learning Teachable Agents

Knowledge-learning TAs incorporate machine-learning engines, allowing TAs to learn skills on the go. They are argued to be able to emulate the tutor-tutee interaction more accurately.

As an example of knowledge-learning TA, Michie et al. [86] developed the Math Concept Learning System (MCLS). This research developed a TA for solving linear equations in one variable. As a result of MCLS, problems are represented by attributes that can be either values or operators. Students can specify computation rules and sequences for some linear equations using the system. In order to interact with the system, students can (i) demonstrate how to solve an equation to the system, (ii) examine the rules it has already learned, (iii) ask the system to solve an equation using the current rule they are teaching, and (iv) ask it to solve an equation and provide feedback at each step. By inducing the various actions that can be taken to solve equations and when to apply each rule from past examples, MCLS learns how to solve equations. An inductive machine-learning technique called "Iterative ID3" is used to generate a set of generic rules based on input from the student. A linear equation would be solved separately by the student and the system, and if the solutions were different, the system would prompt the student to choose the correct answer. The process of generating computational rules by computer is not visible to students in this TA system. In other words, as the student could not read the reasoning mechanism of the TA system, it would be difficult for him/her to identify any errors.

SimStudent is another example of a knowledge-learning TA. It is a simulated learner that has been used to investigate student-tutor learning in the context of mathematics problem solving [75]. Two novel ways of using teachable agents were examined in the Carnegie Mellon University teachable agent project. The first involves developing teachable agents as cooperative tutors for a cognitive tutoring system, while the second involves providing educational researchers with virtual students (the teachable agents) to experiment with learning theory. SimStudent is taught

by students by asking it to solve an algebraic problem. SimStudent attempts to solve the problem by applying previously learned production rules. When a rule is used (that is, when a step is completed), the student provides binary feedback that indicates whether the rule was applied correctly or not. SimStudent tries to apply another rule when there is negative feedback. SimStudent approaches the tutor agent for help when it is unable to complete a step correctly. The student then gives SimStudent a suggestion by demonstrating the step. SimStudent learns skills by generalizing from the examples. A positive example is generated when the student gives affirmative feedback on a step that SimStudent completed, or when the student demonstrates a step to SimStudent as a hint. When SimStudent receives negative feedback from the student on a step that it completed, a negative example is created. SimStudent generates production rules that cover all positive examples but none of the negative examples as a result of generalization. SimStudent was proven to be successful in teaching procedural skills but not conceptual ones. It was also more effective when students taught it correctly and used the feedback and quizzing elements provided more effectively.

#### 2.2.4 Teachable Agents and Ikigai

Teachable agents represent an innovative form of intelligent technologies that learn through interactions with humans, reflecting the process of human learning and engaging users in active teaching. Previous research has highlighted the numerous benefits of teachable agents in educational contexts, aiding students in knowledge acquisition, exploration, and problem-solving [68].

However, the utility of teachable agents extends beyond traditional educational frameworks. They have potential applications in a diverse range of fields, where their capacity to learn and respond based on the knowledge acquired through user interaction can be leveraged.

For elderly users, teaching these teachable agents could provide a unique sense of purpose and responsibility. This process mirrors the benefits that students derive from teaching agents in an educational context. This engagement not only allows elderly individuals to learn new things while teaching the agent, but it also fosters a sense of fulfillment and responsibility within them, thereby enhancing their Ikigai.

Moreover, teachable agents are designed to acquire new knowledge and adjust their responses based on information received from user interactions. These agents have the ability to assimilate user information and preferences, which are primarily obtained through user interactions. This key feature enables the agents to deliver personalized experiences, as they tailor their responses based on the knowledge they've accrued about each individual user.

This personalization feature is especially crucial in the context of Ikigai — a concept that is inherently personal and subjective. As people's sources of Ikigai may be different, the ability of the teachable agent to adapt its interactions according to the user's preferences and needs ensures a more personalized and meaningful experience. Thus, teachable agents hold great promise in supporting the elderly in discovering and enhancing their Ikigai, ultimately contributing to improved well-being.

## 2.3 Knowledge Graphs

Knowledge graphs have emerged as a vital tool in the realm of artificial intelligence (AI), playing an essential role in learning and representing human knowledge [87]. The necessity for such a tool arises from the requirement of AI systems to comprehend and evaluate their environment, similar to human abilities, but within a machine-understandable context.

Defined as a data structure accumulating and conveying real-world knowledge, knowledge graphs incorporate nodes representing the entities of interest and edges depicting their interrelationships [88, 89]. These relationships are not always symmetrical, so their directionality can provide significant context. Consider the case of a graph modeling the connections within a social network; the edges here are typically undirected, reflecting the mutual nature of friendships. On the other hand, if a graph were designed to illustrate the “following” relationships on a social media platform like Instagram, the edges would be directed, since the following action is unilateral. Furthermore, knowledge graphs are uniquely capable of representing hierarchical relationships, such as those existing among different organisms. For example, animals and plants can be viewed as different types of living organisms, each further divided into multiple species. In Figure 2.2, a rabbit (an animal)

eats carrots (a type of plant), which illustrates the relationship between species and their roles in a food chain. As a result of formal semantics applied to these graphical structures, knowledge graphs facilitate precise and efficient machine interpretation, making them an indispensable tool as big data and AI-driven analytics become more prevalent.

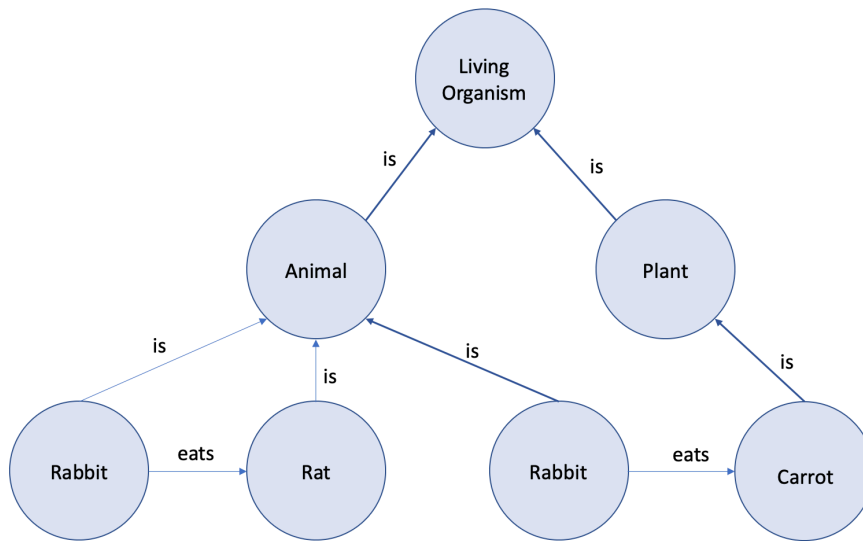


FIGURE 2.2: Example knowledge graph representation

The inception of Google’s Knowledge Graph [90] in 2012 paved the way for the introduction and adoption of various knowledge graphs such as DBpedia [91] and Wikidata [92]. These have been extensively implemented in multiple AI systems [93, 94], demonstrating their utility in diverse fields such as education, healthcare, recommender systems, question answering, and information retrieval [95, 96].

Knowledge graphs represent a directed and labeled graph where nodes and edges possess well-defined meanings. Nodes typically denote an entity, a real object or an abstract concept, while the edge between two nodes illustrates the semantic relation between the entities [97]. These graphs can be managed and represented using Resource Description Framework (RDF) and Labeled Property Graphs (LPGs), two popular methods in the field [98, 99]. The fundamental unit of these graphs is a triple, i.e., (subject, predicate, object), for instance, (Nanyang Technological University, locatedin, Singapore).

Beyond their use in AI systems, knowledge graphs also offer a method for capturing domain-specific meanings associated with nodes and edges. These meanings can be documented in a human-understandable language or expressed in a formal

specification language, offering different levels of accessibility and usability based on the specific application needs. Information can be added to a knowledge graph through a combination of human-driven, semi-automated, or fully automated methods, with the expectation that the recorded information is easily comprehensible and verifiable by humans.

Moreover, knowledge graphs can adapt to the requirements of specific applications. For instance, the Resource Description Framework (RDF), a popular model used over the World Wide Web, uses International Resource Identifiers (IRIs) to uniquely identify entities [100]. Property graph models associate properties and values with each node and edge, allowing for a high degree of customization [101]. These adaptations allow for detailed and tailored querying of the information in the knowledge graphs, making them a versatile tool in the AI toolbox.

Knowledge graphs have found considerable application across various domains including education, scientific research, and health and medical care, due to their capability to manage complex data structures and provide meaningful insights.

One significant application of knowledge graphs in offline education revolves around the crucial task of course allocation in universities. Recognizing the importance of this task, [102] proposed a knowledge graph-based course management approach for automated course allocation. They built a course knowledge graph wherein the entities comprised courses, lecturers, course books, and authors. This structured representation of data allows for a systematic suggestion of relevant courses to students, facilitating a more efficient and personalized academic journey.

Further aiding offline teaching, [103] introduced KnowEdu, a system dedicated to educational knowledge graph construction. KnowEdu begins by extracting the instructional concepts of subjects and courses, using them as entity features. It then identifies educational relations based on students' assessments and activities, aiming to amplify the teaching effect. Such an approach not only assists teachers in structuring their pedagogical methods but also enriches the learning experience for students.

While these applications aim to improve offline school teaching, the advent of digital technologies and unforeseen circumstances such as the COVID-19 pandemic have caused a significant shift towards online learning. This shift, however, presents its own set of challenges. Students often struggle with the vast and potentially

confusing online content, including low-quality learning material on social media. Thus, creating a conducive and effective online learning environment has become a research priority.

In response to this need, several researchers propose constructing education-efficient knowledge graphs to streamline the online learning process. For instance, Zablith [104] proposed a solution that bridges formal learning and social media. He suggested building a knowledge graph that integrates social media and formal educational content. This approach would help filter social media content, focusing on information beneficial for formal learning. Consequently, it would make online learning more efficient and meaningful for students.

Knowledge graphs have increasingly become a cornerstone in the scientific research process. They have emerged as a powerful tool, assisting researchers in exploring research knowledge and identifying relevant materials in a convenient and efficient manner. These knowledge graphs typically interlink a vast array of information, including documents such as research articles and patents, actors such as authors and organizations, and other pertinent entities like topics, tasks, and technologies. They also encompass other contextual information like projects and funding sources.

Several specific examples illustrate the scope and utility of knowledge graphs in scientific research. The Microsoft Academic Graph (MAG) [105], for instance, is a heterogeneous knowledge graph that comprises metadata from over 248 million scientific publications. It includes information on citations, authors, institutions, journals, conferences, and fields of study. This extensive network allows researchers to map connections and draw insights from a vast array of academic data.

Another prominent example is the AMiner Graph [106], a corpus that consists of over 200 million publications. It has been used by the AMiner system to generate a vast knowledge graph for academic research. To further expand the scope of academic knowledge graphs, the Open Academic Graph (OAG) integrates the Microsoft Academic Graph and the AMiner Graph, forming an even larger and more comprehensive network of academic data.

AceKG [107] is another large-scale knowledge graph in this domain. It provides around 3 billion triples of academic facts, encompassing papers, authors, fields of study, venues, institutes, and the relations among them. Such a vast network can

guide researchers towards relevant studies and collaborations, thus boosting the efficiency of their work.

Beyond their role in organizing and mapping academic information, knowledge graphs also contribute significantly to the development of various applications that benefit scientific research. They can aid in scientific publication management, helping non-researchers understand methodologies for sustainability derived from research thinking [108].

Knowledge graphs also power several scientific recommender systems. An instance of this is the knowledge graph-based reviewer assignment system designed by Yong et al. [109]. This system utilizes knowledge graphs and recommendation rules to establish a rule engine, enabling precise matching of reviewers and papers.

The exponential growth of medical information has necessitated efficient and accurate methods of medical knowledge analysis. As a result, there has been an increase in integrating medical information into knowledge graphs, thereby equipping intelligent systems to swiftly and correctly understand and process medical knowledge. Biomedical knowledge graphs, for instance, are now widely available and frequently used in numerous healthcare applications. One such application is the Health Knowledge Graph Builder (HKGB), introduced by Zhang et al. [110], which incorporates clinicians' expertise to construct comprehensive medical knowledge graphs.

Among the myriad of intelligent healthcare applications, three stand out as particularly prominent: medical decision-making, health misinformation detection, and drug discovery.

Medical decision-making is becoming increasingly essential in the ever-evolving medical industry. With the abundance of medical choices available today, individuals often grapple with selecting the most appropriate and personalized medical treatment. To address this issue, biomedical knowledge graph-based recommender systems, such as doctor and medicine recommender systems, have been proposed. Gong et al. [111] offered an innovative approach to medicine recommendation, wherein they created a heterogeneous graph featuring medicines, diseases, and patients as nodes. This allows for more accurate and safe medicine prescriptions, particularly for patients with complex health conditions. In [112], the use of knowledge graphs in a Health Well-being application is described, specifically focusing

on supporting decision-making in organ transplantation using argumentation theory. Moreover, [113] reports a survey on the application of knowledge graphs in Clinical Decision Support Reasoning Systems, showcasing their potential in aiding healthcare professionals in making informed decisions.

Despite the healthcare sector's earnest efforts to disseminate accurate medical information, health misinformation remains a pervasive problem. This misinformation can be defined as incorrect information contradicting established medical knowledge or biased information that only partially reflects the facts. The spread of such misinformation, particularly through healthcare platforms and social media, can lead to harmful medical malpractice. To combat this, researchers have utilized authoritative medical knowledge graphs to detect and filter misinformation. An example of this is the model DETERREN developed by Cui et al. [114], which uses a knowledge-guided attention network that combines an article-entity graph with a medical knowledge graph.

Drug discovery, including drug repurposing and drug-drug interaction prediction, has recently emerged as a key research area in intelligent healthcare. Medical knowledge graphs prove particularly beneficial in this area due to their rich entity information (e.g., the ingredients of a drug) and relationship information (e.g., the interaction of drugs). Lin et al. [115] presented KGNN, an end-to-end framework for predicting drug-drug interactions that leverages the relationships between drugs and potential neighborhoods in medical knowledge graphs. Another noteworthy endeavor is COVID-KG, a knowledge discovery framework developed by [116] for generating COVID-19-related drug repurposing reports. It begins by constructing multimedia knowledge graphs from images and texts and then utilizes these graphs to generate reports.

Besides these general-purpose knowledge graphs, there are efforts made in the area of personalized knowledge graphs [117] and personal knowledge graphs [118] to achieve better personalization. Gyrard et al. [117] developed a personalized health knowledge graph. This graph is created by gathering information from diverse sources such as medical datasets and IoT devices. It is important to note that this personalized health knowledge graph is a subset or subgraph of larger knowledge graphs. Unlike the comprehensive general-purpose KGs, this personalized graph contains only the information that is specifically relevant to the user's needs and profile. By tailoring the knowledge graph in this way, it aims to provide

more targeted and personalized insights in the domain of health and well-being. [118] proposed their Personal Health Knowledge Graphs (PHKGs) where events play a central role in representing a patient's experience with a specific disease. These events encompass various aspects, including visits or encounters, reported complaints and symptoms (recorded as observations), procedures performed, prescribed medications, finalized diagnostic reports, and even applied care plans. Additionally, self-management activities such as exercise, self-measurements, or sleep monitoring can be included.

In the context of this research about Ikigai, a knowledge graph not only may not only be used to manage current literature and studies about the complicated concept, but a personal knowledge graph may also be used to better understand the person and their Ikigai for more personalized approaches to improve their Ikigai.

## 2.4 Machine Learning in Predictive Well-being

Machine learning, an important facet of artificial intelligence, has earned significant recognition for its potential to revolutionize diverse fields, including well-being. The concept of well-being extends beyond the boundaries of physical health and also encapsulates aspects such as positive emotions and moods [119]. With its potential for prevention, early detection, and management of health and disease risks [120], well-being has been an important area for machine learning applications.

Well-being is typically assessed through self-reported surveys, which gather information about various physical and mental factors [121]. In recent years, much research has been done to apply machine learning to predict, monitor, and detect aspects of people's health, emotions, and mental health conditions. These machine learning models take in a wealth of data from diverse sources. They incorporate sensor data [122, 123], survey responses [122, 124], social media use information [125–127], and even voice samples [128]. Machine learning's strength lies in its ability to uncover latent and important patterns from this large amount of data. These patterns may easily go unnoticed or misinterpreted by conventional rule-based approaches [129, 130].

The breadth and complexity of the data involved, coupled with the inherently nonlinear correlations between different data points, pose a formidable challenge

for traditional data processing techniques. This is where machine learning comes into play, with its inherent capability to handle large-scale, complex datasets and unravel valuable insights [131–133]. Various machine learning algorithms, such as decision trees, support vector machines, and neural networks, have been deployed for creating predictive models. These models have shown great efficacy in predicting psychological issues like stress, depression, and anxiety [134].

In recent years, there has been substantial progress in the field. For instance, researchers have been able to predict the mental well-being of university students by employing machine learning models trained on diverse cross-sectional survey data [124]. This data includes factors like health-risk behaviors, grade point averages, years of study, and so on. Another exciting development is the use of machine learning for predicting elderly well-being in private home environments [122]. Here, domestic sensor networks and daily surveys provide the data for training the predictive models. Other innovative applications of machine learning in well-being include prediction models trained on short voice recordings [128], as well as those that utilize data from wearable devices, mobile phones, and even weather information to predict mood, health, and stress levels [135, 136].

The advent of deep learning models has further enriched this domain, enabling the detection of mental health problems like depression using user-generated content on social media platforms [125, 126]. Additionally, wearable gadgets and smart devices are increasingly being used to gather data that, in conjunction with AI-based models, can detect and categorize stress levels [123].

Despite the impressive strides made in this area, significant gaps remain, particularly in relation to mental and psychological well-being. One notable gap is the lack of exploration of the concept of Ikigai within the context of AI [137]. Ikigai, a term emanating from Japanese culture, is often translated as 'reason for being' and encapsulates the concept of having a purpose in life or the elements that make life worth living. In the context of well-being, it is associated with a comprehensive sense of life satisfaction, happiness, and even longevity. Despite its considerable impact on overall well-being, Ikigai remains a largely unexplored area within the artificial intelligence and machine learning field.

Bringing machine learning into the realm of Ikigai provides an exciting prospect in predictive well-being and personalized interventions. Machine learning, with its

capability to analyze complex, multidimensional data, can potentially predict, enhance, and provide individualized recommendations to improve one's Ikigai. The data inputs for such models could be expansive and multifaceted, encompassing demographic details, behavioral data, self-reported surveys, and even social interaction data.

Machine learning algorithms are adept at identifying intricate patterns and correlations within this wealth of data, providing insights into the unique interplay of various factors contributing to an individual's Ikigai. These insights could aid in recognizing the core elements that imbue an individual's life with purpose, as well as provide actionable recommendations to foster environments and habits that encourage the pursuit of their Ikigai.

Furthermore, these machine learning models can adapt and learn over time, continuously refining their predictions and recommendations as they accumulate more data about an individual. This dynamic learning capability could allow for real-time adjustments and updates, fostering a constantly evolving understanding of an individual's Ikigai.

Nevertheless, despite these promising prospects, the intersection of machine learning and Ikigai remains largely unexplored. To the best of our knowledge, there is no previous research on the application of machine learning to enhance Ikigai. This gap presents an exciting opportunity for innovation and discovery within the realm of predictive well-being, pushing the boundaries of traditional applications of artificial intelligence and machine learning. As we venture into this new frontier, we open up possibilities to not only improve well-being but also foster a deeper understanding of what makes life truly worth living.

## 2.5 The Interplay of Teachable Agents, Knowledge Graphs, and Machine Learning on Ikigai

### 2.5.1 Teachable Agents

Teachable agents are innovative tools grounded in the “learning by teaching” paradigm, and while their use has traditionally been centered around education, they present a wide array of applications that can extend to diverse populations, including the elderly. These agents essentially function as naive learners, capable of learning from users. When repurposed for the elderly, teachable agents can present a novel approach to learning about health-related topics, like navigating diet. In this context, the agents not only can present the effects more directly to the elderly, but also act as companions that accompany the individual on their learning journey, promoting a proactive role in maintaining their health. Moreover, teachable agents can also be designed to encompass a broad spectrum of subjects beyond health. The elderly, often facing a void post-retirement, can fill their time with meaningful and engaging learning activities that align with their interests. What makes the use of teachable agents even more compelling is their potential to foster a sense of responsibility, motivation, and satisfaction in learners. By acting as a learner who learns from users, it may stimulate a sense of responsibility to help the agent, thus helping cultivate self-efficacy and resilience. Upon successfully helping the agent, users may gain a sense of satisfaction and boost self-esteem.

More importantly, the underlying programming allows teachable agents to learn about a user’s preferences, interests, and health status, ultimately providing highly personalized and relevant suggestions.

### 2.5.2 Knowledge Graphs

Knowledge Graphs, on a macro level, bring immense value in representing the intricate and multidimensional concept of Ikigai. The concept of Ikigai revolves around many aspects. For example, Takeda [138] identified self-esteem, purpose in life, personal energy, and life satisfaction are considered as the most appropriate

factors to explain the concept of Ikigai. These elements, when intertwined, contribute to an individual's Ikigai. A Knowledge Graph can serve as a powerful tool to encapsulate this notion, presenting a structured overview of these elements and the relationships between them. Moreover, these graphs can be the foundation for the development of dynamic questionnaires or interactive tools designed to assess individuals' Ikigai levels. This interactive process may act as a catalyst for personal reflection and self-discovery, enabling users to gain a better understanding of their Ikigai.

On a more granular level, personal knowledge graphs provide a way to capture and organize an individual's specific attributes, including abilities, interests, values, and even life experiences. This kind of graph is highly personalized, reflecting a rich and detailed snapshot of the individual's life and identity. These personal knowledge graphs can also offer unique insights that can drive personalized advice and recommendations. Furthermore, the dynamic nature of these graphs allows them to evolve with the individual, adapting to changes in interests, circumstances, and goals over time.

### 2.5.3 Machine Learning

Machine Learning techniques offer a robust and dynamic approach to understanding and enhancing one's Ikigai. Given an individual's profile, which can include a vast array of data points such as interests, health, and cognitive conditions, these techniques can yield insightful predictions and recommendations tailored to the individual.

One of the key strengths of machine learning is its capacity to identify patterns, trends, and correlations in large and complex data sets. In the context of Ikigai, these techniques can delve deep into the individual's profile data, finding hidden connections and patterns that might otherwise remain undiscovered. Machine learning algorithms can be trained to predict an individual's Ikigai level based on these patterns. This prediction can act as a barometer for the individual's current sense of purpose and fulfillment.

Additionally, machine learning can be employed to provide recommendations tailored to enhance an individual's Ikigai. By understanding an individual's unique

profile and the complex interplay of elements that contribute to their Ikigai, these algorithms can suggest activities, that could help enhance their sense of Ikigai.

#### 2.5.4 The interplay of Concepts

The interplay of teachable agents, knowledge graphs, and machine learning provides an innovative approach to understanding and improving Ikigai.

Teachable agents, originally used for educational purposes, have the potential to play an integral role in exploring and enhancing one's Ikigai. These agents can help users learn things that they are interested in. In the process of teaching the agents, a deeper sense of responsibility, motivation, and satisfaction may be fostered, and these are crucial aspects of Ikigai. Moreover, these intelligent systems can be designed to interact with individuals, learning about their physical conditions, interests, and values. These can form the basis for personalized advice and recommendations on improving Ikigai.

Knowledge graphs, on the other hand, serve as an ideal tool for visualizing and understanding the multifaceted and complex concept of Ikigai. This can aid an intelligent questionnaire system for assessing an individual's Ikigai level. Additionally, a personal knowledge graph might capture various elements such as a person's skills, interests, and values, as well as their relationships and personal circumstances, offering a holistic view of their current Ikigai status.

Machine learning can enhance this journey further by analyzing these complex data structures. By examining an individual's profile, including those learned through the interaction between the user and teachable agent, machine learning algorithms can detect patterns and correlations between various elements of their life. These algorithms can predict an individual's state of Ikigai, or identify factors that may enhance or inhibit their journey towards finding Ikigai.

