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Predicting and Improving Ikigai

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Abstract

The Japanese concept of ikigai, increasingly recognized globally, is often referred to as 'life's purpose' or 'the reason to live'. It encompasses elements including but not limited to work and relationships. This paper introduces machine learning methods to predict and enhance ikigai, the concept that has been associated with many benefits including longevity and well-being. Our experimental study confirms the effectiveness of the proposed methods, marking a pioneering effort in using machine learning to assess and enhance ikigai.

I. Introduction

Ikigai, a Japanese concept that can be dated back to the 14th century [7], is associated with health and life satisfaction [16]. It's a multifaceted construct embodying life's meaning, motivations, and values [11, 19], found in aspects like family, friends, work, and hobbies. A high level of ikigai is associated with many benefits, including longevity [1, 2, 17], well-being, and quality of life [3].

Ikigai, a personal and dynamic concept, typically revolves around a key aspect influenced by one's past, present, or future life experiences [15]. Distinct from the goal-driven concept of happiness prevalent in Western culture, ikigai emphasizes finding joy in the simple, routine activities of daily life, infusing a deep sense of satisfaction and significance into the seemingly trivial moments. This facet of ikigai is particularly powerful, as it provides enduring motivation and a sense of purpose, even during periods of discontent or adversity, as highlighted in Kamiya's exploration of the concept [10]. Gaining global recognition [13, 4, 5], ikigai offers a fresh perspective on personal happiness and values, with a significant impact on mental and emotional well-being. This broader applicability of ikigai, transcending cultural boundaries, marks its importance in the study of human happiness and resilience.

In this paper, we focus on hobbies, a key source of ikigai, and present machine learning methods to predict a person's ikigai from their user profile and to improve their ikigai level by recommending the person to take up a new hobby. Experimental results show that the proposed method can accurately predict and improve a person's ikigai level. To the best of our knowledge, this is the first work that uses machine learning to predict a person's ikigai and to improve it.

II. Related Works

Machine learning, particularly AI, has made significant strides in mental health and well-being. It's been used for predicting happiness [12], detecting depression through social media analysis [18, 9], categorizing stress with wearable technology [8], and enhancing well-being through conversational agents for depression [6].

Despite these advancements, many aspects of mental well-being, beyond depression and stress, remain unexplored in AI research. Notably, the concept of ikigai has not been linked with the field of AI [20], offering promising avenues for future research and application.

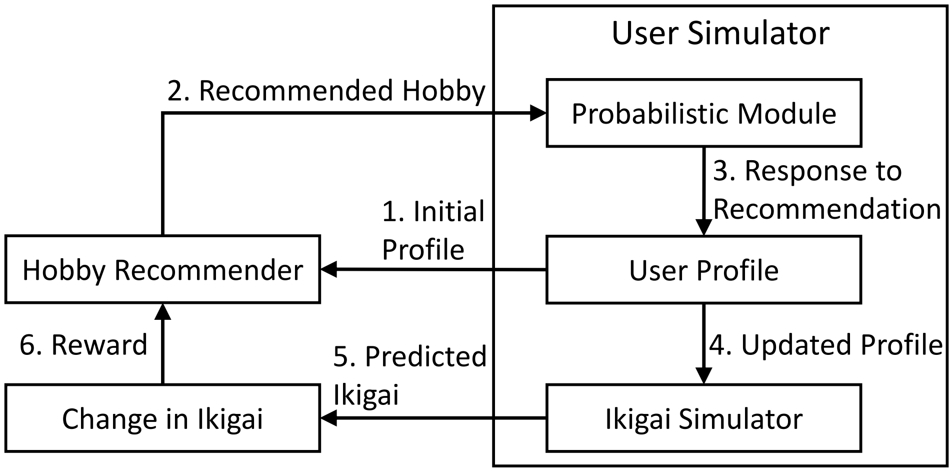

Fig 1 An overview of our hobby recommender training procedure using reinforcement learning.

III. Proposed Approach

To improve people's ikigai through hobby recommendations, we first studied how various hobbies impact ikigai levels. We gathered data on individuals' basic information, hobbies, and ikigai levels, and developed an ikigai simulator to predict ikigai based on user profiles. Our approach involves both supervised and reinforcement learning models for hobby recommendation.

Our reinforcement learning model, depicted in Figure 1, focuses on two key questions: Can ikigai be estimated from a user's profile? And, can hobby recommendations based on this profile enhance ikigai? We designed a user simulator, incorporating a probabilistic module to reflect the likelihood of a user accepting a recommendation, thus adding realism to the simulation.

A. Data Collection and Ikigai Simulator

To train our hobby recommender, we first developed a user simulator using data from an initial study, focusing on demographics, physical and cognitive conditions, medical history, personality, hobbies, and ikigai levels. A questionnaire was used to collect this information. An individual's ikigai level was measured using ikigai-9 [5], a psychometric tool rating ikigai on a five-point Likert Scale. 542 responses were collected from the study, and after removing 28 invalid responses, we used the remaining 514 entries to build the simulator. The Institutional Review Board approved this study.

The ikigai simulator, a multi-layer perceptron, predicts responses to the ikigai-9 scale based on user profiles, excluding the ikigai-9 responses. It's trained using cross-entropy loss for each item in the scale. Additionally, a probability-based module assesses the likelihood of a user accepting and engaging with a recommended hobby, influenced by the collected data indicating participants' perceptions of hobby difficulty.

B. Hobby Recommender

To train our hobby recommender, we utilized the user simulator developed earlier, exploring two methods: supervised learning and reinforcement learning (RL). Supervised learning involves creating a dataset of profile-hobby pairs, where the best hobby for each profile is identified using the ikigai simulator and then used for training with a cross-entropy loss function.

For RL, the user simulator serves as the training environment. The process starts by calculating the initial ikigai level from the ikigai-9 questionnaire. The recommender then suggests a