Thus, the amalgamation of teachable agents, knowledge graphs, and machine learning provides a powerful toolkit for individuals to improve their Ikigai. A teachable agent acts as a medium for interactive, personalized guidance, knowledge graphs provide a holistic, structured view of one's life, and machine learning contributes predictive and prescriptive insights. This interplay can foster self-understanding, and facilitate personalized approaches for enhancing the individual's Ikigai level.

## 2.6 Phenomenography

Phenomenography is a qualitative research methodology “for mapping the qualitatively different ways in which people experience, conceptualize, perceive, and understand various aspects of, and phenomena in, the world around them” [139]. It was developed in Sweden in the early 1970s, and initially employed to investigate why some people were more successful at learning than others [140]. It does so by focusing on two key aspects of learning: the content aspect and the act aspect. The content aspect of learning pertains to the diverse ways in which students understand the content they are learning, whereas the act aspect focuses on how students experience the learning situation itself and their specific actions during the learning process.

Phenomenography centers on understanding the qualitatively different ways individuals perceive, comprehend, and interpret a particular phenomenon. Rather than investigating the phenomenon itself, phenomenographic researchers are interested in the various experiences and understandings of that phenomenon among different people. Marton [141] described phenomenography as a form of research aimed at the “description, analysis, and understanding of experiences.” This essentially means that the research approach focuses on experiential descriptions—how individuals make sense of their world.

The phenomena that are experienced and thought about, as well as the human beings who are experiencing and thinking about the phenomena, are not the only focus of phenomenography. It is also unconcerned with perception and thinking as abstract phenomena unrelated to the subject of thought and perception. Phenomenography is the study of the relationships that exist between people and the phenomenon (Figure 2.3). In another word, it adopts a “second-order” perspective [141] where the focus is not describing things as they are, nor debating whether they can be described as they are, the focus is about describing how they appear to people.

Phenomenography is less about the individual and more about the collective experiences. In a phenomenographic study, the individual serves as a provider of data, but the analysis is not about the individual. It’s about a collective understanding of a phenomenon. Individuals are seen as bearers of views, but those individual views are aggregated to provide a depiction of the different ways a phenomenon can

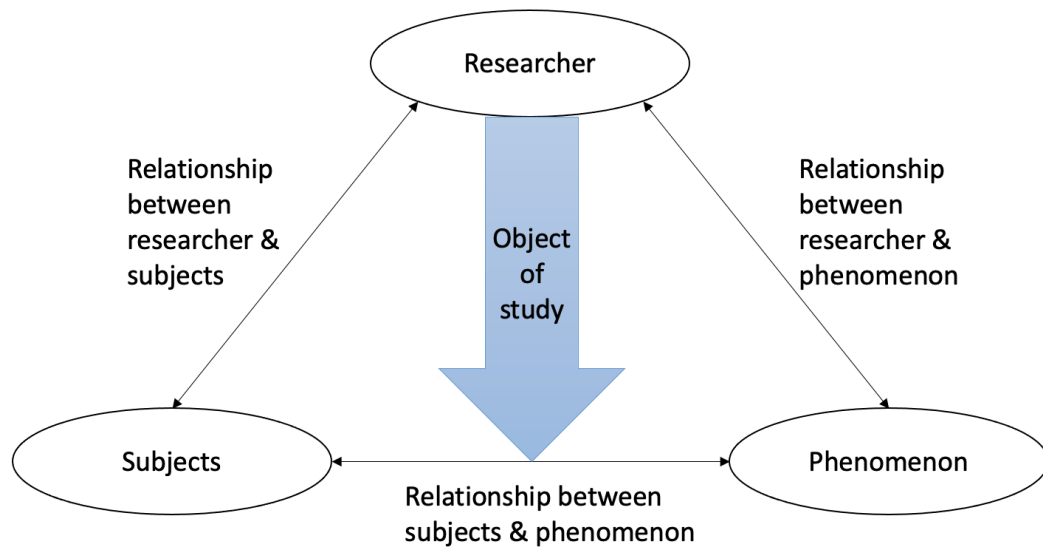


FIGURE 2.3: Phenomenographic relationality [1]

be experienced [140]. As a result, phenomenography often yields an outcome space that “is the complex of categories of description comprising distinct groupings of aspects of the phenomenon and the relationships between them” [140].

Phenomenography posits that there are limited, distinct ways that a particular phenomenon can be experienced or understood. The basic principle of phenomenography is that “whatever phenomenon we encounter, it is experienced in a limited number of qualitatively different ways” [140]. This principle is important as it allows for shared understanding and communication. It is why phenomenographic research findings can often be generalizable to larger populations, despite being based on the experiences of a limited sample of individuals. Marton and Booth [140] argues that “the worlds we inhabit are recognizable and communicable at all means that the number of ways of experiencing any phenomenon in the world is limited”. It is what allows phenomenography to offer a structured, organized perspective on how people experience and understand various aspects of their world.

However, while phenomenography seeks to identify these limited categories of experiences, it also acknowledges the complexity and diversity of human experience. The categories of description are not intended to oversimplify or reduce people’s experiences, but to capture the key dimensions of how a phenomenon is understood or experienced within a specific context.

### 2.6.1 Phenomenography and Phenomenology

Phenomenography is different from phenomenology though both study human experiences. In phenomenology, “the researcher is exploring her own experience by reflecting on it”, whereas in phenomenography, “the researcher is exploring other people’s experiences by reflecting on them” [140]. In addition, “phenomenology makes a distinction between the appearance of something and its essence” [142]. It seeks to explore and describe the lived experiences of individuals in order to reveal the “essence” or inherent nature of a phenomenon. The focus is on the subjective, lived experiences and consciousness of individuals, with a goal of understanding phenomena from the first-person perspective. Phenomenology involves “the understanding of the essence of the phenomenon”, whereas phenomenography focuses on “investigating the experience of others and their subsequent perceptions of the phenomenon - their reflections on the phenomenon” [142].

This fundamental difference thus sets phenomenography apart from many other research methodologies. While most traditional research methods are aimed at describing or explaining the phenomenon itself, phenomenography is about mapping the range of possible interpretative or experiential outcomes of that phenomenon among a specific group.

Through capturing these diverse experiences, phenomenography provides insights into the variation in understanding, thinking, and practicing within a specific context. As such, it has found significant use in areas such as educational research and design, where understanding these variations can directly inform and improve practice.

Phenomenography does not seek a single “truth” or definitive explanation of a phenomenon. Instead, it acknowledges and explores the multifaceted nature of human experiences and perceptions, recognizing that each individual’s experience is unique and holds value in enhancing the collective understanding of a phenomenon. This emphasis on individual experiences and perceptions makes phenomenography a powerful tool for capturing the complexity and richness of human experiences.

## 2.6.2 The Use of Phenomenography in this Research

Incorporating a teachable agent as a method to enhance Ikigai level, in the lives of the elderly introduces a novel component within the existing frameworks of elder care. To the best of our knowledge, there are no prior reports capturing the experiences related to interactions with such teachable agents.

Our proposed agent acts as a virtual companion for the elderly. This means the agent will be there to facilitate learning, provide companionship, and offer assistance round the clock. The experiences and perceptions of the elderly in regard to this novel agent form a significant part of our research investigation. This is because their responses and feedback can greatly influence the efficacy and impact of the agent's implementation.

Should the elderly population develop a positive perspective towards the teachable agent, there's a strong likelihood that the agent could effectively improve their Ikigai levels. This would result in not just an enhancement in the quality of life for the elderly but also a reduction in the burden for their caregivers. On the other hand, any negative feedback provides valuable insights for us to further optimize the agent, ensuring its capabilities are better attuned to the needs and preferences of the elderly, and hence more effective in enhancing their Ikigai.

In this context, phenomenography, a research approach that delves deep into studying and understanding human experiences, becomes a highly relevant tool for achieving our research goals. The insights drawn from a phenomenographic study could prove to be pivotal in our research. This is primarily because phenomenography appreciates and recognizes the different ways in which we humans perceive, interpret, and comprehend our surrounding world.

Specifically, within the scope of our research, which is focused on understanding the elderly's experiences with an intelligent teachable agent, the use of second-order phenomenography is highly effective. This is because it allows us to collect and analyze feedback directly from the elderly individuals themselves, ensuring a first-hand, unfiltered understanding of their perceptions, emotions, and experiences. This authentic understanding would then feed into further refining our methodologies and interventions, allowing us to create a more impactful and beneficial teachable agent experience for the elderly population.

# Chapter 3

## Assessing Ikigai

The journey towards enhancing one's Ikigai, a traditional Japanese concept embodying a sense of purpose and satisfaction in life, starts with a thorough and accurate assessment of its current state. Ikigai, while deeply personal and subjective, is rooted in an individual's motivations, values, and perceived life's meaning. Recognizing its multifaceted nature, the path to improvement becomes clearer only when we comprehend where an individual stands on their Ikigai journey. Thus, we must understand one's Ikigai before we can improve it.

In this section, we delve into the comprehensive examination of assessing Ikigai - a complex, multifaceted concept ingrained in the Japanese culture, which encapsulates an individual's sense of purpose, fulfillment, and satisfaction in life. Assessing Ikigai is not a straightforward task, given its inherently personal and subjective nature. This intricate process involves the identification of an individual's motivations, values, and life's meaning, all intertwined in a harmonious blend that signifies Ikigai.

Given the inherent challenges in assessing something so deeply personal and subjective, we introduce innovative approaches that leverage the power of knowledge graphs and machine learning techniques. These methods allow for the creation of a dynamic and adaptive system capable of engaging with individuals on a personal level, accurately assessing their Ikigai levels continuously, and subsequently providing actionable insights for enhancement.

In this section, we want to address the first research problem, which is how to continuously assess an individual’s Ikigai. We first present existing scales and measurements for Ikigai, followed by a detailed description of the Ikigai-centric knowledge graph we have developed. We will discuss the dynamic question-generation process we use to evaluate a person’s Ikigai and explain the machine learning techniques we employ to predict an individual’s Ikigai level based on their provided profile.

Finally, we will present our findings and observations from the application of these methods, shedding light on the efficacy of our approach, the potential challenges encountered, and the avenues for future research. Through this in-depth exploration, we aim to provide a comprehensive understanding of assessing Ikigai and its implications for enhancing the quality of life, particularly for the aging population.

## 3.1 Existing Scales and Measurements

Several scales or measurements have been developed and validated for assessing one’s Ikigai level. In this section, we delve into the exploration of existing scales and measurements used for assessing Ikigai. These scales and measurements provide quantitative means to understand and evaluate an individual’s sense of Ikigai, thus offering valuable insights into their personal fulfillment and overall well-being. They serve as essential tools in establishing a baseline Ikigai level, thereby aiding researchers, clinicians, and even individuals themselves in tracking progression and identifying areas of improvement.

### 3.1.1 Ikigai-9

The Ikigai-9 [35] is a psychometric tool that consists of nine items measuring one’s Ikigai across three dimensions. The dimensions include “optimistic and positive emotions toward life”, “active and positive attitudes towards one’s future”, and “acknowledgment of the meaning of one’s existence”. It is first proposed and validated in Japan in 2012. Fido et al. [16] translated the scale to English and validated it in the United Kingdom (UK). The translation of the Ikigai-9 from Japanese to English was done by a bilingual researcher, before being translated back

from English to Japanese by another bilingual researcher, and any discrepancies in translation were resolved through discussion. It originally measures one's feelings for one's life, attitude towards one's future, and the acknowledgment of one's own existence. However, the three-dimensional structure was not supported by the confirmatory factor analysis of the English version of the scale [16]. It seems that the data from that study supported a single-factor Ikigai structure. To assess one's Ikigai level, he/she needs to rate whether each of the nine statements applies to himself/herself on a five-point scale (1 = *Does not apply to me*, 5 = *Applies to me a lot*). The nine statements are as shown following:

1. I often feel that I am happy.
2. I would like to learn something new or start something.
3. I feel that I am contributing to someone or the society.
4. I have room in my mind.
5. I am interested in many things.
6. I think that my existence is needed by something or someone.
7. My life is mentally rich and fulfilled.
8. I would like to develop myself.
9. I believe that I have some impact on someone.

### 3.1.2 Four-Factor Ikigai Scale

Takeda [138] developed and validated a four-factor scale to measure Ikigai. Self-esteem, purpose in life, personal energy, and life satisfaction are considered as the most appropriate factors to explain the concept of Ikigai. Self-esteem here is similar to the concept of 'the self', like self-awareness, self-worth, ego-identity, and so on. It is the fundamental level of Ikigai. Purpose in life is the most crucial and fundamental element of Ikigai, as it concerns one's reasons for living and meaning/purpose in life. Personal energy is the degree of activeness and concentration of a person in participating in various activities. It is the 'tangible source of Ikigai' that is based on the two aforementioned factors. Life satisfaction is the result

of the first three factors and it can only be obtained if the first three have been met. The four elements are arranged in such a way that they reflect a person's level of consciousness. Firstly, about one's 'self', which represents the deepest and unconscious level of Ikigai; secondly, purpose in life, which is a vital component of Ikigai; thirdly, about one's 'interest', which is the observable and tangible level of Ikigai; last but not least, life satisfaction, is the result of the three elements. Based on previous measurements for the four elements, Takeda first proposed a 49-item Ikigai scale using a five-point rating scale (1 = *Strongly Disagree*, 5 = *Strongly Agree*). After a pilot study, Takeda finalized the five-point, 28-item Ikigai Scale which has the four factors. Below are some example statements from the scale:

1. I have a lot of goals.
2. I am satisfied with my current life.
3. I believe I am an irreplaceable person for my family and friends.
4. I am energetic when working.

### 3.1.3 K-I Scale

Kondo [143] developed a 16-item K-I Scale to assess one's *ikigai-kan*, the feeling that life is worth living. Four-factor models are assumed: self-realization and will, sense of life fulfillment, will to live, and sense of existence. The K-I Scale has a 3-point Likert scale that ranges from 2 (yes) to 0 (no). However, due to the limited response options, there is less data variance. At the same time, to the best of our knowledge, there is no validated English translation of the scale.

### 3.1.4 Limitations of Existing Scales and Measurements

While a number of measurement tools have been developed to assess an individual's level of Ikigai, their use comes with certain limitations that necessitate further exploration. Primarily, existing scales and measurements typically ask a series of specific and statically ordered questions, to which the participants may respond with provided alternative answers such as multiple choice answers. This method, while structured, demands a lot of resources and manpower for implementation.

Moreover, these approaches are less dynamic, exploratory, and interactive, and usually not as informative as face-to-face interviews [144]. They often focus only on determining the overall level of Ikigai without providing comprehensive insights into the specific reasons behind lower levels of Ikigai. They lack the nuanced approach necessary to identify and analyze the underlying factors that could be hindering an individual's sense of purpose and fulfillment. This lack of detailed information poses significant challenges for the subsequent stages of intervention. Without a clear understanding of the specific elements that contribute to a person's low Ikigai level, it becomes more difficult to develop personalized and effective interventions. An individual's path to enhancing their Ikigai is a deeply personal journey that cannot be effectively facilitated with a one-size-fits-all approach.

Traditional Ikigai assessment tools tend to measure Ikigai in broad strokes, using general indicators such as overall life satisfaction, sense of purpose, or motivations. However, Ikigai is a complex and multifaceted construct, encompassing various aspects of an individual's life, including their relationships, personal interests, and more. The inability of these tools to delve deeper into these areas may result in a surface-level understanding of Ikigai, rendering the data collected less informative and less conducive to meaningful interpretation.

Moreover, incorporating equivalent questions at various points throughout a survey can significantly improve the quality and reliability of responses [145]. The repetition of similar queries also helps gauge the consistency of responses, thereby measuring the respondent's conviction in their answers. Despite these known benefits, such practices are not commonly applied in Ikigai-related surveys. The absence of these strategic redundancies within the survey design can lead to less reliable data, potentially skewing the interpretation of an individual's Ikigai level. In addition, people may respond inaccurately in such psychological measurement due to impression management. Thus, finding ways to evaluate one's Ikigai level without much self-report is also important.

## 3.2 Ikigai Knowledge Graph

In this section, we introduce the development of a knowledge graph-based intelligent survey system. Existing survey systems, which tend to be the go-to method

for Ikigai self-assessment and research, may be labor-intensive and often fail to capture the deeply personal and subjective nature of Ikigai. The inherent limitations in these traditional surveys, such as static question structures and the difficulty in reusing, customizing, or linking structured knowledge, often result in a lack of depth and personalization in the insights obtained.

Drawing inspiration from the work of Edelstein et al. [146], who employed a knowledge-driven intelligent survey system to study linguistic features and syntactic relationships, we adapt this methodology to the study of Ikigai. Researchers have proposed several dynamic and informative solutions for an intelligent survey system that is based on knowledge graphs [147] to make the traditionally rigid survey system more dynamic in order to collect more informative responses. Unlike traditional surveys that usually have a static and fixed-question structure, the knowledge graph-based survey uses knowledge input from the researcher and structures it into a knowledge graph in order to pose appropriate questions to participants, rather than the same set of questions being presented to all respondents in a predetermined order. The unique, dynamic structure of the proposed system allows for the generation of highly personalized, insightful data on an individual's Ikigai level. This goes beyond merely determining the level of Ikigai, to understanding the underlying factors contributing to a high or low Ikigai level. This distinction is critical because Ikigai is a highly subjective concept, and the factors contributing to it can vary widely among individuals.

Through the use of a knowledge graph-based intelligent survey system, we aim to revolutionize how Ikigai is assessed and understood. The intelligent system is designed to interactively select questions from a pool, thereby providing a more personalized and dynamic experience for the respondent, automating Ikigai assessment. By mimicking the level of informativity and responsiveness of face-to-face interaction, the system manages to replicate the advantages of interview-based data collection.

By making the survey process more adaptive and intuitive, we anticipate obtaining more detailed and personalized information about an individual's Ikigai. This, in turn, can pave the way for targeted and effective interventions by caregivers or self-improvement strategies by individuals to enhance one's sense of purpose and fulfillment in life. This novel approach has the potential to make significant contributions to the field of personal well-being and gerontechnology.

### 3.2.1 Knowledge Graph Design

Through comprehensive literature reviews of current Ikigai measurement tools and previous research on intelligent survey systems that utilize knowledge graphs, we developed an Ikigai survey system based on knowledge graphs that incorporates the best practices of previous research and addresses the limitations of existing Ikigai models and tools in an innovative way. By leveraging knowledge graphs and advanced machine learning techniques, this system offers a promising new approach to understanding and improving one's level of Ikigai. We will explore in detail the design and features of this knowledge graph-based survey system for Ikigai in the following subsections, demonstrating how this novel approach can revolutionize the way we study and cultivate life satisfaction and well-being.

#### 3.2.1.1 Equivalent Questions

Researchers have found that the phrasing of questions can significantly influence respondents' answers [148]. For example, using phrases like "not allowed" versus "forbid" can elicit different reactions and answers from respondents. Despite this known phenomenon, existing Ikigai surveys tend not to ask the same question in different ways, a common practice designed to ensure response validity and measure the respondent's strength of conviction. By not adopting this approach, these surveys may risk collecting responses that are not as accurate or nuanced as they could be.

To bridge the gap identified in the current Ikigai assessment tools and models, this research adds a distinctive aspect of the knowledge graph-based survey system, the introduction of equivalent questions that are synonymous with each other. The primary motive behind this method is to enhance the quality of responses. By using synonymous questions, we aim to ensure that respondents genuinely understand the question being asked and that their responses accurately reflect their levels of Ikigai. This method also helps us gauge the consistency of respondents' answers, thereby providing an additional layer of validity to the results.

### 3.2.1.2 Dynamic Experiences

The implementation of knowledge graphs in the construction of surveys brings about a key benefit: dynamism. Traditional surveys, including the ones used for assessing Ikigai, often stick to a static structure of questions. In such surveys, the questions are pre-determined and ordered, offering no room for adaptability based on the participant's inputs. For instance, Ikigai-9, a popular tool for evaluating Ikigai, poses a sequence of specific questions that are always presented in the same order. Participants answer each question on a scale from 1 to 5, regardless of their previous responses.

Contrarily, the knowledge graph-based survey system introduced in this research leverages the dynamic capabilities inherent in knowledge graphs. This allows the system to select and sequence questions based on the participant's previous responses, making the survey a responsive and personalized experience. Therefore, instead of asking a standard set of questions to all participants, the survey tailors its questions to the individual, ensuring a higher degree of relevance and thus a more accurate and detailed understanding of their Ikigai.

This approach is a significant upgrade to existing methods, allowing for a more nuanced exploration of Ikigai and providing a basis for more effective, personalized interventions to enhance it. The dynamic nature of the survey also has the potential to increase participant engagement, as the questions are more pertinent to their personal experiences and views.

### 3.2.1.3 Enabling Modifications

As the concept of Ikigai is complex and multi-dimensional, it is inappropriate and insufficient to merely affirm or negate a fixed state of Ikigai when scrutinizing it as a psychological construct [27]. Such a static view does not capture the fluid and individual nature of Ikigai, which may evolve over time and vary considerably from one person to another. Consequently, it can be inferred that the models and tools used for evaluating Ikigai must be flexible, adaptable, and open to evolution, reflecting the ongoing discoveries and adaptations relating to this intricate concept.

This requirement presents a significant challenge to existing methods of assessing Ikigai, which are often rigid and unyielding. In contrast, the knowledge graph-based survey system proposed in this research is specifically designed to be flexible and adjustable. It enables easy modifications to the survey questions as the need arises, ensuring that the system remains up-to-date with the latest understandings and interpretations of Ikigai. This inherent adaptability makes it an exceptionally effective tool for studying Ikigai, poised to adapt to future shifts and developments in our understanding of this intricate psychological construct.

### 3.2.2 Construction and Implementation

In order for the survey system to be reusable and extensible, the basic concepts of a generic survey system are separated from the Ikigai-specific survey system. As a result, for the proposed system, two knowledge graphs will be created: one for general-purpose survey ontology and the other for domain-specific ontology concerning Ikigai.

The knowledge graph for general survey ontology contains key classes like User, SurveyResponse, SurveyAnswer, SurveyQuestion, and AnswerOption, and its key relationships and attributes include `hasUser` (which connects Response and User), `hasSurveyAnswer` (which connects SurveyResponse and SurveyAnswer), `hasSurveyQuestion` (which connects SurveyResponse and SurveyQuestion), `hasAnswerOption` (which connects SurveyQuestion and ResponseOption), `respondOnDate` (which connects SurveyResponse and its attribute Date). Figure 3.1 shows the proposed general survey ontology.

The dependencies of the classes and relationships in the general survey ontology are specified as follows:

- For each survey response, there exists only one user.
- For each survey response, there exists only one survey answer.
- For each survey response, there exists only one survey question.
- For each survey question, there exists at least one response option.
- For each survey response, there exists at least one date.

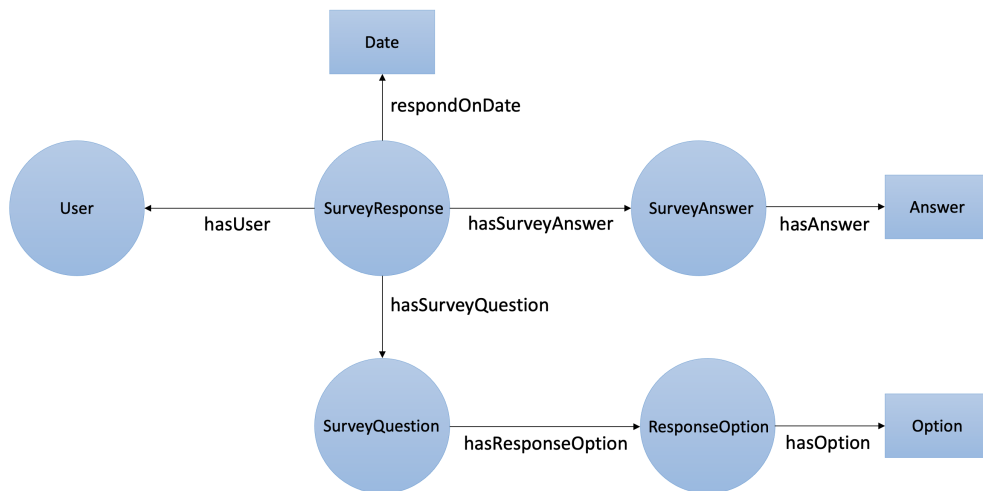


FIGURE 3.1: General survey ontology

As for the domain-specific ontology for Ikigai, it includes key classes like `SurveyQuestion`, and key relationships like `hasContent` (which connects `SurveyQuestion` to `QuestionContent`) and `hasPositiveFollowUp` (which is self-connected from and to `SurveyQuestion`). Figure 3.2 shows the Ikigai ontology.

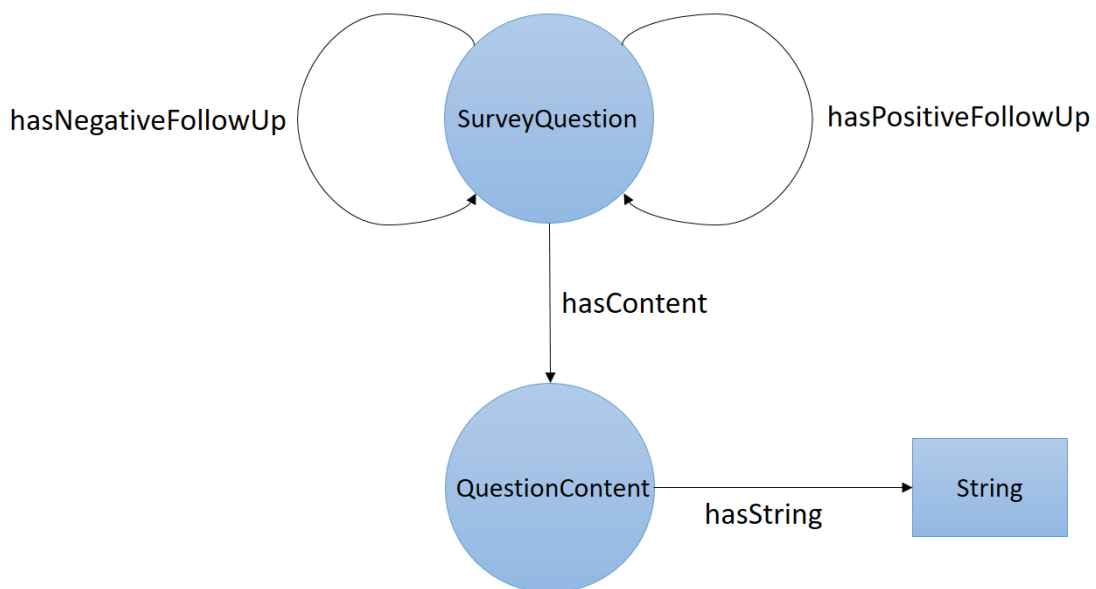


FIGURE 3.2: Domain-specific ontology on Ikigai

The dependencies of the classes and properties in the Ikigai ontology are specified as follows:

- For each survey question, there exists only one question content.

- For each question content, there exists at least one string for the question.
- For each survey question, there exists at most one positive follow-up question.
- For each survey question, there exists at most one negative follow-up question.

Taking the question, ‘I often feel that I am happy’, as an example to illustrate the survey system, some relevant triplets are as shown below:

- (Q1, rdf:type, SurveyQuestion)
- (S1, rdf:type, QuestionContent)
- (Q1, hasContent, S1)
- (S1, hasString, ‘I often feel that I am happy.’)
- (O1, rdf:type, ResponseOption)
- (Q1, hasResponseOption, O1)
- (O1, hasOption, 5)

Users’ responses are translated to knowledge graph assertions for later analysis and activation of relevant open-ended questions. Below are example assertions to be made if the user chooses option 4 for Q1:

- (R1, rdf:type, SurveyResponse)
- (U1, rdf:type, User)
- (R1, hasUser, U1)
- (Q1, rdf:type, SurveyQuestion)
- (R1, hasSurveyQuestion, Q1)
- (A1, rdf:type, SurveyAnswer)
- (R1, hasSurveyAnswer, A1)
- (A1, hasAnswer, 4)

### 3.2.2.1 Equivalent Questions

The initial phase of implementing the knowledge graph-based survey system for Ikigai involved generating a set of equivalent questions that correspond to each of the nine questions presented in the English version of the Ikigai-9. The objective was to design questions that essentially ask the same thing, but with different phrasing to mitigate potential bias in responses. These equivalent questions were formulated by substituting words in each original question with appropriate synonyms, while ensuring that the semantic integrity and intent of the original question remained intact. This strategy not only improves the validity of responses but also provides us with a richer, more nuanced understanding of an individual's Ikigai.

In order to achieve this, we utilized the Natural Language Toolkit (NLTK), a Python library specifically designed for working with human language data. The NLTK was used to tokenize each question from the Ikigai-9, breaking them down into smaller components, or "tokens". In the context of language processing, a token typically refers to a word, but it can also represent punctuation or other meaningful units of text.

After the questions were tokenized, the NLTK was used to assign a part-of-speech (POS) tag to each token. POS tagging is a process of labeling the words in a sentence based on their grammatical role, such as nouns, verbs, adjective, etc. The outcome of this process was a list of tuples as shown in Figure 3.3, where each tuple contained a token from the original question and its corresponding POS tag. This structured representation of the questions facilitated the next step of generating equivalent questions using synonyms.

The process of substituting words in a sentence with their synonyms to generate equivalent questions necessitates careful consideration of the grammatical roles the words play in their original context. In theory, only specific categories of words, such as nouns, verbs, adjectives, and adverbs, can be replaced in an English sentence without altering its fundamental structure or meaning. The POS tags associated with these categories include 'NN', 'NNS', 'NNP', 'NNPS' for nouns; 'VB', 'VBD', 'VBG', 'VBN', 'VBP', 'VBZ' for verbs; 'JJ', 'JJR', 'JJS' for adjectives; and 'RB', 'RBR', 'RBS' for adverbs. Thus, our process involved identifying and extracting the tokens assigned to these particular POS tags for further synonym substitution, thereby creating equivalent versions of the original questions.

```
[ [ ('I', 'PRP'),
    ('often', 'RB'),
    ('feel', 'VBP'),
    ('that', 'IN'),
    ('I', 'PRP'),
    ('am', 'VBP'),
    ('happy', 'JJ'),
    ('.', '.')]
  [ ('I', 'PRP'),
    ('would', 'MD'),
    ('like', 'VB'),
    ('to', 'TO'),
    ('learn', 'VB'),
    ('something', 'NN'),
    ('new', 'JJ'),
    ('or', 'CC'),
    ('start', 'JJ'),
    ('something', 'NN'),
    ('.', '.')] ]
```

FIGURE 3.3: Examples of the tuples (token, pos tag)

Having identified appropriate tokens for substitution, the next phase involved finding suitable synonyms using the NLTK WordNet synsets. Each of these synonyms was used to replace its corresponding token in the original question, thereby generating a distinct equivalent question. For instance, the token “often” in the original question “I often feel that I am happy” could be replaced with its synonym “frequently”, resulting in the equivalent question “I frequently feel that I am happy”.

In order to maintain the integrity of these new questions, it was imperative to ensure that their syntax and semantics remained unimpaired. The language-tool-python Python package was thus employed to correct any grammatical errors or spelling mistakes that may have arisen during the word substitution process. As a result of these procedures, we managed to generate a varying number of equivalent questions for each original question from the Ikigai-9, with quantities ranging from 4 to 34. Figure 3.4 shows the equivalent questions generated for the original question “I often feel that I am happy”.

In order to ensure the reliability of the newly generated equivalent questions, we adopted a rigorous testing methodology. This involved subjecting these questions to an internal consistency evaluation using Cronbach’s Alpha. This statistical

```
{ 'qn1': { 'I frequently feel that I am happy.',
          'I oft feel that I am happy',
          'I often experience that I am happy.',
          'I often feel that I am felicitous.',
          'I often feel that I am glad.',
          'I often feel that I am happy.',
          'I often feel that I am well-chosen.',
          'I often find that I am happy.',
          'I often finger that I am happy.',
          'I often palpate that I am happy.',
          'I often sense that I am happy.',
          'I oftentimes feel that I am happy.',
          'I ofttimes feel that I am happy.'}}
```

FIGURE 3.4: Questions equivalent to the original question “I often feel that I am happy”

model is a widely acknowledged tool for measuring the internal consistency or reliability of a test score for a group of items. It is calculated by:

$$\alpha_s t = \frac{N * \bar{r}}{1 + (N - 1) * \bar{r}} \quad (3.1)$$

where  $N$  represents the number of items (questions) in the measure, and  $\bar{r}$  is the mean correlation between the items.

We aimed to ascertain that these new questions were not merely semantically equivalent to the original questions, but also maintained the same degree of reliability as measured in the Ikigai-9 questionnaire. By doing so, we sought to ensure the preservation of the survey’s reliability, even after the inclusion of the equivalent questions. Any equivalent question not reaching a satisfactory Cronbach’s Alpha score in this validation process would need to be revisited and revised until the required reliability was established.

A preliminary study was conducted. We recruited 20 participants to answer both the original questions, and 4 equivalent questions each. Participants were asked to provide open-ended feedback on the survey experience. While the calculated Cronbach’s Alpha of each set of questions (1 original question and 4 equivalent questions) showed that the questions were internally consistent (all Cronbach’s Alpha values were greater than 0.9), a majority of the respondents had feedbacked

that there were too many questions in the survey and they had found some of the questions to be very similar and/or repetitive.

Revising our approach in light of the feedback received from initial survey respondents, we decided to enhance our algorithm for generating equivalent questions. Instead of just replacing one word per question with a synonym, all possible words in each question were replaced with suitable synonyms, derived from the NLTK WordNet synsets. For instance, in the original question “I often feel that I am happy”, all replaceable words like “often”, “feel” and “happy” were substituted simultaneously with synonyms “frequently”, “find”, and “glad” respectively. This modification gave rise to the equivalent question “I frequently find that I am glad”.

Subsequently, we employed the language-tool-python Python package to eliminate any resultant sentences with grammatical errors or spelling mistakes. This revised algorithm resulted in generating a smaller and more manageable number of equivalent questions for each item in the Ikigai-9, ranging from 2 to 13 per question.

A second round of surveys was then distributed to another set of 20 respondents to assess the internal consistency of these newly generated questions. Our aim was to verify that these revised questions still maintained a high level of internal consistency with the original Ikigai-9 items and offered a more streamlined and less repetitive survey experience to the participants.

In comparison to its predecessor, Version 2 of the Ikigai-9 questionnaire received significantly fewer complaints regarding the length of the questionnaire. Additionally, there were no direct comments concerning the similarity and repetitiveness among the questions. This indicated that the modifications made in Version 2 had successfully addressed the respondents’ feedback, leading to a more positive and efficient survey experience.

Cronbach’s Alpha values were calculated for each set of questions (1 original question and 2 equivalent questions) as shown in Table 3.1.

Having achieved Cronbach’s Alpha values above 0.8 for all sets of questions, it was concluded that the questions within each set maintained a high level of internal consistency and validity. Therefore, these questions were deemed reliable for assessing the intended aspects of Ikigai. However, an interesting observation was made regarding the 5th set of questions, which included the original question – “I

TABLE 3.1: Table of Cronbach’s Alpha for each original question

Question	Cronbach’s Alpha
I often feel that I am happy.	0.93984
I would like to learn something new or start something.	0.95173
I feel that I am contributing to someone or the society.	0.98036
I have room in my mind.	0.96518
I am interested in many things.	0.82012
I think that my existence is needed by something or someone.	0.90128
My life is mentally rich and fulfilled.	0.93973
I would like to develop myself.	0.98656
I believe that I have some impact on someone.	0.97548

am interested in many things”, and its equivalent questions – “I am concerned in several things” and “I am engrossed in numerous things”. This particular set of questions yielded the lowest Cronbach’s Alpha value, a significant deviation from the other sets, with a value of 0.82, while all other sets boasted a Cronbach’s Alpha value above 0.9.

The reason behind this discrepancy could likely be traced back to the negative connotations associated with the term “concerned”, which contrasts with the neutral and positive implications carried by the terms “interested” and “engrossed”. This difference in connotation could potentially lead to more polarized and distinct interpretations of the synonymous questions, hence resulting in the lower Cronbach’s Alpha value observed. Nonetheless, it’s widely accepted that a Cronbach’s Alpha value above 0.7 indicates a satisfactory level of consistency, validity, and reliability among a group of items. Consequently, all 9 sets of questions were deemed acceptable and were adopted as part of the default questionnaire in the creation of the knowledge graph for the Ikigai survey system.

### 3.2.2.2 Open-Ended Follow-up Questions

It may be interesting and advantageous to ask follow-up questions to go deeper and study the causes for various responses when measuring respondents’ level of Ikigai. Face-to-face interviews frequently involve interviewers asking a simple “Yes” or “No” question followed by an open-ended question to elicit clarifications or explanations. As a result, including a responsive open-ended question selection function

allows our Ikigai survey system to achieve the same levels of interactivity and information as face-to-face interviews. Besides, the answers to open-ended questions may be helpful in understanding the person better which aid later intervention.

Open-ended follow-up questions can be added to the survey system. For example, for questions like ‘I often feel that I am happy’, in addition to the rating given by the user, it may be more useful to know the reason(s) for the happiness or unhappiness. The reason(s) for unhappiness, in particular, may be especially helpful in assisting the person to improve his/her level of Ikigai. Below shows the assertions to be added to the knowledge graph for open-ended follow-up questions for this example question:

- (Q55, rdf:type, SurveyQuestion)
- (S55, rdf:type, QuestionContent)
- (Q55, hasContent, S55)
- (S55, hasString, ‘What make(s) you feel happy?’)
- (Q1, hasPositiveFollowUp, Q55)
- (Q56, rdf:type, SurveyQuestion)
- (S56, rdf:type, QuestionContent)
- (Q56, hasContent, S56)
- (S56, hasString, ‘What make(s) you feel unhappy?’)
- (Q1, hasNegativeFollowUp, Q56)

### 3.2.2.3 Enabling Modification

As Ikigai is an intricate and dynamic concept that continually grows and adapts, this knowledge graph-based survey system designed for assessing Ikigai can conveniently accommodate these changes. Currently, the survey incorporates the original 9 items from Ikigai-9, along with 2 equivalent questions for each item. This configuration allows for the measurement of one’s “reason for being” through various

dimensions including one's emotions toward life, attitudes toward the future, and recognition of one's existence.

Should a researcher wish to add an additional dimension, such as those from the four-factor Ikigai scale [138], into the Ikigai assessment, they can effortlessly include it in the survey system. The system's adaptable design ensures that it can evolve concurrently with the ever-expanding understanding of the Ikigai concept, and remain a reliable tool for comprehensive Ikigai evaluation.

In conclusion, the integration of knowledge graphs into the assessment of Ikigai offers a transformative approach to understanding and measuring an individual's sense of purpose and satisfaction in life. Through the dynamic nature and remarkable adaptability of knowledge graphs, we can gain a deeper understanding of the nuanced reasons underlying varying Ikigai levels. By presenting equivalent questions based on the individual's unique context, this not only ensures evaluations are tailored to individual experiences, but also ensures their reliability. Furthermore, it is also easy to be modified to incorporate measurements of different aspects of Ikigai that are not present in the existing scales. Such innovative tools are imperative to promoting the well-being and holistic health of the elderly as the world grapples with an aging population. It illustrates the potential of interdisciplinary approaches to addressing contemporary challenges when they combine traditional concepts like Ikigai with modern technology like knowledge graphs.

### 3.3 Machine Learning Approaches

Ikigai is also a dynamic concept. It is a deeply personal concept, intricately intertwined with one's evolving life experiences, changing interests, and health conditions. Therefore, a person's Ikigai level may change substantially over time. The traditional method of repeatedly asking individuals to complete the same survey may prove inefficient and could result in lower participation rates due to survey fatigue. Moreover, since Ikigai is deeply rooted in personal factors and characteristics, a person's traits could have substantial correlations with their level of Ikigai. This introduces an exciting opportunity to potentially predict a person's Ikigai level based on their profile information. By extracting key attributes from

an individual’s profile, like demographic data, personality traits, and interests, it may be feasible to construct a predictive model of Ikigai levels.

Moreover, people may respond inaccurately in psychological measurement. A persistent propensity to respond incorrectly to a significant indicator that leads to a regular mistake in prediction is known as a response bias [149]. The context of self-report measurement has revealed a range of response biases. For example, positive impression management (PIM), and negative impression management (NIM). PIM is the failure to report abnormal behaviors and is known as a “socially desirable response”, and “faking nice” when it occurs in conjunction with concrete evidence of undesirable traits like psychopathology. NIM, on the other hand, entails behaving in an extremely deviant way, known as “faking bad”, or “malingering”, depending on whether it is combined with substantive signs of negative qualities. Some of these expressions, like “faking bad”, are well-liked but potentially problematic since they imply a particular reason why the misrepresentation occurred. Thus, finding ways to continuously evaluate one’s level of Ikigai without much self-report on such issues is also important. Machine learning models which take in user profiles to predict an individual’s Ikigai level may be a solution to this problem.

In this section, we propose the use of an Ikigai simulator  $I$  that takes as input a user profile  $p$  and predicts answers to the Ikigai-9 questionnaire.

The Ikigai simulator here is a multi-layer perceptron that is trained using a cross-entropy loss for each question in the Ikigai-9 scale. The network initializes with an input size that corresponds to the number of dimensions of the user profile containing information like medical history and hobbies. The architecture comprises a single hidden layer with 16 neurons, a relatively modest configuration that suggests a focus on capturing essential patterns without overcomplicating the model. The MLP features several output layers, each corresponding to different Ikigai-9 items on a 5-point scale, as it is a list containing nine entries of value 5. This setup suggests the model is designed to predict multiple aspects of Ikigai, with each of the nine output layers providing a 5-dimensional prediction. This multi-output approach allows the network to offer a comprehensive analysis across various dimensions of personal fulfillment and purpose. Activation functions play a critical role in introducing non-linearity to the model, enabling it to learn complex patterns. In this case, the ReLU (Rectified Linear Unit) function is employed, for its effectiveness in various neural network applications and its ability to mitigate

the vanishing gradient problem. In the forward pass, the model takes in the concatenated inputs from various personal data dimensions, processes them through the hidden layer with ReLU activation and then forwards the activated outputs to each of the nine output layers to produce the final predictions. These predictions are then stacked, providing a multidimensional output that reflects the network's comprehensive analysis of factors contributing to an individual's Ikigai.

### 3.3.1 Data Collection

In order to train the predictive model, we first collected data from participants in an initial study. We aim to obtain a diverse set of data across various key characteristics relevant to the study of Ikigai. To ensure the predictive model could account for a wide range of factors that potentially influence Ikigai, the researchers included a comprehensive set of demographic and personal characteristics in the questionnaire. Demographics, physical and cognitive conditions, medical problems, personality, and hobbies were covered in the questionnaire. The questions are either multiple choice or checkboxes, depending on the section. The questions are either multiple choice or checkboxes, depending on the section. A section includes the Ikigai-9, which is a psychometric tool that measures one's Ikigai rated on a five-point Likert Scale [16].

In total, 542 online questionnaire responses were collected during the initial study. After verifying their validity, 28 invalid responses were removed. The final dataset contains 514 entries. The characteristics of the collected responses are shown in Table 3.2. This study is approved by the Institutional Review Board.

We conducted a primary analysis with the survey data collected, with particular attention paid to correlations between personal traits and Ikigai scores. For instance, when examining participants' Ikigai scores by age, as illustrated in a box plot (Figure 3.5), we observed distinct distributions of Ikigai scores across different age groups. Notably, the median line for the group aged above 85 fell outside of the boxes representing other age groups. This demonstrated that this group's median score was lower than the lower quartile scores of any other group, suggesting a likely difference between this group and others. Another example can be seen when considering physical condition (Figure 3.6). In general, participants who reported

TABLE 3.2: Characteristics of collected responses (n=514).

	Number of Participants
<b>Age</b>	
18-24	11
25-44	65
45-64	408
65-74	15
75-84	10
Above 85	5
<b>Gender</b>	
Male	133
Female	381
<b>Educational Level</b>	
No formal or primary	26
Secondary	72
Tertiary	416
<b>Living Arrangement</b>	
With family	439
Alone	75
<b>Occupation</b>	
Employed	357
Unemployed	5
Retired	101
Student	21
Others	30

more physical issues tended to have lower Ikigai levels. However, on examining individual physical problems, we found variations in the distributions of Ikigai scores (Figure 3.7). The comparable proportions of people without physical problems suggest that other factors might correlate with an individual’s Ikigai level.

Given the multidimensional nature of our data, identifying all patterns manually is nearly impossible. Machine learning algorithms, however, are capable of recognizing complex patterns and correlations within large data sets, providing unique insights into the myriad of factors contributing to an individual’s Ikigai.

We thus leveraged this data to construct an Ikigai simulator, denoted by  $I$ . This simulator inputs a user profile  $p$ , predicting responses to the Ikigai -9 questionnaire. A user profile is composed of responses to the questionnaire, excluding the Ikigai -9 section, which is not incorporated into the Ikigai simulator.

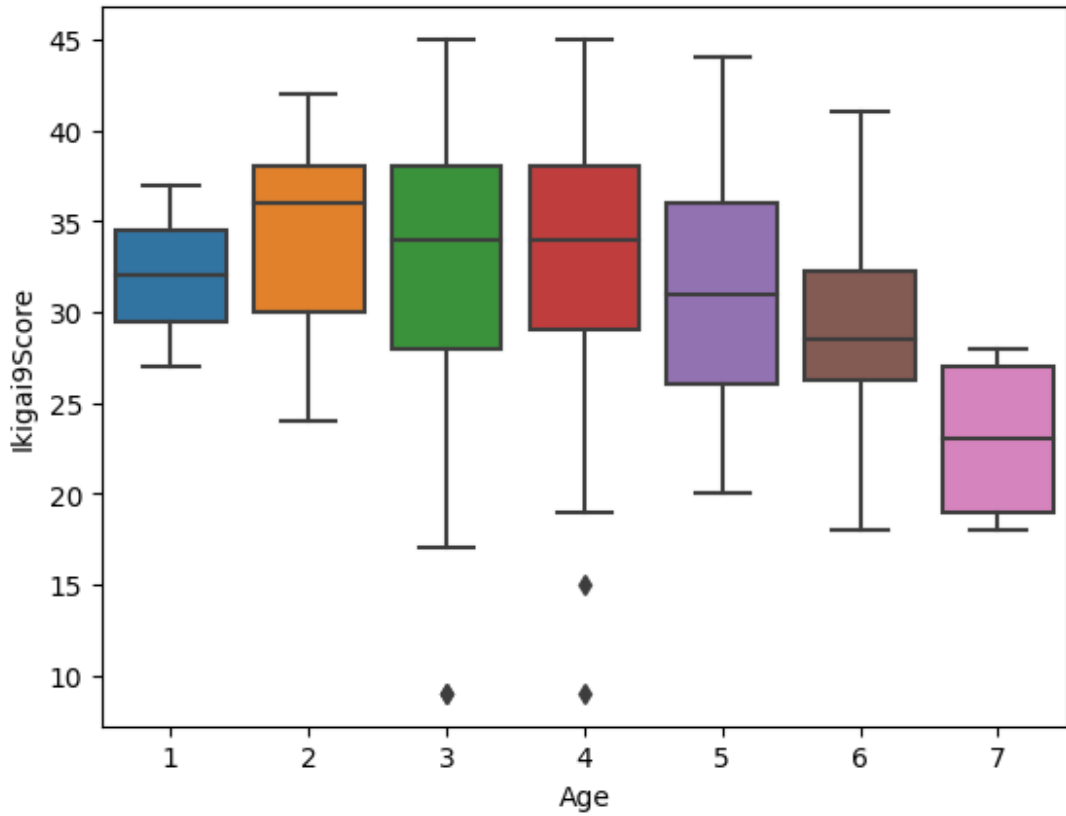


FIGURE 3.5: Participants' Ikigai scores by age (1: Below 18, 2: 18-24, 3: 25-44, 4: 45-64, 5: 65-74, 6: 75-84, 7: above 85)

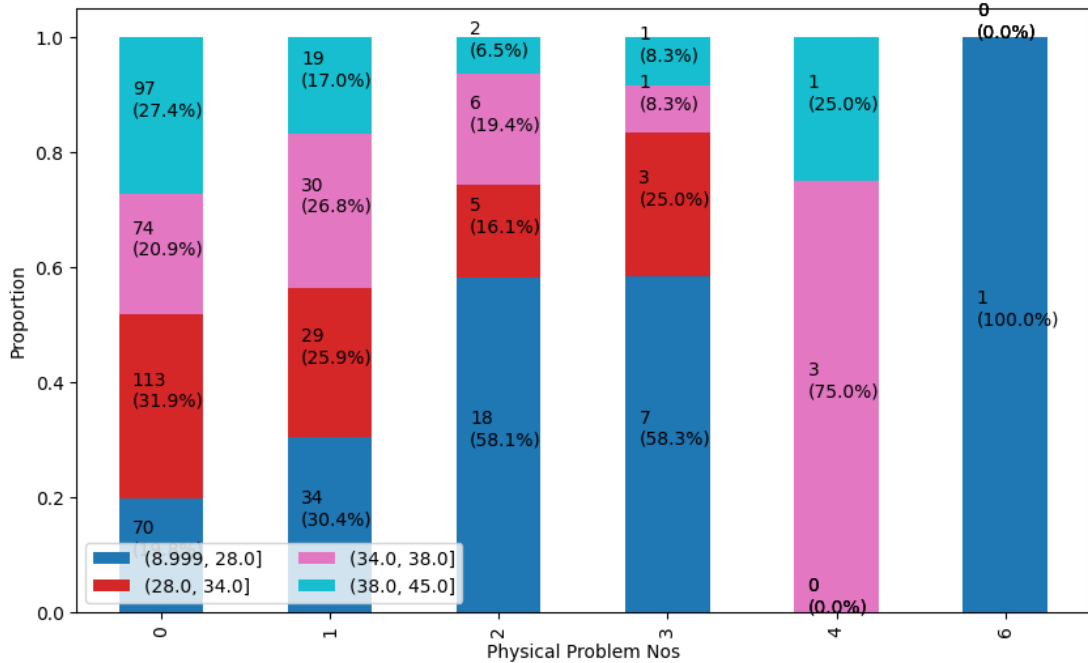


FIGURE 3.6: Participants' Ikigai scores by the number of physical problems reported

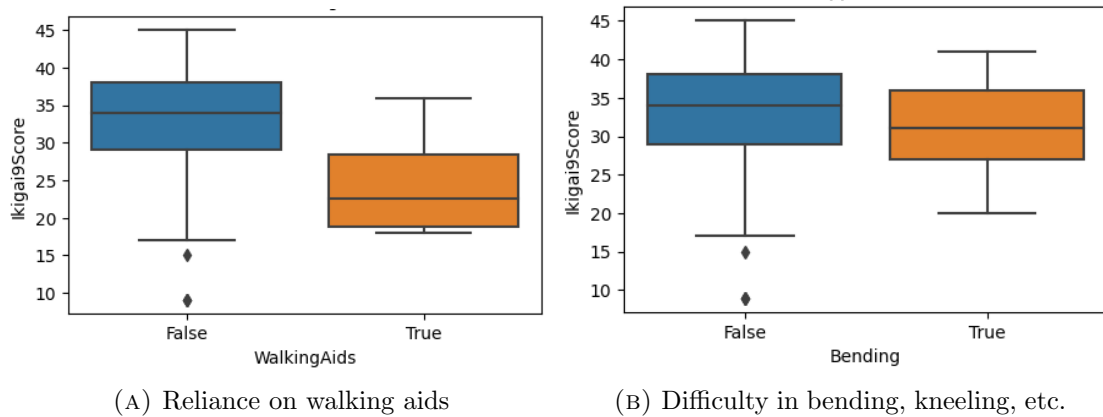


FIGURE 3.7: A figure showing participants' Ikigai scores by different physical problems

### 3.3.2 Evaluation

To train the models, we split the dataset into train, validation, and test sets. Twenty independent experimental runs were conducted in order to ensure that the insights we draw are robust. In each of these runs, the training, validation, and testing datasets were shuffled randomly using a unique seed. As our dataset was relatively small, we train models for 200 epochs and selected the model that performed best on the validation set for evaluation.

Given a specific input profile, the Ikigai simulator generates a set of responses to the Ikigai-9 questionnaire. Each response falls within a 1 to 5 numerical range, a representation of a Likert scale rating system. To identify the most effective model, we evaluated three different models within the Ikigai simulator.

First, we have the random model, which selects responses randomly without regard to user profiles. This approach lacks sophistication, but it serves as a baseline to compare with more complex models.

In our second model, we choose answers based on their frequency in our dataset. This model creates a probability distribution across all possible answers, and then selects responses based on its distribution. The overall trends in the dataset are still largely used in this method, even though it incorporates not much of user profile consideration.

TABLE 3.3: Results for the Ikigai simulator showing the average distance across all runs on the test set. The performance is measured as the distance from the ground truth, therefore a lower number is better.

	Random	Probabilistic	Supervised
Distance	1.495	1.102	0.658

The last model, the proposed supervised learning model, offers a more personalized approach. It is based on user profiles and generates a set of responses to the Ikigai-9 based on those profiles. As a multi-layer perceptron, this model is trained with a cross-entropy loss function, a strategy that minimizes the difference between predicted and real outcomes.

We measure the model’s performance using the distance between its predictions and the actual ground truth. Since the Ikigai-9 scale uses a Likert scale, it’s important to emphasize that responses closer in numerical value indicate a greater degree of similarity. Considering the ground truth for a specific item within a certain profile to be 1, a prediction of 2 would be considered significantly more accurate than a prediction of 5, despite the fact that the predictions are not exactly in line with one another.

Table 3.3 presents the results from the test set, offering a comparative analysis of the performance of the different models. The empirical results reveal that supervised learning outperforms others in terms of performance. Moreover, the model’s enhanced capability to surpass random projections and responses derived based on probability distribution points to a tangible correlation between the Ikigai-9 questionnaire responses and an individual’s profile.

This correlation carries the promising potential to effectively predict an individual’s Ikigai level. This finding has profound implications for the understanding of Ikigai, its fluctuations, and its potential impact on a person’s well-being. Therefore, interventions could be customized based on this insight to promote and maintain higher Ikigai levels.

In conclusion, by predicting Ikigai levels based on user profiles, machine learning methodologies represent a groundbreaking step forward in personal well-being assessment. By harnessing the power of intricate algorithms, this approach is poised to unravel the subtle intricacies of an individual’s life and their intrinsic sense of

purpose. This allows for continuous assessment without answering the existing scales and measurements over and over again. Moreover, as more data is fed into the system, machine learning can be continuously refined, ensuring that predictions become more accurate. With society continuing to evolve and individual experiences diversifying, machine learning adaptability ensures that Ikigai can be gauged and nurtured effectively as society evolves. Technology offers tremendous promise for enriching our understanding of human well-being and purpose when combined with Ikigai assessment.

# Chapter 4

## Improving Ikigai

Understanding and identifying one’s Ikigai is just the beginning of a life-long journey. The real challenge lies in nurturing, enhancing, and maintaining a high level of Ikigai in daily life, in order to lead a satisfying, meaningful, and joyful existence. In this section, we aim to answer the second research problem, how to enhance an individual’s Ikigai level, and introduce two proposed approaches for improving one’s Ikigai level.

The first proposed approach is the use of a teachable agent. This method leverages the “learning by teaching” paradigm, in which individuals enhance their understanding of a concept or enhance a skill by teaching it to others. In this case, the “others” are intelligent virtual agents. Here, the elderly are required to teach the virtual agent about health-related concepts. This method is particularly suited to the elderly population, given that it provides a non-judgmental and patient platform for learning. This interaction not only helps in enhancing their understanding of health-related concepts, thereby leading to better personal health management, but also provides them with a sense of purpose and contribution, which are vital components of Ikigai.

The second approach utilizes reinforcement learning for hobby recommendation. Reinforcement learning is a type of machine learning where an agent learns to make decisions by taking actions in an environment to maximize some notion of cumulative reward. In the context of Ikigai, the agent could learn to recommend hobbies or activities that would likely increase a person’s Ikigai level. The agent would suggest activities based on the user’s past preferences and experiences, and

learn from the user's feedback on these recommendations based on a user simulator. This approach not only helps individuals discover new interests and passions, but also promotes an active and engaged lifestyle, contributing to the enhancement of their Ikigai level.

Both these approaches underline the critical role of active engagement, whether in the form of teaching or pursuing recommended hobbies, in fostering a high Ikigai level. They showcase the potential of AI in personalizing and enhancing the pursuit of Ikigai, making the journey towards a fulfilled life more accessible and enjoyable for all.

A phenomenographic approach is adopted in the research to uncover the spectrum of experiences that individuals have with the proposed approaches to improving the Ikigai level: the teachable agent and the reinforcement learning-based hobby recommender. Phenomenography is a qualitative research methodology that studies the qualitatively various ways in which individuals perceive or think about something [139]. In this way, we can explore the range of experiences and perceptions of users, from their initial impressions to how their interactions with the system impact their sense of purpose and satisfaction, their understanding of health-related concepts, and their engagement with recommended hobbies.

This phenomenographic study will help us to understand the effectiveness of these proposed approaches in real-world settings, as well as to refine the design and functionality of the systems based on users' experiences and feedback. This approach emphasizes the diversity of user experiences and perceptions, providing rich insights that quantitative methods might miss, and informing the development of a more inclusive and effective Ikigai improvement system.

## 4.1 Teachable Agent that Enhances Elderly’s Ikigai

<sup>1</sup>The elderly tend to lose feelings of Ikigai as they age due to reasons such as retirement, loss of functional abilities, and loss of loved ones. These changes may lead to a decrease in some aspects of Ikigai like self-esteem [138], and self-efficacy [37]. At the same time, a large number of the elderly are facing the obstacle of limited health literacy though they’d like to pursue a healthy lifestyle [150, 151]. This cross of problems inspired us to invite a TA in the study of healthy lifestyle adoption of the elderly.

Teachable agents (TAs) have been demonstrated to be useful in enhancing self-efficacy and self-esteem in education applications during the process of “learning by teaching”. Can it produce a similar desired effect on the elderly? If TAs are utilized to help the elderly learn health-related topics, not only may the elderly feel more motivated to learn new things, but their self-esteem and self-efficacy may also be well-protected. These are important factors that affect one’s Ikigai level. The process of teaching the agent may make the elderly feel that they are needed by someone, and that they can still have some impact on, and help, others. Following this, may be an increase in their self-esteem and satisfaction, and these may, in turn, improve the elderly’s Ikigai level. This inspiration motivated us to propose and design a teachable agent to improve the well-being of the senior population by providing both knowledge and psychological support.

### 4.1.1 Teachable Agent Architecture

To define the proposed TA, we begin with a basic definition of a generic agent system. Franklin and Graesser [152] define an agent to be a system that is positioned within an environment that perceives that environment and acts on it over time in order to further its own agenda and influence what it senses in the future. Figure 4.1 shows an agent architecture proposed by [153].

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<sup>1</sup>The work in this section has been published as Ping Chen, Xinjia Yu, Su Fang Lim, and Zhiqi Shen. 2023. A Teachable Agent to Enhance Elderly’s Ikigai: Extended Abstract. In *Proceedings of the 22nd International Conference on Autonomous Agents and Multiagent Systems*, AAMAS 2023.

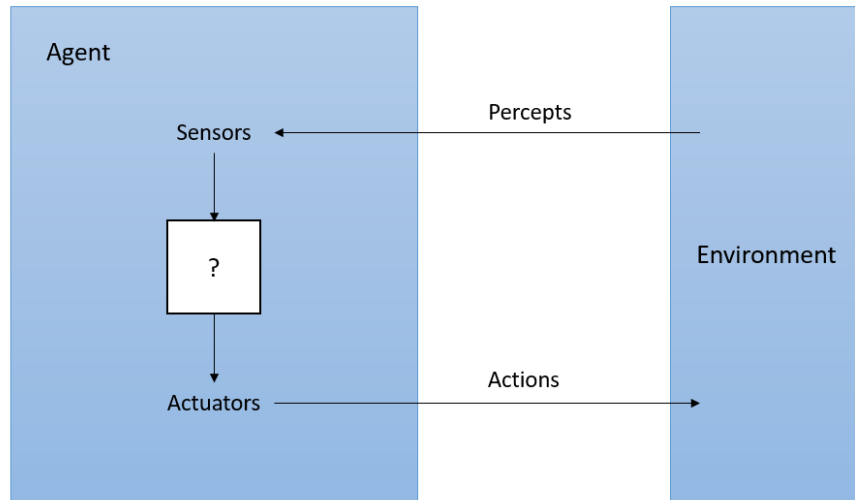


FIGURE 4.1: Agent architecture

Thus we define:

**Definition 4.1** (Agent). An agent,  $Ag$  is a tuple  $Ag = (E, Et, K, R, A)$ , where

$E$  is the set of environments that an agent interacts with;

$Et$  is the set of perception states or events that the agent perceives from the environment;

$K$  is the set of knowledge that the agent learned;

$R$  is the set of reasoning mechanisms employed by the agent;

$A$  is the set of actions that the agent takes.

A TA is a specific type of intelligent agent that learns through interactions with humans, simulating human learning processes [154]. The reasoning mechanism distinguishes a TA from other types of intelligent agents. As TAs are intended to help one teach, their reasoning focuses mostly on how to learn from the users' input or any useful information in the system. Figure 4.2 shows an agent architecture proposed by [68].

**Definition 4.2** (Teachable Agent). A teachable agent,  $TA$ , is a tuple  $TA = (E, Et, K, R, A)$ , where  $E$ ,  $Et$ ,  $K$ , and  $A$  follow the definitions in Definition 4.1, and  $R$  is the set of reasoning mechanisms that allow the TA to learn knowledge.

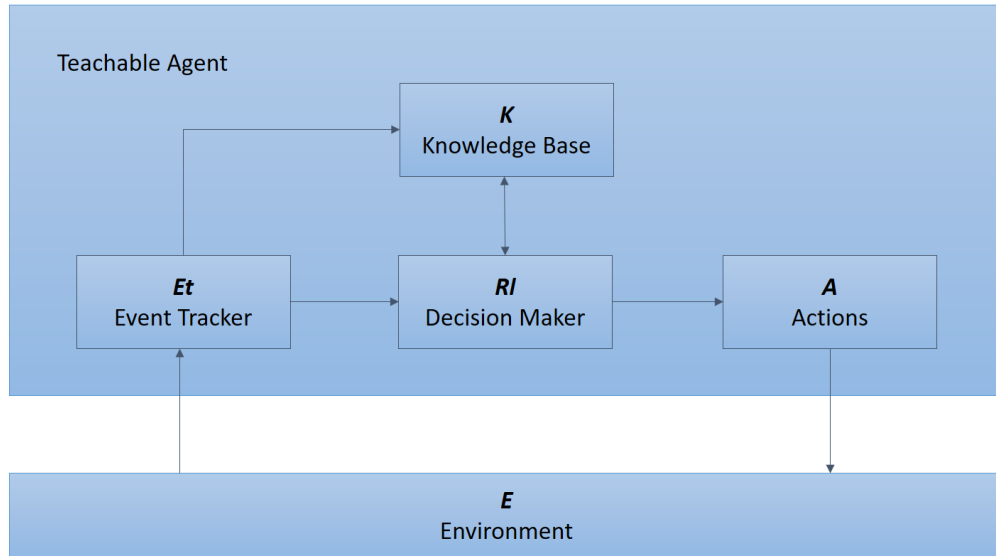


FIGURE 4.2: Teachable agent architecture

This generic teachable agent architecture depicts a teachable agent that executes the perceive-reason-act cycle. For instance, in the Betty’s Brain system, the teachable agent perceives students’ input, stores it in the knowledge base, performs causal reasoning based on what it has learned, and provides different feedback to students. The approach allows the agent to be taught, but it lacks a proactive mechanism for it to learn new knowledge or practice what it has learned.

To make the teachable agent more proactive, a goal-oriented reasoning selection component is added to the existing TA architecture. With this, an agent is able to determine the appropriate sequence of actions to take for it to reach its goal. Firstly, to be taught about, or in other words, to learn new knowledge. Secondly, to practice the knowledge learned to examine the effectiveness of learning. This is important in this context, as the agent is expected to proactively practice what it has learned when a decrease in Ikigai is inferred. Last but not least, the agent needs to be able to assess one’s Ikigai level. There are three goals for a TA.

The proposed teachable agent for Ikigai is as shown in Figure 4.3.

**Definition 4.3** (Teachable Agent for Improving Ikigai). A teachable agent for improving Ikigai,  $T_{AII}$ , is a tuple  $T_{AII} = (E, Et, K, R, A)$ , where  $E$ ,  $Et$ ,  $K$ , and  $A$  follow the definitions in Definition 4.1, and  $R$  is a tuple  $R = (Ev, Tr, Pr)$ .

**Definition 4.3.1.**  $R$  is a tuple,  $R = (Ev, Tr, Pr)$ , where

$Ev$  is the Evaluation Reasoning that enables the agent to evaluate the person's level of Ikigai;

$Tr$  is the Teachability Reasoning that enables the agent to learn new knowledge;

$Pr$  is the Practicability Reasoning that enables the agent to practice the knowledge learned.

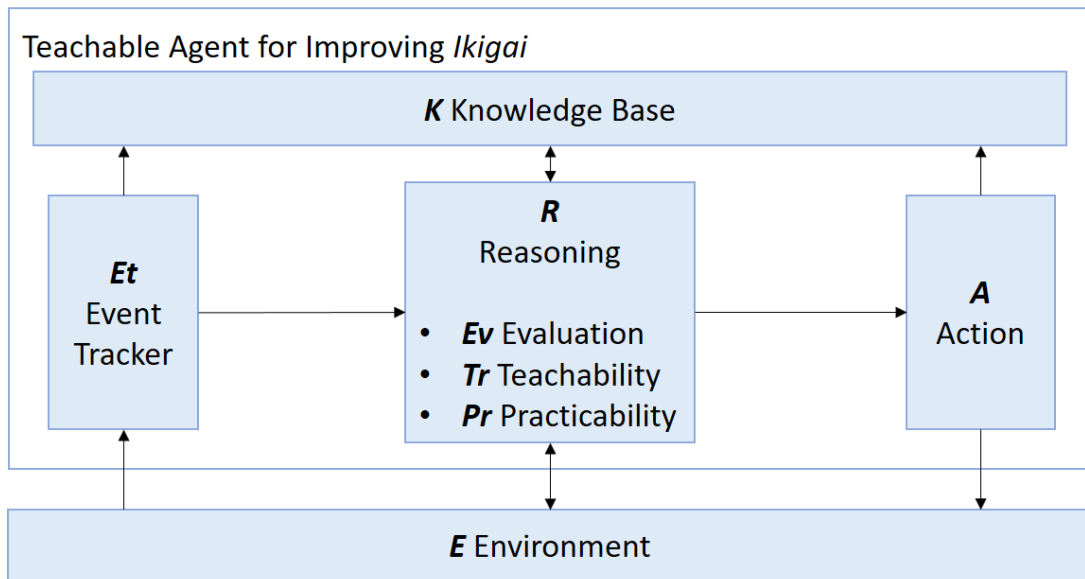


FIGURE 4.3: Teachable agent for Ikigai architecture

The proposed model enables the agent via three primary types of tasks, which are repeated and form three running cycles.

- Evaluation Cycle:  $EtR(KA)$ 
  1. Perceive: The agent perceives the environment.
  2. Reasoning: The agent selects a suitable reasoning accordingly. For example, if there is a new user and there is no information about the user's Ikigai level in the Knowledge Base, Evaluation Reasoning  $Ev$  is selected. The agent determines the appropriate evaluation process to evaluate the person's level of Ikigai.
  3. Knowledge Base: The agent receives user responses and stores them in the knowledge base.
  4. Actions: The agent responds according to the situation.

- Teaching Cycle: *EtRK*
  1. Perceive: The agent perceives the environment. For example, data about an elderly's activities is collected by sensors.
  2. Reasoning: The agent selects a suitable reasoning accordingly. For example, if the agent has no knowledge about how to react to the current situation which may cause one's Ikigai to decrease, Teachability Reasoning *Tris* is selected. The agent asks for help and learns the knowledge taught. The agent interprets information into knowledge representations using Teachability Reasoning.
  3. Knowledge Base: The agent stores the knowledge representations in the knowledge base.
- Practising Cycle: *EtR(KA)*
  1. Perceive: The agent perceives the environment.
  2. Reasoning: The agent selects a suitable reasoning accordingly. For example, the agent already learned about how to react in the perceived situation, Practicability Reasoning *Pr* is selected. The agent determines the appropriate responses to the perceived scenario in order to improve one's Ikigai.
  3. Knowledge Base: The agent retrieves the response from the knowledge base if it is pre-determined.
  4. Actions: The agent responds according to the situation.

#### 4.1.1.1 Ikigai Assessment

To assess the user's Ikigai level, the four-factor Ikigai scale [138], a psychometric tool that consists of twenty-eight items, is used. Self-esteem, purpose in life, personal energy, and life satisfaction are considered the most appropriate factors to explain the concept of Ikigai. Self-esteem here is similar to the concept of 'the self', like self-awareness, self-worth, ego-identity, and so on. It is the fundamental level of Ikigai. Purpose in life is the most crucial and fundamental element of Ikigai, as it concerns one's reasons for living and meaning/purpose in life. Personal energy is the degree of activeness and concentration of a person in participating

in various activities. It is the ‘tangible source of Ikigai’ that is based on the two aforementioned factors. Life satisfaction is the result of the first three factors and it can only be obtained if the first three have been met. The four elements are arranged in such a way that they reflect a person’s level of consciousness [138]. To assess one’s Ikigai level, one needs to rate whether he/she agrees with each of the twenty-eight items on a five-point rating scale (1 = *Strongly Disagree*, 5 = *Strongly Agree*). A person’s Ikigai level is the sum of the ratings of all 28 items in the scale. Below are some example statements from the scale:

- I believe I am an irreplaceable person for my family and friends. (*Self-esteem*)
- I have a lot of goals. (*Purpose in life*)
- I am energetic when working. (*Personal energy*)
- I am satisfied with my current life. (*Life satisfaction*)

While the Ikigai-9 scale [16] offers a general assessment, capturing a wide range of feelings and attitudes contributing to an individual’s sense of Ikigai, the four-factor scale [138] provides a more detailed and structured analysis by breaking down Ikigai into specific, measurable components. This approach facilitates a nuanced understanding of the contributing elements to Ikigai and allows for the observation of changes in these components before and after the study.

#### 4.1.1.2 Knowledge Teaching and Practicing

Knowledge graphs have been gaining much attention since Google used them for its search engine [155]. They represent information in a semantic graph. Many researchers believe that their ability to provide semantically organized information has significant promise for the development of more intelligent machines [156]. This trait offers important potential solutions for many tasks, including question answering, information retrieval, and recommendation. Similar to the current question-answering (QA) system, the semantic representations of knowledge can be used to construct queries and statements that can be used to ask or test users’ understanding of a certain concept.

To help the agent find possible misunderstandings that a user may have regarding a certain concept, and react appropriately, a knowledge graph of the concept to be taught is created and pre-stored in the Knowledge Base. As the TA learns from a user, it checks what it learned with the ‘correct answers’ as stored in the knowledge graph. The entities and relations are extracted from the user input text and compared with what is stored in the knowledge graph. If the agent perceives that there may be a misunderstanding regarding a certain concept, i.e. different triplets for user input and knowledge graph, it then generates questions regarding the concept to test whether the user understands it. If the user fails to understand the knowledge, a tailored message depicting the negative effects of carrying out actions according to what the user taught will be sent to the user. This is to guide him in understanding the knowledge and prompting that he may need to take a closer look at the concept.

### 4.1.2 Modelling of the Agent

Throughout its lifetime, a TA senses, reasons, and acts on its environment. The agent’s main routine is the repeated cycle, which may be modeled using the goal-oriented agent modeling, known as Goal Net [157, 158]. With this, the TA can be more proactive in assessing the elderly’s Ikigai level, incorporating new knowledge learned from the elderly user, and practicing the knowledge learned from the elderly. Goal Net is made up of nodes representing states that the agents must complete in order to reach their goal. It can be defined as:

**Definition 4.4** (Goal Net). A Goal Net,  $GN$  is defined as a tuple  $GN = (S, A, T, B)$ , where

$S$  is the set of goal states that the agent wants to achieve;

$A$  is the set of arcs that define how one goal state connects with another;

$T$  is the set of transitions which specify what tasks the agent must do before moving to the next goal state;

$B$  is the set of branches which denote the boundary of the Goal Net. If a goal state is too sophisticated to be represented as a single state, it can be split into Sub Goal Net. The branches from the upper goal state are used to lay out the Sub Goal Net.

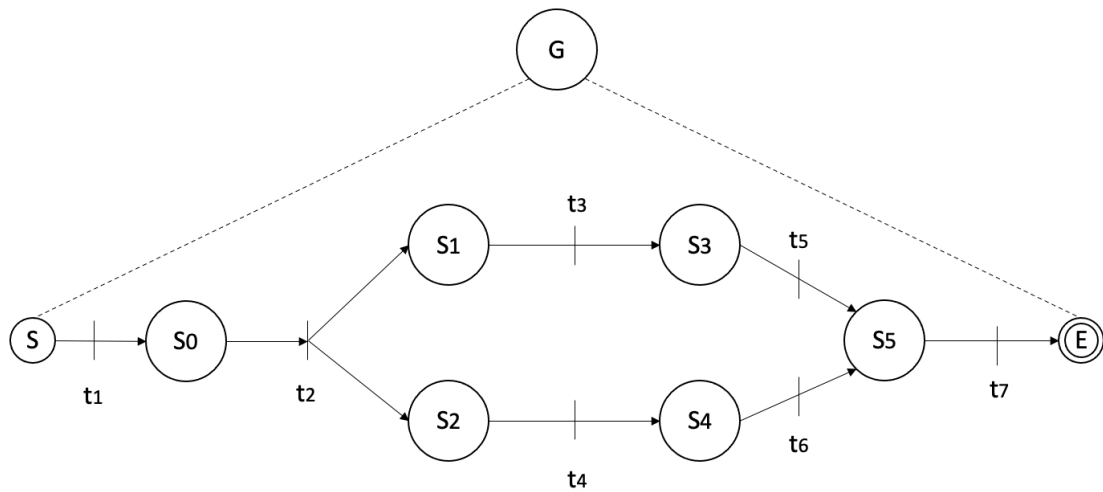


FIGURE 4.4: An example illustration of the Goal Net model

Figure 4.4 depicts an example of the Goal Net model. Goal states,  $S$  is represented by the nodes  $S_0$  to  $S_5$ . Special states  $S$  and  $E$  denote the start and the terminated state. Arcs are shown as arrows connecting various goal states. Transitions are represented by vertical bars,  $t_0$  to  $t_7$ , with  $t_2$  being a special Choice Transition indicating a selectable path from one state ( $S_0$ ) to another ( $S_1$  or  $S_2$ ). Branches are shown as dashed lines. Within the Goal Net, an agent's goal is to achieve the final desirable goal state by completing sub-goals in sequential order.

The main routine of the Goal Net for the proposed TA is depicted in Figure 4.5. The TAIL definition, along with the corresponding states and transitions specified in the main routine in Figure 4.5, are shown in Table 4.1. As long as the agent is pursuing its goal, the main routine will continue to run. In each cycle, the agent looks for an event update. For every event detected, the agent first selects the appropriate reasoning. The agent will go back to its initial start node at the end of each cycle to begin a new cycle. To assess, to learn, and to practice are the three sub-goals in the main routine. These sub-goals enable the agent to choose the most relevant reasoning goals based on the current situation.

Appropriate reasoning is selected based on rules. For example, if the elderly first uses the agent, and there is no information about the elderly's level of Ikigai, the Assessment Reasoning will be selected. After the assessment, the agent may request teaching from the elderly. If the TA finds that the elderly may have some misunderstanding regarding the concept, it then proceeds to check the elderly's

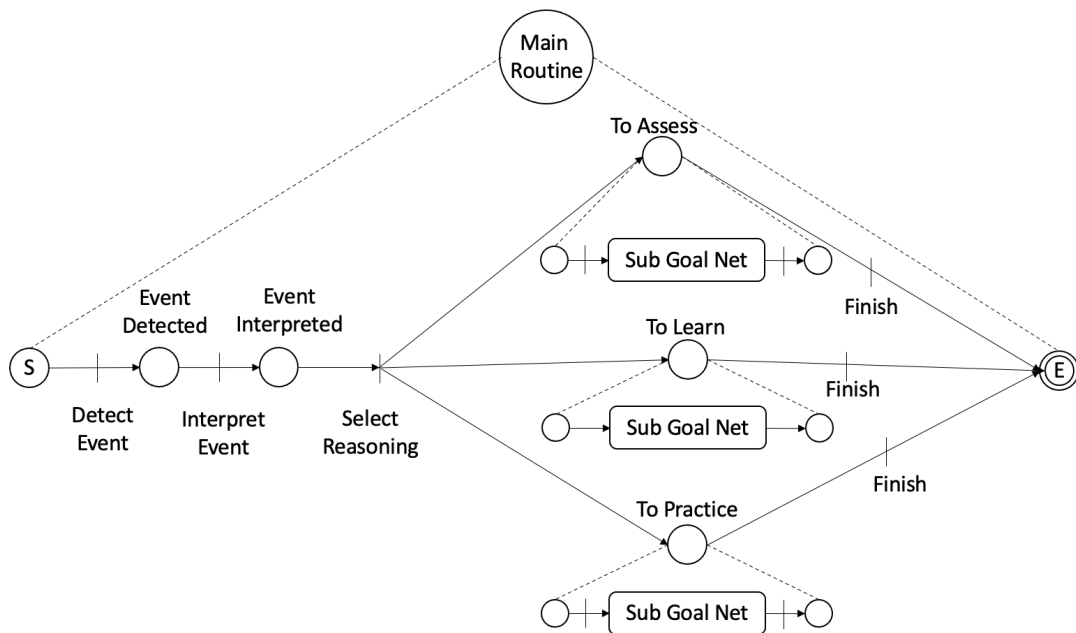


FIGURE 4.5: Goal Net model of the proposed TA's main routine

TABLE 4.1: TAI definition corresponding to States/Transitions in Main Routine

TAII Definition	States/Transitions
<i>Et</i> , Event Tracker	Detect Event, Event Detected, Interpret Event, Event Interpreted
<i>R</i> , Reasoning	Select Reasoning, To Assess, To Learn, To Practice
<i>As</i> , Ikigai Assessment Reasoning <i>A</i> , Actions	To Assess
<i>Tr</i> , Teachability Reasoning	To Learn
<i>Pr</i> , Practicability Reasoning <i>A</i> , Actions	To Practice

understanding by asking questions (practicing). Appropriate reactions and hints are given to prompt the elderly to learn more and teach the agent.

Figures 4.6, 4.7, and 4.8 depict illustrations of the three sub-Goal Net models for the agent to assess, learn, and practice.

#### 4.1.2.1 To Assess

Figure 4.6 illustrates the agent's sub-goal of determining the user's Ikigai level. The agent requests that the user complete the assessment to determine their Ikigai level.

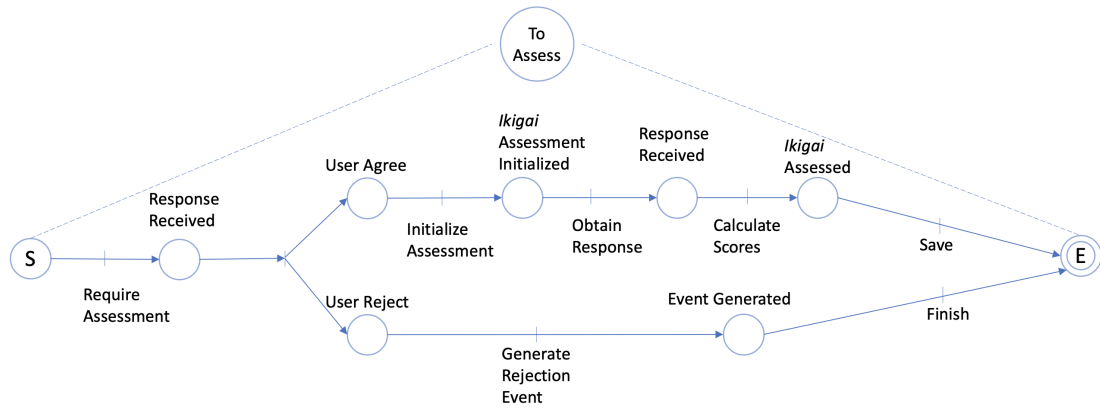


FIGURE 4.6: Sub Goal Net for agent to assess

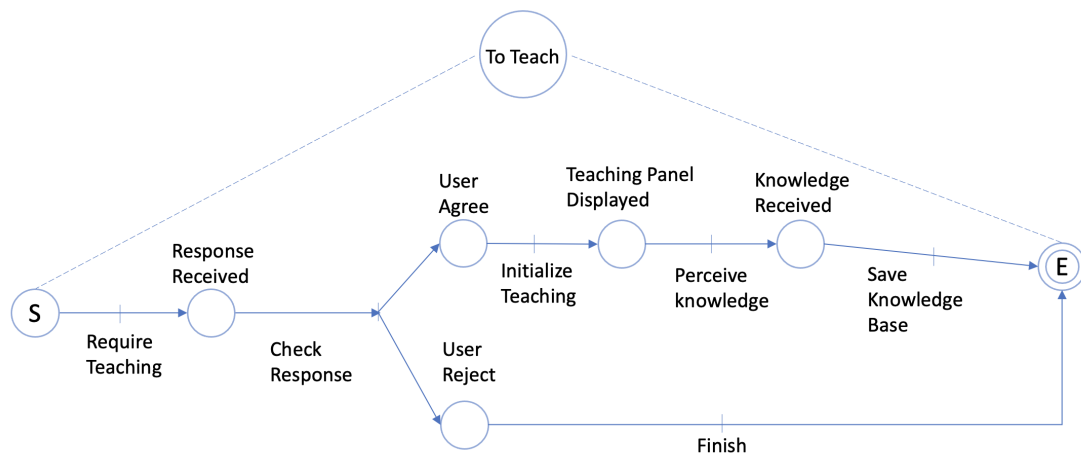


FIGURE 4.7: Sub Goal Net for agent to learn

The agent checks whether the request is accepted or refused after receiving the user's response. If the user accepts, the Goal Net starts the assessment. The user responds, and the agent determines the user's level of Ikigai after the assessment is initialized. The cycle is finished after the user's Ikigai level is stored in the Knowledge Base.

#### 4.1.2.2 To Learn

The agent's drive to acquire new knowledge is shown in Figure 4.7. The agent requires the user to teach itself in this sub-goal. After receiving the response, the agent determines whether the user accepted or rejected the request. The Goal Net initiates teaching if the user accepts to do so. After initializing teaching, the agent

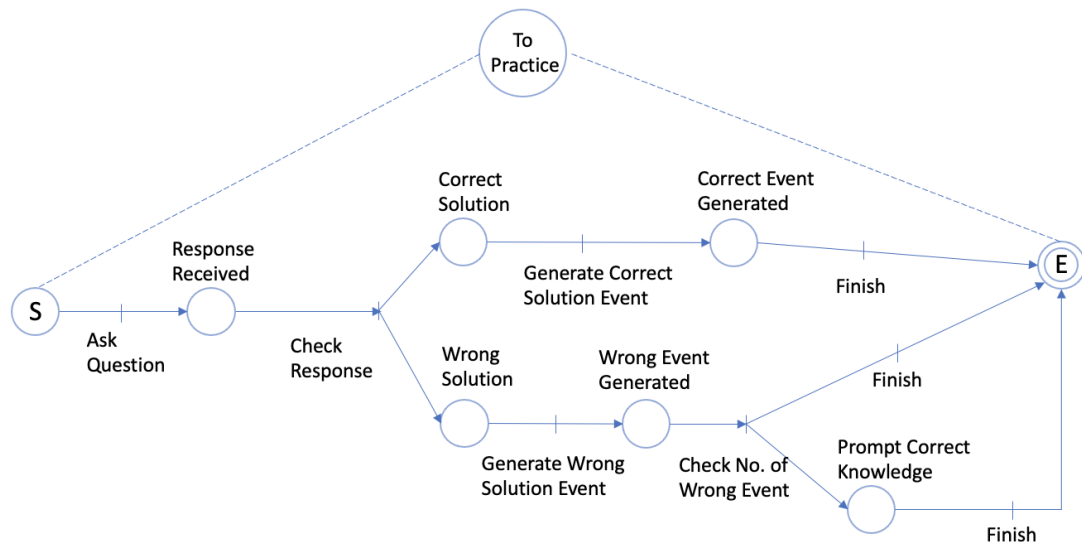


FIGURE 4.8: Sub Goal Net for agent to practice

acquires knowledge after saving previously acquired knowledge, and the cycle is complete.

#### 4.1.2.3 To Practice

As shown in Figure 4.8, the sub-goal of practice begins with the agent posing a query to the user based on its comprehension of the knowledge. If the agent misinterprets the knowledge or is incorrectly instructed by the user, it may make erroneous statements or take actions that pose a health risk in the query. By providing feedback on the user's instruction, it simulates the agent's ability to reflect on the knowledge that has been acquired and apply its knowledge. The agent will execute a correct or incorrect solution depending on whether the user corrects them. If the agent executes an incorrect solution event, it will need to be taught again by the user in the subsequent cycle of the agent's Goal Net. If the agent consistently implements the incorrect solution, the agent will respond with the appropriate information to let the user know that there is a conceptual misunderstanding.

### 4.1.3 Agent Design

Research has shown that there is a need to improve health-related knowledge among the elderly to help them with healthy aging [159, 160]. In this study, we focus on the concept of glycaemic index (GI) for the elderly to teach the agent, named Akeso. It is named after a Greek goddess with the power of healing. The elderly are given a set of basic materials about GI, including the definition, health risks related to consuming too much high GI food, benefits related to consumption of low GI food, as well as the GI values of various food.



FIGURE 4.9: Example sub-graph about some food and their GI value

Akeso first engages the elderly with some ice-breaking chat. Then she starts to ask questions regarding the concept of GI and requires the elderly to teach her. The elderly then teaches Akeso based on his/her understanding. Akeso then learns and stores the knowledge in the Knowledge Base. The learned knowledge is checked with the knowledge graph created for correctness. Parts of the knowledge graph about GI are shown in Figure 4.9. Nodes shaded in green are example food, while nodes shaded in blue are categories that the food belongs to. The numbers on the red edges are the respective GI values of the food. The GI value is considered high

if it is greater than 60. Akeso practices what she has learned from the elderly. If she misinterprets the concept or the elderly teaches her wrongly, Akeso makes erroneous statements or intends to carry out actions that may lead to adverse effects on health. If the elderly do not correct Akeso, the effects of her actions are then shown to the elderly. In the situation, where Akeso has taken multiple wrong actions, she will prompt correct knowledge to the elderly.

The development of Akeso's script started with an in-depth review of the scientific literature on the GI and its implications for health. This initial phase was crucial, ensuring that the content was not only engaging but also scientifically sound and accurate. The crafted scripts aimed to make the complex subject of GI approachable, guiding users through the nuances of how different GI values affect health and offering actionable advice for adopting healthier dietary habits.

To make the learning experience interactive and captivating, we developed scenarios that encouraged users to actively apply their understanding of GI. Central to this interactive learning model is the knowledge graph, which encompasses a comprehensive repository of GI-related information, categorizing foods according to their GI values. By leveraging this rich database, Akeso dynamically generates scenarios that mirror the everyday dietary choices individuals face. These interactive elements were designed to simulate real-life decisions, such as choosing between foods with different GI values, thus enhancing user engagement and promoting the practical application of knowledge. For instance, users might be presented with a scenario where they must choose between two breakfast options—oatmeal (a low GI food) and white toast (a high GI food)—and then discuss the potential impact of each choice on blood sugar levels. These scenarios are carefully crafted to prompt users to reflect on their dietary habits, encouraging them to consider the GI values of the foods they consume and their implications for health. The integration of such scenarios within the conversational flow with Akeso ensures that learning is not only theoretical but grounded in the realities of daily life. Users are encouraged to actively engage with the information, making decisions that simulate real-life dietary choices. This active engagement is pivotal in translating abstract GI concepts into tangible, actionable knowledge. Furthermore, the scenarios are designed to adapt based on user responses, offering personalized feedback and advice. If a user consistently selects high-GI foods, Akeso might introduce a scenario emphasizing the benefits of incorporating more low-GI foods into their diet, backed by

information from the knowledge graph. This adaptive approach ensures that the learning experience is tailored to the user's existing knowledge level and dietary preferences, making the educational content both relevant and impactful.

We applied Natural Language Processing (NLP) technologies to interpret user inputs with high precision, allowing Akeso to respond with relevant scripted content dynamically. This was achieved through parsing user questions, identifying key terms, and understanding the context of inquiries. This allows for dynamic, context-aware responses that enhance the naturalness of interactions. The identification of key terms enables Akeso to delve into the context of inquiries, leveraging its knowledge base to draw connections between the user's questions and the relevant information on the Glycemic Index (GI). This contextual understanding is critical for generating responses that are not only accurate but also tailored to the user's specific informational needs. For instance, when a high-GI food choice is identified, Akeso articulates the potential negative health impacts, ensuring the interactive experience with smooth and informed dialogue. This ensures Akeso not only disseminates knowledge effectively but also becomes a companion in the journey towards understanding and implementing GI-conscious dietary habits.

Example dialogues between the agent and the elderly are shown in Table 4.2.

#### 4.1.4 User Study and Results

To assess the effectiveness of our proposed philosophy and design of TA in enhancing the Ikigai level of the senior population, we conducted a 1-month user study following the phenomenographic approach. Phenomenography, as a qualitative research method, is rooted in philosophical study. It is a qualitative research methodology that studies the qualitatively various ways in which individuals perceive or think about something [139].

##### 4.1.4.1 Participants

In this study, we recruited 10 senior participants aged between 55 to 68 ( $n=10$ , mean=61.75, std=3.52). They are all ethnically Chinese. Three of them are male, while the other seven are female. None of the participants is suffering from any

TABLE 4.2: Example dialogues

Dialogues	Remarks
<b>Agent:</b> Hello! Glad to meet you! My name is Akeso. My doctor told me to monitor my blood glucose level, keep it stable and take some low-GI food. But I have little idea about GI of food. My friend introduced you as an expert in this. Would you like to help me?	Icebreaking chat
<b>Elderly:</b> I am not an expert. I just learned something about it.	
<b>Agent:</b> Let's learn something together targeting to be healthier!	Require teaching
<b>Elderly:</b> OK.	
<b>Agent:</b> Do you know why should we choose low GI food?	Teaching (Detect wrong knowledge)
<b>Elderly:</b> It contains less sugar.	
<b>Agent:</b> I'll take a cup of classic Nanyang Copi, coffee with condensed milk. Yummy! What do you think?	Practice related knowledge
<b>Elderly:</b> Sounds great.	Detect wrong knowledge
<b>Agent:</b> Oh no, my blood sugar increased sharply.	Hint for wrong knowledge
<b>Agent:</b> To avoid blood glucose fluctuation, I should not take anything sweet, is it correct?	Practice related knowledge
<b>Elderly:</b> Yes.	Detect wrong knowledge
<b>Agent:</b> I consulted with my doctor. No worries. Some delicious fruit with low GI such as pears can satisfy us with the taste of sweet.	Reply with correct knowledge
<b>Elderly:</b> Oh, I thought high GI was equal to high sugar.	Notice concept misunderstanding
<b>Agent:</b> Scientists used to think that sugary foods cause a more rapid rise in blood glucose compared to starchy foods but this is not true.	
<b>Elderly:</b> I see.	Confirm

chronic diseases or mental health problems. This study is approved by the university's Institutional Review Board (IRB).

#### 4.1.4.2 Experiment Procedure

Before the experiment, all participants completed the four-factor scale [138] to measure their Ikigai level as a benchmark. Following a brief introduction to the study, they received a 3-page learning material about a health-related definition of the Glycemic Index (GI) [161, 162]. After mastering the basic knowledge, the participants were told to communicate with Akeso every day, our teachable agent installed on their smartphones, to help them learn knowledge regarding GI. During the 1 month experiment period, Akeso talked with each participant about the same content. She asked the participants questions such as *“I’d like to take some fruit, which one should I choose? Watermelon or cherry?”*. The participant teach her knowledge based on answering her questions. They can also start a conversation by asking Akeso questions. This communication takes place at least 3 times a day. The textual conversation and behaviors of the participants were recorded for analysis. After the experiment, all the participants completed the four-factor scale [138] again. Furthermore, they need to complete a 5-point Likert Scale about the acceptance of Akeso including questions about their overall feeling and some features of Akeso including intelligibility, attractiveness, and usefulness. A semi-structured interview followed to understand the experiences of the participants and the reasons behind the phenomena.

#### 4.1.4.3 Measurement

- Ikigai: the fluctuation of Ikigai level of each participant was measured by the comparison of the pre and post-experiment questionnaire results. The changes in each factor, such as self-esteem, are also analyzed.
- Learning results: the learning result of each participant was tested by their correct rate of answering Akeso’s questions.
- Human-agent interaction engagement: the engagement during the interaction with the agent was assessed by combined approaches. Firstly, a semi-structured interview after the study guided by the human-agent engagement questionnaire including the factors of realism, attractiveness, potential to use, etc. [163] were used. Secondly, the behavior features of the participants, such as the length of dialogues, were observed during the study[164].

- The information on the experiences of the participants was collected based on both the conversational context and the post-study interview results analysis.

#### 4.1.4.4 Data Analysis

After the one-month experiment, we recorded 3574 rounds of conversations from all the participants ( $n=10$ ,  $\text{mean}=357.4$ ,  $\text{SD}=183.7$ ). One round contains at least 1 meaningful line and a reply from the other part. The most talkative participant contributed over 800 rounds of lines while the least one communicated with Akeso for 176 rounds.

Following the phenomenological approach, we categorized the participants into 2 groups based on the different changes in their Ikigai level after the study. Group 1 contained the 5 participants who showed an increase in Ikigai after the experiment. Meanwhile, the participants in Group 2 showed no significant Ikigai raise.

Then, we compared the behavioral differences between the 2 groups to hunt for the phenomenological themes. Two researchers went through the transcripts independently to code their experiences. Based on the raw results, we discuss and define the themes by summarizing the homogeneity within a group and the heterogeneity between groups collaboratively. The learning effectiveness of the participants and the engagement during the human-agent interaction were also compared between the two groups. Besides these, the original average Ikigai level of each group was considered to conquer bias.

#### 4.1.4.5 Results

The post-study questionnaire results showed a high acceptance of Akeso with a score of 4.57 out of 5. All the participants felt that they liked Akeso and had a nice time during the communication. Eight out of ten of our participants would like to use Akeso in their daily life.

Data analysis in this study revealed no significant differences in terms of learning effectiveness and interactional engagement between the group of participants who experienced Ikigai enhancement and the one that did not. This suggests that the

TABLE 4.3: Categories of experiences with the proposed teachable agent

Category	Sub-categories	Description
Proactive interaction with the agent	Asking questions to the agent Searching for further knowledge Rectifying the behaviors of the agent	Participants who enjoyed Ikigai improvement tend to be actively engaged with the agent
The personification of the agent		Participants who enjoyed Ikigai improvement tend to believe and treat the agent as human being
Emotional engagement with the agent		Participants who enjoyed Ikigai improvement tend to express a range of emotional responses

integration of the concept of Ikigai into the teachable agent did not adversely affect the learning outcomes or the level of interaction.

The phenomenographic analysis of the participants' experiences, however, unveiled three distinct categories of interaction: proactive interaction with the agent, personification of the agent, and emotional engagement with the agent as shown in Table 4.3.

The categories were formed adhering to the criteria stipulated by [140]: first, "the individual categories should each stand in clear relation to the phenomenon of the investigation so that each category tells us something distinct about a particular way of experiencing the phenomenon"; second, "the categories have to stand in a logical relationship with one another, a relationship that is frequently hierarchical"; third, "the system should be parsimonious, which is to say that as few categories should be explicated as is feasible and reasonable, for capturing the critical variation in the data". In the context of this research, each category illustrates a unique experience that occurred during the elderly's interactions with the teachable agent. Collectively, these categories encompass the diversity of participant experiences throughout the study.

The meanings of each category are explained in the following sections, with representative quotations extracted from the textual conversations with the agent and interview data for illustrative purposes.

### **Category 1: Proactive Interaction with the Agent**

In this category, participants who enjoyed Ikigai improvement tend to be actively engaged with the teachable agent. During the interaction with the agent, they demonstrated behaviors such as asking questions, seeking further knowledge, and rectifying the agent's behavior. Their interaction style shows a sense of ownership and responsibility in learning the health-related concept. At the same time, this also suggests that they have an implicit drive to learn and help the agent to have a healthy diet. This category comprises three sub-categories.

#### ***Sub-Category 1.1: Asking Questions to the Agent***

The major communication pattern of our agent system is asking by the agent and answering by the users. All the participants in Group 1 ask questions to the agent actively. One instance of this type of dialogue is as follows:

*Agent: If I take some watermelon after dinner, will my blood glucose level rise dramatically?*

*Participant: No. Watermelon is a low-calorie food. You can take it.*

*Agent: Oops, we are wrong. Watermelon is a high-GI food. It raises my blood glucose immediately.*

*Participant: what is the difference between high-GI and high-calorie food?*

The participants in the non-improvement group did not show this behavior. Their dialogue stopped when the agent corrected the answer.

Some other participants with a high level of Ikigai in Group 1 even started a conversation actively to consult the agent. As one of them asked the agent “*When is the suitable time to take fruit?*” without any stimulation from the agent.

#### ***Sub-Category 1.2: Searching for Further Knowledge***

When the agent asked questions beyond the learning materials in the participants' hands, they showed different replies. For example, when the agent asked ‘I'd like to skip my dinner, what will happen to my blood glucose level?’ The participants in Group 2 generally answered based on their own knowledge:

*“I do not know.” Or*

*“I guess it may cause some problems. You should not jump over any meals. Regular life will benefit your health.”*

On the other hand, the participants in the improved group replied with active knowledge-seeking behaviors like:

*“I do not know. But I searched via Google. It seems like you should not skip your dinner. When you do this, you may suffer from low blood sugar. And the long-time hunger may cause stimulation of your glucose hormone secretion. Your glucose level will fluctuate like a roller coaster.”*

### ***Sub-Category 1.3: Rectifying the behaviors of the agent***

Compared with the passive behaviors of the no-progress group, Group 1 showed a specific tendency of correcting the agent. Some of the corrections were not related to the key knowledge GI. For example, the agent showed a picture of her lunch and asked for a prediction of her blood glucose changes. The passive participants responded with regular answers such as:

*“Your glucose will be stable since they are all low-GI food.”*

Unexpectedly, one of the participants who improved her Ikigai replied with additional advice:

*“Your glucose will be all right. But you should not take cucumber and tomato together. Some biochemical element in cucumber will destroy the vitamin C in tomatoes.”*

## **Category 2: Personification of the Agent**

In this category, participants who experienced an Ikigai increase tend to see and treat Akeso as a human being, rather than just a computer program or robot. On the contrary, the majority of participants in the other group believe it is a robot. As one of the former group remarked during the interview:

*“I believe Akeso is a real person. I feel very happy when I answered her question and helped her.”*

Another evidence of this theme is that participants tend to seek for help from Akeso. Imitating Akeso’s behavior of taking and sharing photos of her meal and asking for evaluation, the participants also reported their meals to Akeso and asked for her opinion. When we asked the participants who did not show improvement in their Ikigai level why they did not interact with Akeso actively, they responded like the follow:

*“It is just a robot with pre-designed dialogue mode. I did not expect personalized replies.”*

Such personification points towards a deeper, more personal engagement with the agent, reflecting an emotional connection and a stronger rapport.

### **Category 3: Emotional Engagement with the Agent**

In this category, participants who experienced Ikigai improvement tend to express a range of emotional responses.

To understand the psychological experiences of the participants, we asked the participants to describe their feelings about the four factors of Ikigai to supplement the objective results of the questionnaire in the semi-structured interview. The participants in Group 1 expressed more emotional feelings during their interaction with Akeso:

*“I feel satisfied when I learned new knowledge.”*

*“I feel confident when Akeso confirmed my answer.”*

*“I like to be relied on by Akeso.”*

*“I feel strong and powerful when Akeso admits her fault and commits to changing her behaviors.”*

These perceptions were reflected in their questionnaire results as the significant elevation of their “self-esteem” score. The mapping of these interview results and corresponding survey results demonstrated the effectiveness of Akeso in improving Ikigai, especially in the self-esteem aspect. We also detected the positive emotion

of the participants in their tones and rhetoric of dialogues. Their sentences seem to be more relaxed, determined, and humorous. They use words such as “*I’ve learned this. I know it. You should ...*” instead of “*It seems like. I guess. Maybe...*” which are more popular in Group 2. Though the participants in Group 2 did not express so many emotional sentences in their interview transcripts, some of them also mentioned “feeling happy when my answer is correct”. The main difference exists in the perception of feeling being needed.

This emotional engagement demonstrates a level of immersion and personal connection with the agent, contributing to a richer and more personal interactional experience.

#### 4.1.4.6 Discussion

The analysis reveals aspects of the lived experience of senior users in using our proposed teachable agent Akeso. The results show the effectiveness of Akeso in enhancing the Ikigai level of the elderly. The thematic description of the common elements of the experience of the participants who gained an improvement of Ikigai after 1-month interaction with Akeso includes “proactive interaction with the agent”, “personification of the agent”, and “emotional engagement with the agent”. These three elements reflect the key to successful Ikigai interventions.

Learning by teaching Akeso enhances self-esteem more significantly among the 4 factors of Ikigai. The teaching experiences left the participants’ self-imaginings as acquainted, useful, and powerful. The participants who did not experience significant Ikigai improvement also showed positive emotional satisfaction during their interaction with Akeso although they did not perceive similar self-esteem strengthening. We can not conclude that a teachable agent does not work for them. They may need a longer time to establish a relationship with the agent. Or they may need a more humanized conversational design. A long-term user study with a larger sample size in the future will help us to understand this question.

This finding inspires our future study of teachable agents. We need to understand how to encourage the active behavior of the users, as well as how to improve the humanized cognitive features of the agents in conversation functions. This potential piece of knowledge will not only nourish our own agent design but also benefit the general human-agent engagement studies.

Furthermore, during the study, we found out that some expressions in both words and non-verbal behaviors of the participants can reflect their Ikigai level. For example, when Akeso thanks the user for correcting her wrong belief, the user replies “You make me feel useful. I am so glad”. This type of conversation appears frequently in their daily chat. In future studies, we will attempt to embed a dynamic system in Akeso to assess the Ikigai level and its changes of each user based on semantic analysis and knowledge graph. This proposed design can help the users to skip the long and boring questionnaire on one hand. On the other hand, we can assess the Ikigai changes of the users at any time and tailor the messages according to it immediately.

## 4.2 Hobby Recommender

The results of an opinion poll study on Ikigai show that 51.2% of respondents consider hobbies to be key components of their Ikigai [165]. [166] also identified hobbies as a key component of one’s Ikigai. Participants were provided with a selection of 17 widespread hobbies that people commonly have, including photography, outdoor activities, and travel, from which to choose. While participants with more hobbies tend to have higher Ikigai scores (Figure 4.10), different hobby seems to have a different correlation with one’s Ikigai level (Figure 4.11). Engaging in hobbies that resonate with an individual’s passions, interests, and values not only provides pleasure and relaxation but also helps cultivate a deeper sense of meaning and fulfillment in life.

Building upon this understanding, we developed a reinforcement learning-based hobby recommender system to enhance an individual’s Ikigai level. This system aims to offer personalized recommendations of hobbies, tailored to the individual’s preferences, experiences, and personal conditions. Utilizing state-of-the-art reinforcement learning algorithms, the recommender system learns from the feedback and adjusts its recommendations over time to optimize the increase in Ikigai level.

In this way, the hobby recommender serves as a personal guide, helping users discover and explore activities they might not have considered, yet that could potentially enrich their lives and boost their Ikigai. This section delves into the design,

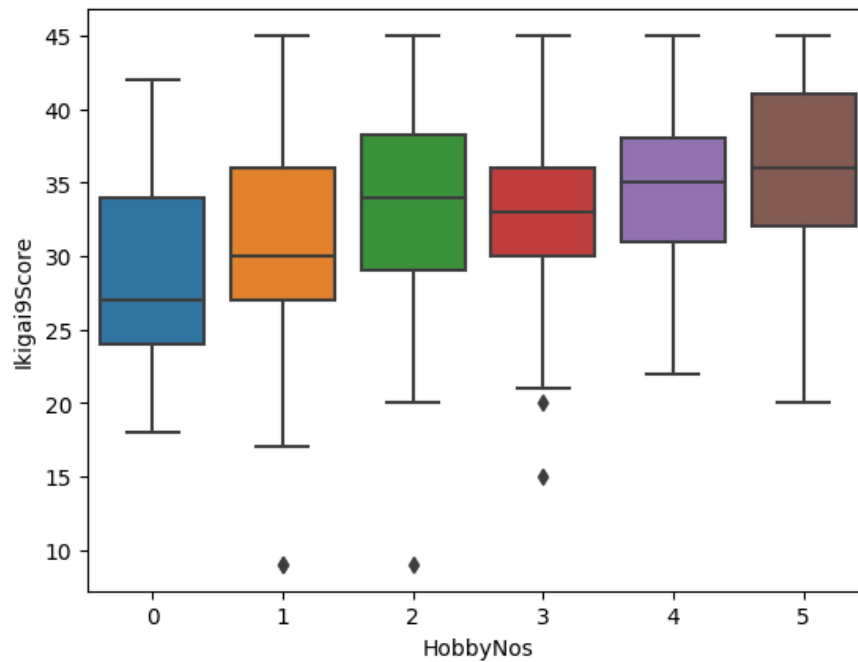


FIGURE 4.10: Participants' Ikigai scores by the number of hobbies reported

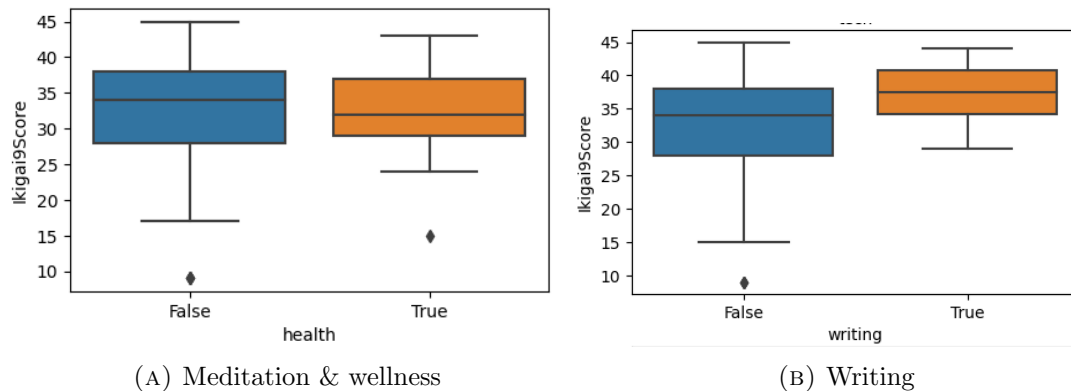


FIGURE 4.11: A figure showing participants' Ikigai scores by different hobby

implementation, and evaluation of the Reinforcement Learning-based Hobby Recommender, highlighting its potential as an effective tool for Ikigai improvement.

To enhance people's Ikigai by recommending hobbies, we first need to understand more about different people's Ikigai and how different hobbies may affect the Ikigai level. To do so, we first collected data containing people's basic information, hobbies, and their Ikigai level, and build an Ikigai simulator to predict one's Ikigai level from the user profile as explained in the earlier section. Then, both a supervised learning and reinforcement learning model were proposed to recommend hobbies to people to enhance their Ikigai.

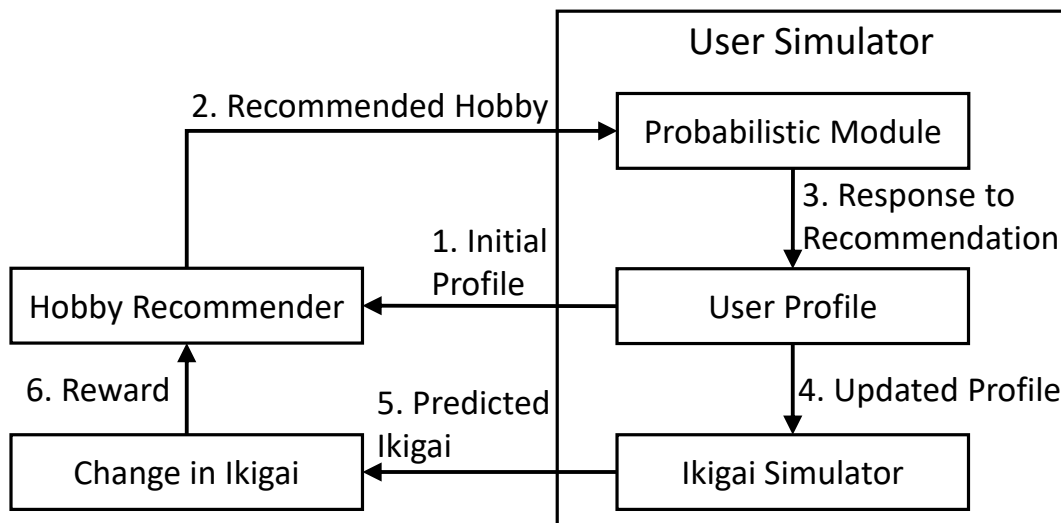


FIGURE 4.12: An overview of our hobby recommender training procedure using reinforcement learning.

An overview of our proposed model using Reinforcement Learning is shown in Figure 4.12. We developed the model with a few key questions that we wanted to answer. The first is whether Ikigai can be estimated from a user profile. The second is if hobby recommendations based on a user’s profile can improve the person’s Ikigai. Thus, we created a user simulator to try to replicate how a person would react to a hobby recommendation. In attempting to create a more realistic user simulator, we added a probabilistic module. The probabilistic module decides whether a recommendation is accepted or not since a user will not always accept recommendations. More details about our proposed method will be described in the following sections.

### 4.2.1 Proposed Approaches

Given the user simulator from the previous section, we can train a hobby recommender that learns to recommend hobbies to maximize a given user’s Ikigai level. We propose two ways to train the hobby recommender: supervised learning and reinforcement learning (RL). Our choice of RL is based on its strength to optimize performance through indirect supervision.

### 4.2.1.1 Supervised Learning Approach

The supervised learning model for recommending hobbies operates on the principle of learning from a labeled dataset, where each input (a user's profile including physical attributes, medical conditions, current hobbies, and personality traits) is associated with one or more correct output labels (recommended hobbies). This model involves a neural network that processes the input features through multiple layers, including an input layer sized according to the combined feature dimensions, a hidden layer with 64 neurons to capture complex relationships, and an output layer with a neuron for each potential hobby to be recommended. In this case, 17 different hobbies are explored.

To use supervised learning, we need to first create a dataset that can be used to train the recommender. To do this, we go through each profile in the training dataset and we add hobbies one at a time. Then we use the Ikigai simulator to estimate the profile's Ikigai after adding a given hobby. The hobby that increases Ikigai the most is used as the ground truth hobby that should be recommended for the profile. Thus, we create a dataset of profile-hobby pairs that can be used to train the hobby recommender, which is done using a cross-entropy loss function.

During training, the model is presented with batches of user data and the corresponding correct hobbies. It learns by adjusting its internal parameters to minimize the discrepancy between its recommendations and the actual hobbies users are interested in. This discrepancy is quantified using cross-entropy loss, which is well-suited for problems where the goal is to predict the likelihood of each class (hobby) for a given input.

### 4.2.1.2 Reinforcement Learning Approach

The reinforcement learning (RL) model for hobby recommendation takes a different approach by framing the recommendation process as a sequence of decision-making steps where the model, acting as an agent, learns to make recommendations by interacting with an environment (the user and their responses to previous hobbies). The model receives a state representation (similarly composed of user profiles, including physical attributes, medical conditions, current hobbies, and personality

traits) and must choose an action (recommend a hobby) that maximizes expected rewards over time.

To train the recommender using reinforcement learning, the user simulator acts as the environment that the recommender interacts with. Our overall training algorithm is described in Algorithm 1, and Figure 4.12 visually depicts an overview of our training method. In this context, the reward signal is crucial and often designed to reflect user satisfaction or engagement with the recommended hobbies. Given a user profile, we calculate the initial Ikigai level by summing the responses to the Ikigai-9 questionnaire, and then we pass the profile to the hobby recommender to get a recommendation. To ensure the recommended hobbies align with the person’s physical abilities, we employ a capability matrix that filters out unsuitable activities. For instance, hobbies requiring physical exertion are not suggested for individuals who use walking aids.

The selected hobby is then evaluated by a probabilistic module, which decides on its adoption and the frequency of engagement if accepted. This module computes probability distributions for the perceived difficulty of potential hobbies, utilizing data from questionnaire responses. It then assesses the probability of a hobby’s acceptance by considering its ease (which is inversely related to its perceived difficulty) and the individual’s interest level. The frequency of engagement with the hobby is then decided based on whether the likelihood of acceptance meets or exceeds certain set thresholds.

If a hobby is accepted, the user’s profile is updated to include this new hobby. If not, the recommender system is prompted to suggest an alternative. Once a hobby is successfully integrated into the user’s profile, it is passed to the Ikigai simulator, which then predicts responses to the Ikigai-9 questionnaire, reflecting the potential impact of the new hobby on the user’s Ikigai level.

The reward given to the recommender is measured by the change in the user’s Ikigai level, which is given by subtracting the new Ikigai by the initial Ikigai. More formally, the reward given to the agent is defined as:

$$r = \begin{cases} \text{new\_ikigai} - \text{init\_ikigai} & \text{if accepted} \\ 0 & \text{otherwise} \end{cases}, \quad (4.1)$$

where `init_ikigai` is the initial Ikigai level from the user’s profile calculated by summing the answers to the Ikigai-9, and `new_ikigai` is the new Ikigai after accepting a hobby recommendation, updating the user’s profile, and predicting the new Ikigai level using the Ikigai simulator. The RL model uses this reward feedback to adjust its policy, which governs how it selects actions given states, to favor actions that lead to higher rewards.

Training an RL model involves exploring the space of possible recommendations to discover which sequences of actions (hobby recommendations) lead to the most positive outcomes. This exploration is balanced with exploitation of the known good actions to ensure the model continues to learn effectively without getting stuck in suboptimal patterns. We use Advantage Actor Critic (A2C) [167] to train our recommender. It enables the model to navigate this exploration-exploitation trade-off and refine its recommendation strategy over time. A2C is a policy gradient method that aims to maximize the rewards obtained by a policy  $\pi$  by updating its weights  $\theta$  using gradient ascent with the following gradient:

$$\nabla_{\theta} J(\theta) = \mathbb{E} \left[ \sum_{t=0}^{T-1} \nabla_{\theta} \log \pi_{\theta}(a_t | s_t) A(s_t) \right], \quad (4.2)$$

where  $T$  is the length of a trajectory,  $a_t$  is the action taken by the agent at timestep  $t$ ,  $s_t$  is the environment state at timestep  $t$ , and  $A$  is the advantage function, given by:

$$A(s_t) = r_t + \gamma V(s_{t+1}) - V(s_t), \quad (4.3)$$

where  $r_t$  is the reward obtained at timestep  $t$ ,  $\gamma$  is a discount factor, and  $V$  is the value function. The value function  $V$  is trained to estimate state values using the following formula:

$$V(s_t) = \begin{cases} r_t & \text{if } s_t \text{ is terminal} \\ r_t + \gamma V(s_{t+1}) & \text{otherwise} \end{cases}. \quad (4.4)$$

---

**Algorithm 1:** Reinforcement Learning for Hobby Recommendation to Improve Ikigai

---

**Input:** A trained user Ikigai simulator  $I$ , a probabilistic module  $P$ , a dataset of user profiles.

**Parameters:** Discount factor  $\gamma$ , episode length `max_recs`, number of epochs.

**Output:** A trained recommender  $\pi$  and critic  $V$ .

```

1: Initialize recommender model  $\pi$  with parameters  $\pi_\theta$ 
2: Initialize critic model  $V$  with parameters  $V_\theta$ 
3: for  $i = 0$  to epochs do
4:   Sample a user profile  $p$ 
5:   init_ikigai  $\leftarrow$  the sum of the Ikigai-9 answers in  $p$ 
6:   Initialize arrays  $v, a, r$  to store episode values, log probabilities, and
   rewards
7:   for  $j = 0$  to max_recs do
8:     hobby  $\leftarrow \pi(p)$ 
9:     freq  $\leftarrow P(\text{hobby})$ 
10:    val  $\leftarrow V(p)$ 
11:    if freq  $> 0$  then
12:      Update  $p$  with the new hobby frequency
13:      new_ikigai  $\leftarrow I(p)$ 
14:      reward  $\leftarrow \text{new\_ikigai} - \text{init\_ikigai}$ 
15:      done  $\leftarrow$  true
16:    else
17:      Update  $p$  to indicate that hobby was rejected
18:      reward  $\leftarrow 0$ 
19:      done  $\leftarrow$  false
20:    end if
21:    Add val to  $v$ , reward to  $r$ , and  $\log \pi(\text{hobby})$  to  $a$ 
22:    if done then
23:      break
24:    end if
25:  end for
26:  Update  $V_\theta$  using mean squared error by using  $v, r, \gamma$  in Equation 4.4
27:  Update  $\pi_\theta$  using  $v, a, r$  in Equation 4.2
28: end for
29: return  $\pi, V$ 

```

---

### 4.2.2 Offline Evaluation

The hobby recommender attempts to recommend a hobby that will lead to the highest gain in Ikigai for a given user. In our training and evaluation, we give models 5 attempts at making a recommendation that is accepted by the user simulator. We compare three models: a random model, a supervised learning model,

and an RL model. The random model will make random recommendations regardless of the given profile. As mentioned in the previous section, we create a dataset using the Ikigai simulator to train a supervised learning model. During training, the model will learn using a cross-entropy loss with the target hobby in the dataset. However, during validation, we use the setup described previously, giving the model 5 attempts to make a recommendation. We run our experiments for 20 times using different random seeds and shuffled train, validation, and test sets. We then select the supervised model that gives the highest Ikigai gain on the validation set for evaluation on the test set. The RL model is selected similarly by using its performance on the validation set.

Based on our results, shown in Table 4.4, the RL model can give the highest average increase in Ikigai through a hobby recommendation. One reason that the RL model achieves better results than the supervised model may be that it interacts with the user simulator during training. This means that it will learn which hobbies are more likely to be rejected by the probabilistic module. Additionally, the RL model can explore other hobby recommendations, whereas the supervised model is fixed in its training. The fact that both the supervised and RL models are able to achieve higher increases in Ikigai than the random model suggests that there is a correlation between a user's profile and hobbies that can lead to greater Ikigai gain.

One interesting result is that the acceptance rate for the RL model is slightly lower than the supervised model, and both the RL and supervised models are slightly lower than randomly recommending a hobby. This is likely due to the fact that the RL model will be punished if the recommended hobby leads to a decrease in Ikigai, but will receive a reward of 0 if no hobby is accepted since the user's Ikigai will not have changed. This leads the model to favor Ikigai gain over the hobby acceptance rate.

### 4.2.3 User Study and Results

To assess the effectiveness of our proposed philosophy in enhancing people's Ikigai level, we conducted a 30-day user study. Using phenomenography, one of the most widely used qualitative methods, we aim to further study how people experience phenomena differently, based on their lived experiences. Using close examination

TABLE 4.4: Results for the recommender on the test set, showing the average increase in Ikigai, and one standard deviation, that each model achieves as well as the acceptance rate of each model’s recommendations.

	Change in Ikigai	Acceptance Rate
Random	$0.509 \pm 0.876$	89.90%
Supervised	$1.481 \pm 1.063$	88.63%
RL	$1.771 \pm 0.950$	88.33%

of individual experiences, phenomenographic analysis attempts to convey meaning and common features of these experiences into a description of their universal essence [168].

#### 4.2.3.1 Participants

In this user study, we recruited another 45 participants, and 5 dropped out during the study. They are all ethnically Chinese. 17 of them are male, while the other 23 are female. There is a wide range of age groups represented in the study, ranging from 18-24 years old to 65-74 years old, with the majority of participants in the 45-64 age group.

#### 4.2.3.2 Experiment Procedure

Before the experiment, all participants completed the same questionnaire containing Ikigai-9 scale [16] as described in the previous section. An additional four-factor scale [138] which is a 28-item on a 5-point scale was included to validate the changes in participants’ Ikigai. It measures one’s Ikigai by four factors: self-esteem, purpose in life, personal energy, and life satisfaction. Participants were divided into three groups. The responses to the Ikigai-9 scale [16] and the four-factor scale were used as benchmarks of the person’s Ikigai level.

In the 30-day study, participants from Groups I to III received a message every six days recommending a new hobby until they accepted the hobby and took action to pursue it. Participants may, for example, receive messages that say “*Based on your response to the questionnaire, we recommend you hobbies related to photography*”. A message asking if the participant has taken any actions related to the recommended hobby was sent to him/her on the other days. Participants were

asked, for example, whether they had taken any action related to photography. In Group I (n=13), the recommended hobbies are generated using the supervised model, while in Group II (n=14) and III (n=13), they are recommended using the reinforcement learning model. The participants in Group III received a second message that attempted to persuade them to develop their hobby every day before accepting one. These messages were designed to highlight the positive aspects of pursuing the hobby or to diminish any hesitations before taking actions. Example messages that were sent to the participants in order to persuade them to take actions related to the recommended hobbies include *“Photography is a good way to preserve your family’s history and memories”* or *“Don’t let the fear of failure hold you back from pursuing something that brings you joy. Give this hobby a try and see where it takes you”*. The textual conversation and behaviors of the participants were recorded for analysis.

After the study, all the participants completed the Ikigai-9 scale and the four-factor scale again. Additionally, we followed up with a semi-structured interview to understand the experiences of the participants and the reasons behind the phenomena.

#### 4.2.3.3 Measurements

- Ikigai: the fluctuation of each participant’s Ikigai level was measured by comparing of the pre- and post-study questionnaire results.
- Attractiveness of recommendation: the attractiveness of the recommended hobbies was determined by if the participant had accepted it and taken actions relating to it or planned to do so in the future.
- The information on the experiences of the participants was collected both through conversational context and through analysis of post-study interviews.

#### 4.2.3.4 Quantitative analysis

As shown by the post-study questionnaire results, in Table 4.5, both the supervised learning model (Supervised) and RL model (both RL and RL + P) can improve people’s Ikigai. The results demonstrate that our proposed methods are effective at improving people’s Ikigai. Both models recommended hobbies that were appealing

TABLE 4.5: User study results for the recommender, showing the average increase in Ikigai measured by the Ikigai-9 scale, percentage of participants who have already taken actions during the study, and the percentage of participants who plan to take actions in the future.

	Change in <i>Ikigai</i>	Current Acceptance	Future Acceptance
Supervised	0.692	23.08%	38.46%
RL	2.214	57.14%	28.57%
RL + P	1.538	53.85%	23.08%

to participants, resulting in over 60% of the participants in the respective groups accepting (“Current Acceptance”) or planning to do relevant actions in the future (“Future Acceptance”).

Table 4.6 shows the changes in participants’ Ikigai levels among different groups measured by the Ikigai-9 scale and the four-factor Ikigai scale respectively. “Current Accept” represents the group of participants who have already taken action during the study, “Future Accept” represents the group of participants who plan to act in the future, while “Reject” represents the group of participants who rejected all five recommended hobbies during the study. Positive numbers denote increases in Ikigai level while negative numbers denote declines in Ikigai. The average increases in Ikigai levels measured by the Ikigai-9 scale among participants in both the RL and RL + P group were confirmed by the increases in Ikigai levels measured by the four-factor Ikigai scale. However, for the Supervised Group, the improvements in Ikigai level measured by the Ikigai-9 were not confirmed by the four-factor Ikigai scale. As for participants who rejected all five recommendations, their Ikigai levels remained relatively unchanged or even decreased. Receiving an additional message that persuades the participant to develop the recommended hobby did not result in a higher acceptance rate of the recommendation. However, they experienced greater improvements in Ikigai measured by the four-factor scale. The average changes in the Ikigai level measured by the two scales for people who have taken action or plan to take action (denoted by “Accept”), and those who reject all recommendations (denoted by “Reject”) across groups are as shown in Table 4.7.

Paired t-tests were performed to investigate whether the difference between the after-study and before-study Ikigai scores for the three groups was different for each group. Upper-tailed paired t-tests were performed for all three groups to

TABLE 4.6: User study results for average changes in Ikigai for different groups as measured by Ikigai-9 scale and the four-factor Ikigai scale.

Metrics	Groups	Supervised	RL	RL+P
Ikigai-9	Current Accept	1.333	2.875	1.857
	Future Accept	2.6	1.5	1.333
	Reject	-1.6	1	1
Four-Factor Scale	Current Accept	-0.333	2.5	10.857
	Future Accept	-0.6	6.5	9
	Reject	-3.4	-0.5	-2.667

TABLE 4.7: User study results for average changes in Ikigai for people who have accepted or plan to take actions, and people who rejected the recommendations, measured by the Ikigai-9 scale and the four-factor Ikigai scale.

	Ikigai-9 Scale	Four-Factor Scale
Accept	2.1	4.833
Reject	-0.3	-2.6

examine whether the mean of the after-study Ikigai score was higher than before-study scores, regardless of whether the participants accepted the hobby recommendations. The results are listed in Table 4.8. Paired t-test results showed a significant difference for the before and after Ikigai scores for the RL+P Group for both scales (Ikigai-9  $p = .017 < .05$ , four-factor scale  $p = .012 < .05$ ), and a significant difference for before and after scores for the RL Group measured by the Ikigai-9 scale ( $p = .033 < .05$ ). There was sufficient evidence at 0.05 level of significance to show that the means of the Ikigai scores measured by both scales for RL+P Group increased during the study. At the same time, there was sufficient evidence at 0.05 level of significance to show that the mean of the Ikigai score of participants in RL Group measured by the Ikigai-9 scale increased during the study. These results indicated that participants receiving hobbies recommended using RL enjoyed more Ikigai increase. The persuasive sentence though did not help improve the acceptance rate of the hobby recommended, but somewhat helped improve the participant's Ikigai. The average Ikigai scores did not increase significantly for the Supervised Group.

TABLE 4.8: Paired t-test between before and after-study Ikigai scores

Metrics	Groups	T statistics	p-values
Ikigai-9	Supervised	0.604	0.278
	RL	2.003	0.033
	RL + P	2.379	0.017
Four-Factor Scale	Supervised	-1.053	0.843
	RL	1.478	0.082
	RL + P	2.562	0.012

#### 4.2.3.5 Phenomenographic Analysis

Following the phenomenographic approach, we categorized the participants into 2 groups based on the different changes in their Ikigai level after the study. Group A contained 29 participants who showed at least an increase in Ikigai after the experiment measured in one of the scales. Participants in Group B (n=11) showed no increase in both scales. In order to search for phenomenographic themes, we compared the behavioral differences between groups and coded their experiences independently. On the basis of the raw results, we discuss and define the themes collaboratively by analyzing homogeneity and heterogeneity within and between groups. In addition, two groups were compared on the attractiveness of their recommendations.

Based on the data analysis, a higher proportion of participants in Group A (24 out of 29) have taken action or plan to take action related to the recommended hobbies than those in Group B (6 out of 10). By coding the experiences of the participants, we categorized the commonalities among those who showed an improvement in their Ikigai level into “participant engagement”, and “personal reflection and planning” as shown in Table 4.9.

#### Category 1: Participant Engagement

In this category, participants who enjoyed Ikigai improvement tended to be more actively involved during the study. Two sub-categories under this category, namely “willingness to share” and “engaging with the researcher,” pointed towards active participation from the participants. This category highlights an open-minded and

TABLE 4.9: Categories of experiences with the proposed hobby recommender

Category	Sub-categories	Description
Participant engagement	Willingness to share	Participants who enjoyed Ikigai improvement tend to be more actively involved during the study
	Engaging with the researcher	
Personal reflection and planning	Reflecting own experiences	Participants who enjoyed Ikigai improvement tend to be more introspective during the study
	Having concrete plans	

enthusiastic participation from the participants, including a readiness to communicate personal thoughts and experiences, and to engage in dynamic discussions with the researcher.

### ***Sub-Category 1.1: Willingness to share***

Interactions between researchers and participants were mainly characterized by the researchers providing recommendations or asking for progress updates, which were then responded to by the participants. This pattern was particularly noticeable among participants in Group A, who not only expressed significant interest in the suggested hobbies, but also provided rich, detailed descriptions of their intentions, plans, and actions related to these hobbies. This communicative exchange is best represented through the following dialogue:

*Researcher: Based on your response to the questionnaire, we recommend hobbies related to photography.*

*Participant: Okay! I like it!*

*Researcher: Have you started taking any actions related to photography?*

*Participant: Yes, already started! I am going to buy books on photography. I tried to look up relevant knowledge on the Internet.*

While some participants from Group A showed genuine interest in the suggested hobbies, they were quite transparent about why they hadn't pursued them. In addition to an impending increase in workload as a result of Chinese New Year, other factors, such as the ongoing COVID-19 pandemic or unfavorable weather conditions, discouraged them from participating in outdoor activities as well.

On the other hand, participants from Group B displayed a different communicative style. Their dialogues usually ended with succinct responses, such as “Okay”, “Yes”, “No”, or sometimes there was no response at all. For this group to become more engaged and to foster more proactive communication, a different approach might be necessary.

A potential need to tailor interaction strategies for different types of users can be suggested based on the observed differences in communication patterns between the two groups in the future. It might be possible to explore the impact of personalizing the agent’s communication style on user engagement and, ultimately, Ikigai levels in future research.

### ***Sub-Category 1.2: Engaging with the researcher***

Participants in Group A showed a strong tendency to communicate with the researcher actively. They displayed an eagerness to share their achievements and experiences, taking the lead to initiate conversations about their progress, in addition to responding to the suggested hobbies.

As an example, one participant took up crocheting slipper socks as a hobby and kept the researcher informed with photos of the various crochet hooks she purchased and slipper socks she crafted. Her positive attitude and enthusiasm were shown during her interactions, as she explained, *“The winter is very cold here. These slipper socks are very practical and beautiful. I can make them for myself or give them away as a small gift. I have many different types of crochet hooks, but my work is ugly. Hopefully, it will be better in the future.”*

As another example, a participant with a growing interest in pets shared a picture of a white Bichon Frissé playing in the snow to demonstrate his enthusiasm. Besides merely a picture, the participant engaged the researcher in a playful game, asking the researcher *“Can you find where the dog is?”* These interactions depict a high level of engagement and an open, friendly rapport between the researcher and the participants in Group A.

However, Group B participants lacked such active participation and spontaneous conversation starters. Communication was mostly reactive rather than proactive, and the participants lacked the vivacity seen in Group A.

As a result of these insights, it may be possible to design and develop a teachable agent that emphasizes rapport-building and fosters active engagement, thus enhancing personal growth and Ikigai among users.

## **Category 2: Personal Reflection and Planning**

In this category, participants who enjoyed an increase in Ikigai demonstrated more introspective elements. There are two sub-categories under the category. “Reflecting own experiences” suggested a degree of self-awareness and the ability to retrospectively analyze their personal experience with a particular hobby. “Having Concrete Plans” indicated that participants were able to concretely articulate their future plans about hobbies that they want to develop. These collectively illustrated the participants’ ability to introspect, look forward to their future.

### ***Sub-Category 2.1: Reflecting own experiences***

We observed that reflecting own past experiences may be a crucial component of Ikigai improvement in Group A. Participants connected with their past aspirations and hobbies after receiving hobby recommendations. Rather than simply accepting or rejecting the recommendations, they intertwined them with their own experiences, demonstrating a deeper level of engagement.

An example of a participant who recalled his aspirations to become a librarian was an excellent example of how past interests can be rekindled. A few years after he stopped reading, his enthusiasm resurfaced when the right stimulus was provided. After receiving the recommendation on reading, he replied: *“I used to love reading very much. However, for some reason, I haven’t read a single book since 1990 (35 years old). You must know that when I was growing up in elementary school, I wanted to be a librarian so I could read books while working.”*

Another participant recalled her past ambition, saying, *“I had this intention (to write something). When I was young, I bragged that I would write a few books after the age of 50. I even thought of the titles of the books. Writing requires deep observation, thinking, and reflection on life. Despite my limited education, I understand some truths, but I have not experienced the hardships of major events, so it is also boring. As a child, I wrote poems that moaned without being ill. Looking back, I realize I was naive...”*

Reflection and connection to personal experiences may be factors that potentially contributed to participants' improvement in Ikigai levels. In fact, some participants explicitly mentioned that this study helped them embark on a journey of self-discovery during the interview. This introspection could potentially explain why some participants, despite not accepting any of the recommended hobbies, still demonstrated an improvement in their Ikigai levels.

However, participants in Group B did not exhibit such an introspective response. Their interactions with the researcher were not as personal and did not prompt deep reflection.

### ***Sub-Category 2.2: Having concrete plans***

In comparison to Group B participants who did not take action to develop an accepted hobby during the study, participants in Group A demonstrated a marked difference in their engagement when discussing future plans related to recommended hobbies. Their responses indicated a more specific and committed outlook on their future activities.

Participants in Group A showed concrete and well-thought-out intentions when asked whether they have plans to pursue the recommended hobbies. Examples include “*Yes, I plan to raise a dog in one year*” or “*Yes, I plan to travel to Xinjiang. I'm more attracted to natural attractions than man-made attractions now*”. Not only was the recommendation accepted by the participants, but they also demonstrated a commitment to integrating the hobbies into their lives in the future.

On the contrary, participants in Group B offered less definitive answers. Their future plans were either vague, such as “*Probably after retirement*”, or dismissive, such as “*No*”. These differences might indicate that Group A participants had successfully internalized the recommended hobbies, and saw them as viable, desirable additions to their lives.

The clarity of the plans articulated by Group A participants reflects the potential of our proposed hobby recommender to positively influence individuals' outlook towards new hobbies and activities.

#### 4.2.3.6 Discussion

The results and analysis reveal aspects of the lived experience of participants in interacting with the researcher on hobbies recommended using the proposed models. The results show the effectiveness of our proposed approaches in enhancing people's Ikigai level. The thematic description of the common elements of the experience of the participants who gained an improvement of Ikigai after a 10-day interaction with the researcher includes "willing to share", "engaging with the researcher", "reflecting own experiences", and "having concrete plans". While all four of these suggest that the proposed models can recommend hobbies that are attractive to participants so as to intrinsically encourage them to take related actions, the last two elements reflect the key to successful intervention. During the interview, a number of participants also expressed that hobbies give them some new goals or short-term goals which motivate them to take action while making life more fun and exciting. Meanwhile, many participants believe that the recommended hobbies appeal to them or have appealed to them in the past. One participant was amazed by the recommendations, saying *"Your analysis is really very powerful. If there is more information given, I feel like everyone is running naked as if you can know everything about us."*

While sending additional messages to persuade the participants to develop the recommended hobbies was not related to a higher acceptance rate of the hobbies, these sentences do arouse their thinking. Some participants actively expressed their opinion on the sentences. They replied with short paragraphs beginning with their stance, such as *"I basically agree with this"*, or *"I disagree with the opinion"*, and followed by their thoughts and explanations. Results of the paired t-test also demonstrated that the group of participants enjoyed a significant increase in their Ikigai levels after the study.

Recommending hobbies to people enhances their Ikigai. The participants who did not experience significant Ikigai improvement expressed that they were too busy, COVID-19 disrupted their plans, or they are old and do not want to change. We can not conclude that recommending hobbies does not work for them. They may need a longer period of time so that they can find time to take action, or they simply need a chance to reflect on their own experiences. A long-term user study with a larger sample size in the future will help us to understand this question.

Looking forward, to construct an effective Ikigai improvement system, the insights from the user study suggest a dual emphasis on fostering participant engagement and encouraging personal reflection and planning. The willingness of participants to share their experiences and engage with researchers indicates that the system should be interactive and invite active participation. This can be achieved by creating a welcoming digital environment that encourages users to offer feedback and discuss their progress. Moreover, the system can add features to support personal reflection, allowing users to reflect and understand their experiences at a deeper level. Features such as digital journaling, and reflective questioning can prompt users to consider their growth and learning. In addition to reflection, the system may incorporate features assist users in planning. By offering goal-setting tools, and progress tracking, users can have clear directions on how to integrate their hobbies into their daily lives, which is essential for enhancing their Ikigai.

# Chapter 5

## Conclusion and Future Works

### 5.1 Conclusions

In this thesis, we proposed approaches to assess and improve one’s Ikigai level. Ikigai is a multifaceted concept that is normally referred to as “purpose in life” and “the reason that life is worthwhile”. By utilizing technological components including teachable agents, knowledge graphs, and machine learning approaches, we aim to help individuals uncover and improve their senses of Ikigai.

In Chapter 1, we introduced the research background of Ikigai and highlighted the significance of it in the current situation of the aging population. Through analyzing the challenges, we introduced teachable agents in the study of Ikigai, and specified research problems and objectives.

In Chapter 2, we reviewed existing literature on the concept of Ikigai, highlighting its benefits and challenges associated with dealing with it. Meanwhile, we reviewed the development of teachable agents and their benefits, as well as the techniques used. The use of machine learning in predictive well-being and knowledge graphs in areas like the health and medical field are also reviewed. From these reviews, we discussed the interplay of the concepts in assessing an individual’s Ikigai, and helping individuals to explore and improve their Ikigai level.

In Chapter 3, we tried to address the first research objective, how to continuously assess an individual’s Ikigai level. We began to introduce the proposed approaches for assessing an individual’s Ikigai level. We proposed an Ikigai knowledge graph,

and an intelligent questionnaire system that assesses one's Ikigai and helps better understand the reasons for high/low Ikigai levels, automating the Ikigai assessment process. We also proposed a machine learning approach to predict one's Ikigai level from the profile, which allows for easy assessment of one's Ikigai status.

In Chapter 4, we aimed to address the second research objective, how to improve an individual's Ikigai level. We introduced two approaches for improving one's Ikigai level. We proposed a teachable agent which requires the elderly to teach the agent about health-related concepts. User study results have demonstrated that the proposed teachable can help improve the elderly's Ikigai level, especially in self-esteem. Phenomenography was adopted to study the elderly's experiences with the teachable agents, which paves the way for further study. We also proposed a reinforcement learning-based hobby recommender that recommends hobbies that may improve one's Ikigai. User study results also showed that the proposed approach is effective.

Each of the methodologies proposed in this research can be cohesively embedded into a teachable agent, allowing it to function as a virtual companion for the elderly. This integration involves infusing the agent with a knowledge graph-driven, intelligent Ikigai assessment system and a deep learning model capable of predicting an individual's Ikigai level based on their profile. Moreover, a recommender system can be built into the agent to suggest activities that may contribute to enhancing the user's Ikigai.

This interactive element allows the agent to assess the user's current Ikigai level, as well as to predict potential shifts, enabling timely intervention. It provides an additional tool for bolstering a user's sense of purpose or Ikigai to recommend hobbies.

As a result, this unified approach encourages continuous and personal engagement with the user, thus enhancing the teachable agent's potential to positively influence the Ikigai of older people.

As Singapore faces the challenges of an aging population, the adoption of the agent as discussed in the thesis could be transformative. The agent may enhance elderly well-being by offering personalized care and companionship, addressing key issues like loneliness and social isolation prevalent among older adults. By stimulating their interests and engaging the elderly in activities that have the potential to

enhance their Ikigai levels, the agent could significantly improve their quality of life. This approach not only caters to the unique needs of each individual but also presents a scalable solution for elder care without the need for extensive human resources. Thus, integrating AI into elder care could potentially revolutionize how Singapore manages its demographic shift, enhancing the well-being of its aging population.

## 5.2 Summary of Contributions

1. We've pioneered the introduction of the Ikigai Knowledge Graph, a unique dynamic questionnaire system powered by knowledge graphs. This innovative tool aids in unraveling the intricate construct of Ikigai, shedding light on the contributors to an individual's sense of personal fulfillment and purpose in life. To our understanding, this represents the first initiative to craft a knowledge graph for the specific purpose of enhancing Ikigai.
2. We've embarked on the exciting venture of developing a teachable agent aimed at Ikigai Improvement. By deploying teachable agents, typically reserved for educational contexts, within the realm of aging, we've provided a fresh perspective in gerontechnology. This unique approach is the first to use a teachable agent to enhance an individual's Ikigai and overall well-being.
3. Our research also adopted machine learning methodologies in a novel capacity - to predict and enhance Ikigai levels. This groundbreaking initiative has woven cutting-edge technology into the tapestry of Ikigai research, opening up new possibilities for exploring and enhancing mental well-being.
4. We have employed a Phenomenographic Approach in our user studies to understand the multifarious ways individuals interact with and experience our proposed interventions. The insights gleaned from this method offer an enriching perspective on the experience of Ikigai, paving the way for future research.

These contributions not only underscore the depth and breadth of our research but also highlight its potential to influence and shape the future trajectory of AI-driven wellness interventions. Our findings signify the start of a fascinating exploration

into how technology can serve as an ally in our pursuit of a purposeful and fulfilled life. In this thesis, we presented the knowledge graph-based assessment system to help us better assess and understand one's Ikigai, a multifaceted concept; we presented a machine learning approach to help continuously assess an individual's Ikigai level; we proposed the use of a teachable agent to help improve elderly's Ikigai level and act as a medium to collect and give advice to the elderly; we also explored machine learning approaches to recommend hobbies to enhance one's Ikigai level. We anticipate that this work will inspire further research and practical applications in the dynamic convergence of technology and the timeless human quest for purpose, satisfaction, and balance. We look forward to the continued evolution of this exploration and the potential for a more holistic, nuanced understanding of our unique paths toward realizing our Ikigai.

## 5.3 Future Works

This research focused on the possible ways to help assess and improve one's Ikigai level using teachable agents, knowledge graphs, and machine learning approaches. Regarding future work, we emphasize and discuss further improvement in the proposed approaches.

### 5.3.1 Automate Continuous Ikigai Assessment for Elderly

Besides the aging population, there is a change in the elderly's living arrangement from co-residence to independent living, meaning that more elderly either live alone or with a spouse only, instead of living with their children [17]. The majority of older adults said that they prefer to age in place, which means they want to stay in their own homes for as long as possible [169]. The elderly who live alone may face increased risks of social isolation, physical frailty, and psychological problems like depression. To help with the situation, there are smart home systems for the elderly developed to monitor their daily activities via sensors.

At the same time, as the elderly age, they are likely to experience changes in the level of Ikigai. Finding a way to constantly assess their Ikigai is important. However, asking the elderly to answer long and tedious questionnaires may not be

an efficient way. Thus, finding ways to continuously evaluate the elderly's level of Ikigai without much self-report is important. In the meanwhile, though the deep learning model can predict one's Ikigai and prompt possible changes when there are changes in the user profile, it may not be able to notice subtle changes since the information collected generally reflected the individual's condition in a recent period.

Data from the smart aging-in-place system, on the other hand, provides more details on one's situation. Such systems constantly collect information on interactions, movements, habits, and activities that could provide significant insight into the person's lifestyle and emotional well-being. This information can include and not limited to movement (via motion sensors), interactions with appliances or devices (via contact sensors), sleep patterns (through bed pressure sensors), and even more detailed health information like heart rate or sleep quality from wearable devices.

Once gathered, the data would be categorized based on its potential relevance to different aspects of Ikigai. For example, "I tend to be very fast doing anything", "I am a competent person", "I feel comfortable with my social status", and "I lead a well-regulated life" from the four-factor Ikigai scale. The answers to these questions may be implied by information collected by the smart aging-in-place system.

Taking the question, "I am a competent person" as an example, it may be highly correlated with one's ability to carry out activities of daily livings (ADLs). ADLs are the basic tasks of one's everyday life, such as eating, bathing, dressing, toileting, and transferring. One who can perform basic ADLs may not consider himself/herself as competent; however, it is highly likely that he/she will feel not so competent when the person cannot perform those activities or suddenly lose those abilities. By using sensors to detect whether an elderly performs these basic activities in a day, can help us understand if he/she has the relevant abilities. If any abnormality was detected, there may be a decrease in the elderly's Ikigai, which will trigger the teachable agent to take further actions. Similarly, for the question, 'I feel comfortable with my social status', if an elderly rated highly for this question and suddenly there is a drop in his social well-being indices which indicates that there is a drop in his participation in social activities, we may infer that the score for the question is going to decrease.

TABLE 5.1: Example data from smart aging in place system that can be used to predict one’s Ikigai level

Questions	Data from Smart Aging in Place System
I am full of life energy.	Time spent on getting up from bed
I tend to be very fast doing anything.	Time spent on meal preparation
I lead a well-regulated life.	Time to go to bed

The answers to the question “I lead a well-regulated life” may be inferred from sensor data as well. Data collected from sensors embedded in the smart aging-in-place system can be used to analyze the pattern of the elderly’s daily activities (Table 5.1). For example, what time does the elderly wake up in the morning, what time does he/she eat breakfast, lunch, and dinner, and what time does the elderly go out or if others visit him/her in a day. With this information and the past history of the elderly’s activities, the system can decide to which extent he/she lives a regular life. If an irregular pattern is detected, there may be a decrease in the elderly’s level of Ikigai, and the teachable agent may react accordingly. Similarly for the question, ‘I tend to be very fast doing anything’, we can derive the average time that an elderly performs certain tasks from sensor data. If there is an increase in the time for performing a task, the score for the question may decrease, and further actions may be required.

With sensor data in hand, we can develop a machine learning model capable of learning patterns and predicting Ikigai levels based on these patterns. The predictive model could be validated through a two-step process. Initially, we would employ a cross-validation technique, dividing the data into a training set to build the model and a validation set to test its accuracy. Next, a longitudinal study will need to be conducted, providing the model’s Ikigai predictions to participating individuals and comparing them against traditional Ikigai assessment methods. This would offer practical insights into the model’s real-world performance and reliability. Based on these results, we could refine and recalibrate our model iteratively, aiming to continually enhance its predictive accuracy and usefulness.

Once validated, the predictive model could be incorporated into our existing teachable agent system. This would provide a dynamic method of Ikigai assessment, based on real-time data and machine learning predictions. Furthermore, the agent could also provide feedback to the elderly users, informing them about potential lifestyle adjustments to improve their Ikigai levels.

In this future work, the integration of smart home sensor data, machine learning algorithms, and our existing teachable agent framework could enable an innovative approach to Ikigai assessment, personalizing interventions and fostering a greater sense of purpose among the elderly population.

### 5.3.2 Enhancement of Teachable Agents for Improving Ikigai

As a result of our user studies, we identified several areas for improvement in our proposed framework of teachable agents. According to the results, the enhancement of the agent's human-like characteristics was positively correlated with an improvement in Ikigai levels perceived by the participants. A significant part of the success of the intervention was attributed to the elicitation of emotional responses from the users. Furthermore, an increase in Ikigai levels among participants was positively associated with encouraging the development of new hobbies. The findings from the hobby recommendation study also emphasize the importance of encouraging the development of new hobbies. Participants who were exposed to persuasive messages did show significant increases in their Ikigai levels even though persuasive messages did not result in a substantial increase in the acceptance rate of the recommendations.

With these findings in mind, we propose the following enhancements to our current teachable agent to increase Ikigai among the elderly:

- **Enhancing Affection:** By developing functionalities that would enable the agent to show affection and empathy, we hope to deepen the emotional bond between users and agents.
- **Enhancing Persuasive Techniques:** Incorporating established persuasive theories into the agent's interaction model may encourage users to adopt positive changes.
- **Enhancing Language Capabilities:** Current advances and success in Large Language Models (LLMs) offer great opportunities to make the agent's interactions more human-like and relatable.

### Enhancing Affection

User study results of the proposed teachable agent show that making the agent more human-like is associated with Ikigai improvement. The proposed teachable agent needs to be further enhanced.

Research has been done in the field on pedagogical agent (PA) communication. There is growing interest in the affective interaction and emotional bond between students and PAs by researchers. According to preliminary research [170], students are willing to engage with a PA, and the prompts and feedback can assist design learning sub-goals that provide higher learning outcomes. For example, affective feedback from PAs was found to boost students' enjoyment and drive to learn [171]. Positive interactions between a student and a PA improved their relationship and raised the students' perceptions of their engagement and understanding, but also increased their reliance on PAs [172]. When communicating with students, PAs deploy various types of messages, each of which has a different effect on learning. For example, Veletsianos [173] categorizes messages into on-task and non-task messages. The results showed that non-task communications were viewed by the students as distracting but memorable, while the on-task messages were effective but impersonal. The inclusion of non-task communications in the on-task lesson initially helped students learn more, but as more non-task messages were added, the student's learning and perception of the PA's communication skills suffered. All in all, the feedback and messages sent by the agent affect users' experience, and user-agent communication is a crucial area to be considered. Therefore, messages by the TAI should be carefully designed to better help the elderly improve their Ikigai.

The current design of the teachable agent in our research prioritizes fundamental functions aimed at enhancing the Ikigai level among the elderly. While this groundwork has been productive, the agent's potential extends far beyond its current capacities, especially in the aspect of user communication. When affective intelligence is integrated into the agent, the interaction with the user could be greatly enhanced.

By incorporating these capabilities into our teachable agent, we can create a more comprehensive and empathetic interaction with the elderly. Affective computing refers to systems and devices that can recognize, interpret, and process human

emotions [174]. In addition to responding to user inputs, emotionally intelligent agents can also perceive and adapt to the emotional state of users. In this way, the elderly can benefit from a more personalized and immersive experience, thus deepening their connection with agents.

A close relationship with the elderly user can be beneficial on many levels. First, emotionally responsive agents can cultivate a closer, more personal relationship with elderly users, so that suggestions from the agent are more accepted and receptive. Any resistance from the elderly to implementing the agent's advice could severely undermine its ability to improve Ikigai. Furthermore, the agent's affective response allows for deeper, more personal conversations, which allow the agent to gain a better understanding of the user's needs and preferences. As the agent gains an understanding of their emotional state and personal preferences, he or she can suggest more effective, tailored strategies that will enhance their sense of Ikigai.

As a feasible approach to modeling the agent's emotional response, Goal Net and Fuzzy Cognitive Maps (FCM) can be used. FCM [175] was proposed to express causal relationships in dynamic systems with fuzzy feedback. In the FCM dynamic system, a collection of concepts is interconnected to reflect the cause-and-effect interactions. In a visual graph representation, FCM is a generally acknowledged way of modeling interconnected causal relationships between diverse elements affecting decisions. As shown in Figure 5.1, there are two major components in an FCM: causal concepts and causal relationships. In an FCM, nodes represent concepts, and directed edges represent causal relationships between concepts. Links between nodes and directed edges reflect informal relationships in the FCM. A positive sign, "+", denotes a causal increase, whereas a negative sign, "-", denotes a causal decrease. The FCM's weighted causal relationships quantify the causal effects' "strength" [176]. The strength is indicated by arbitrary numbers assigned on a weighted FCM.

Adjacency-matrix is used to represent FCMs. Concept values  $C_i$  take in values in real numbers  $[-1, 1]$  and causal edges take in values in  $[-1, 0, 1]$ . The causal edge function value,  $e_{ij} = e(C_i, C_j)$ , represents the causality causal concept node  $C_i$  imparts to  $C_j$ .  $C_i$  causality increases  $C_j$  if  $e_{ij} = 1$ , causality decreases  $C_j$  if  $e_{ij} = -1$ , and imparts no causality if  $e_{ij} = 0$ . Below is an example matrix that shows the causal relationships in the FCM depicted in Figure 5.1.

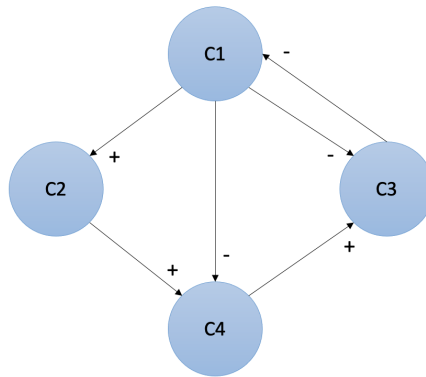


FIGURE 5.1: Example diagram for FCM

$$\begin{bmatrix} 0 & 1 & -1 & -1 \\ 0 & 0 & 0 & 1 \\ -1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

FCM may be easily altered by simply modifying the weights' strength. It's also simple to make adjustments to the model. As a result, FCM is appropriate for use in situations where human behavior is a prominent influence or where problems are difficult due to a high number of variables and no right or incorrect answers exist. The FCM can also be used when there is a lack of data, or when data is missing or partial [177].

Thus, the Goal Net and FCM can effectively simulate the intricacies of emotional intensities [178, 179]. In addition, leveraging recent advancements in emotion recognition technologies would enhance the agent's capabilities by substantially augmenting its capabilities. Moreover, the agent's ability to understand, acknowledge, and reciprocate the emotions of a user could be further enhanced with technologies such as sentiment analysis of text and speech emotion recognition.

As a result of affective computing, the agent is able to establish a genuine bond with the user through enhanced emotional understanding. As a result of this companionship, the user can feel a greater sense of purpose and satisfaction in their lives, which in turn enhances Ikigai. This integration of affective computing offers us the potential to enhance the teachable agent in the future.

**Enhancing Persuasive Techniques:**

In parallel, we need to improve our communication strategies in order to motivate the elderly to carry out the suggested tasks effectively. Incorporating the Elaboration Likelihood Model (ELM) [2, 180], a well-established persuasion theory, provides a structured approach to achieving this goal.

There are two distinct routes to persuasion in the ELM (Figure 5.2): the central route and the peripheral route. The choice between these routes is largely determined by an individual's motivation and ability to perform a task. When an individual has a high level of motivation and the necessary skills to accomplish a particular task, they tend to choose the central route. The process of considering the pros and cons of the task engages them in a comprehensive manner. This type of approach usually produces a more enduring attitude change, strengthening their motivation to engage in the task over the long term. However, peripheral persuasion becomes more prominent when motivation is low, or when the individual is limited in their ability to complete the task. With the individual less inclined to pay attention to the details of the task under these circumstances, the attitude change is less permanent. As a result, a long-term commitment is unlikely because their interaction with the task remains superficial.

The application of ELM in our context requires careful evaluation of the elderly's ability and motivation. In this regard, Fuzzy Cognitive Maps (FCM) can provide dynamic insights into these parameters [81, 181]. According to ELM principles, these insights can help guide the choice of the right persuasion route. It could be more effective for the teachable agent to persuade elderly users based on their motivations and capacities if the persuasion route is strategically aligned with their motivations and abilities. Consequently, the elderly may be more receptive to suggestions that aim to enhance their Ikigai if the agent uses persuasion theories such as the ELM in their communication strategy.

Besides finding ways to determine an elderly's motivation and ability at a specific time, a deeper understanding of ELM could be explored in future work. As an example, understanding how to switch between central and peripheral routes based on changing motivations and abilities over time could help design interactions that are more adaptive and responsive. Additionally, integrating other theories of persuasion and behavior change, such as the Transtheoretical Model [182] or Health Belief Model [183], could provide a more holistic and effective approach to promoting beneficial behaviors and enhancing Ikigai.

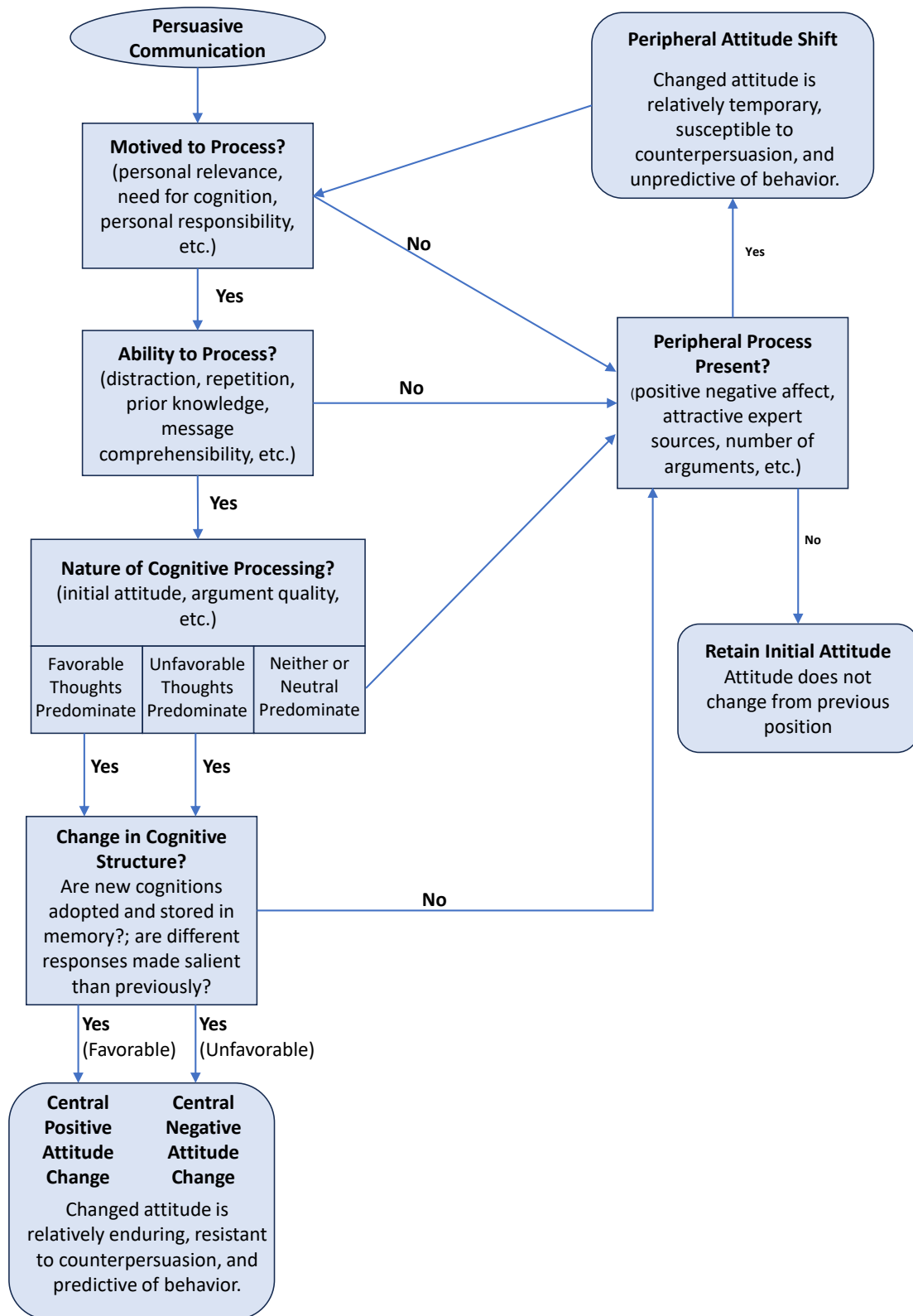


FIGURE 5.2: Elaboration Likelihood Model of persuasion [2]

The architecture diagram of the enhanced teachable agent is as shown in Figure 5.3

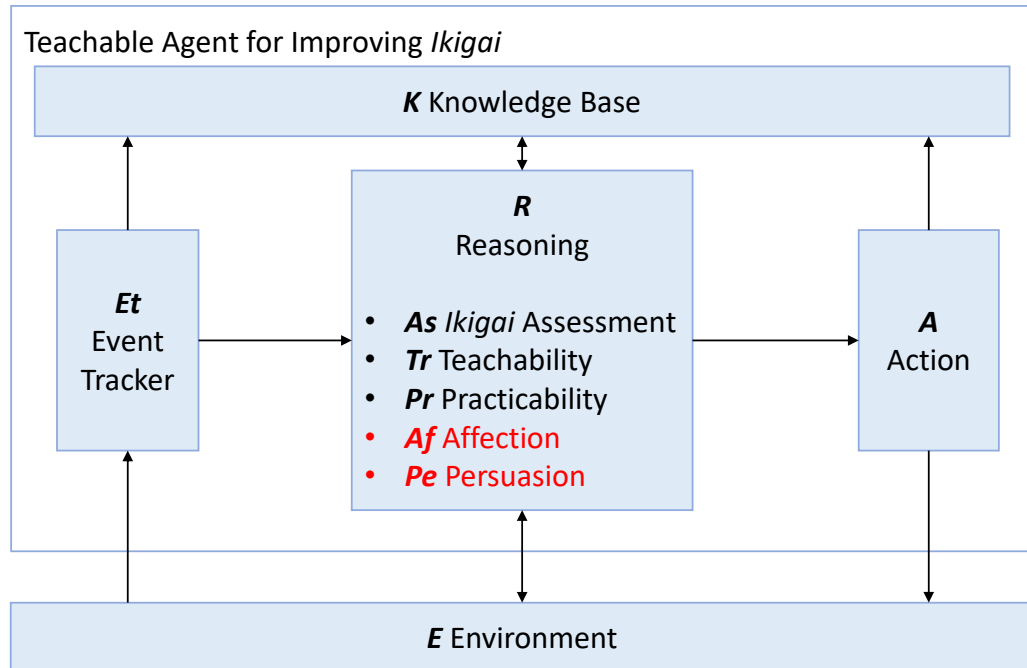


FIGURE 5.3: Enhanced teachable agent for Ikigai architecture

### Enhancing Language Capabilities:

Furthermore, leveraging the linguistic abilities of Large Language Models (LLMs) like ChatGPT can significantly enhance the capabilities of a teachable agent. The user study results of the hobby recommender systems suggest that a simple persuasive message may not be enough to persuade a person to develop the recommended hobby, but it somewhat helps improve one's Ikigai probably because it stimulates deeper thinking and more rounds of conversation with the researcher. The adoption of such advanced language models can facilitate more natural, engaging, and intuitive interactions between the user and the agent, resulting in a more human-like and more engaged experience.

Incorporating ChatGPT into the teachable agent's architecture enables the agent to understand complex human language, respond intelligently to user queries, and generate high-quality content in real-time. The ability to generate human-like text

opens up possibilities for an engaging, conversational interface where the elderly can effectively communicate with the agent.

This approach not only makes the learning process more enjoyable for the elderly but also allows for the agent to better understand and cater to their unique needs. This, in turn, has the potential to increase user engagement, which is a crucial element in improving one's Ikigai level.

### 5.3.3 Development of an Ikigai Measurement for Elderly

Given the importance of Ikigai in contributing to overall life satisfaction and longevity, it is imperative to develop a robust and holistic measurement tool for Ikigai, particularly in the context of the elderly population. While Ikigai-9 and Four-Factor Ikigai Scales are helpful, they could be enhanced to better capture the nuances of the elderly's Ikigai experience. In the future, we aim to propose a comprehensive measure of the elderly's Ikigai, which considers the dimensions from these existing scales, and introduces new dimensions related to elderly people. The elderly's resilience and adaptability, and legacy and life reflection may be two possible dimensions to be added.

Resilience and adaptability seek to measure an elderly individual's perception about his/her own aging, including the ability to recover from adversities and adjust to significant changes in their life. As people age, it is highly possible that they face a multitude of challenges, such as health issues, loss of loved ones, and transition into retirement. These events can cause distress and potentially disrupt their sense of purpose or happiness in life, impacting Ikigai. Resilience refers to the process of effectively coping with, or bouncing back from, adversity. It's about the capacity to maintain or regain one's Ikigai in the face of these stressors. Adaptability, on the other hand, refers to the ability to adjust one's thoughts, emotions, and behaviors in response to changes. In the context of Ikigai, it's about the capacity to recalibrate or redefine one's Ikigai in light of the changing circumstances and embrace the process of aging instead of moaning over it. For example, if a person can no longer engage in a cherished activity due to health issues, their adaptability might be reflected in finding new activities that are just as fulfilling and contribute to their Ikigai.

For many elderly individuals, reflecting on their past and considering the legacy they are leaving behind can bring immense satisfaction, a sense of fulfillment, and a heightened sense of Ikigai. Both of these encapsulate the way individuals perceive their own lives in retrospect, how they view their impact on others and the world, and how this informs their sense of purpose or Ikigai. The concept of legacy represents a person's lasting impact on their community, family, or society as a whole. It's the sum total of their contributions, achievements, values, and teachings that continue to have an effect even after their death. This concept carries significant weight as individuals age and may become a core element of their self-perception and life satisfaction. For the elderly, the legacy they're leaving behind often becomes a prominent source of Ikigai. It gives them a sense of contribution and purpose, knowing that their life has had a meaningful impact on others. This might be reflected in different ways - it could be through their career achievements, raising a family, contributing to a community, or through imparting knowledge and wisdom to the younger generation. The knowledge that their actions and values will live on after them can enhance their sense of life's worthiness, thus heightening their Ikigai. Life reflection, often also referred to as life review, involves a deep introspection and re-evaluation of one's life experiences. As individuals age, they tend to reflect more frequently and deeply on their past - the choices they've made, the paths they've taken, the relationships they've nurtured, and the lessons they've learned. Engaging in such a reflective process often brings a sense of fulfillment and satisfaction, especially when they perceive their life as well-lived and meaningful. This process allows elderly individuals to reconcile with their past, understand their life in a larger context, and ultimately find peace and acceptance. The outcomes of these reflections can greatly influence their sense of Ikigai. For example, reflecting on past accomplishments can enhance self-esteem, while reconciling with past mistakes or regrets can promote emotional well-being and peace. Engaging in life review and legacy creation processes can reinforce the value and purpose they attribute to their life. Incorporating a dimension that measures this aspect can help evaluate the contribution of these reflections to their Ikigai.

We may also explore new dimensions of the elderly's Ikigai by adopting a phenomenological approach. Phenomenology, as a research approach, holds promising potential to unravel the multifaceted aspects of Ikigai among the elderly. It places the human lived experience at the heart of the inquiry, providing us with a unique

lens to delve deeper into the essence of Ikigai as experienced by the elderly. Phenomenology's emphasis on individuals' perceptions and interpretations allows us to shed light on the subjective, nuanced, and dynamic nature of Ikigai, which is especially pivotal considering its deeply personal and culturally bound nature.

To uncover the underlying dimensions of elderly's Ikigai, phenomenological studies could involve a range of qualitative data collection methods such as in-depth interviews, observation, or diary entries, capturing the elderly's daily experiences, practices, and reflections pertaining to their Ikigai. This not only includes what activities or relationships contribute to their Ikigai, but also how these experiences are integrated into their overall life narratives, self-identity, and their views on aging and wellbeing.

Moreover, phenomenology also advocates for a reflexive analysis process, allowing the researcher to critically engage with the data and challenge their preconceptions. For instance, interpretative phenomenological analysis (IPA) could be an effective analytical strategy, offering a detailed and layered understanding of the elderly's Ikigai. Through the iterative process of IPA, which involves cycles of close reading, thematic coding, and interpretative commentary, we can identify key themes that characterize the elderly's Ikigai while also acknowledging the complexity and heterogeneity of their experiences.

In addition, phenomenology's philosophical underpinnings encourage us to consider the contextual factors shaping the elderly's Ikigai. This might encompass aspects like cultural beliefs, societal norms about aging, and the physical and social environments in which they live. By doing so, we can achieve a more comprehensive and contextually grounded understanding of Ikigai that not only encapsulates individual experiences but also the larger social and cultural narratives surrounding aging.

Taken together, the phenomenological approach can significantly contribute to the development of more nuanced and contextually relevant measures of Ikigai for the elderly. By capturing the rich tapestry of their lived experiences, we can better align our understanding of Ikigai with their real-world experiences, thereby informing the design of more effective and personalized interventions to enhance their sense of Ikigai.

# List of Author's Publications

- Ping Chen, Siyuan Liu, Xuehong Tao, Takayuki Ito. 2021. Meaning and Health: A Review on Ikigai. *International Journal of Information Technology* 27(1), 2021.
- Ping Chen, Xinjia Yu, Su Fang Lim, and Zhiqi Shen. 2023. A Teachable Agent to Enhance Elderly's Ikigai: Extended Abstract. In *Proc. of the 22nd International Conference on Autonomous Agents and Multiagent Systems*, AAMAS 2023.
- Yang Qiu, Ping Chen, Huiguo Zhang, Bo Huang, Di Wang, and Zhiqi Shen. 2024. Engaging the Elderly in Exercise with Agents: A Gamified Stationary Bike System for Sarcopenia Management: Demonstration Track. In *Proc. of the 23rd International Conference on Autonomous Agents and Multiagent Systems*, AAMAS 2024.

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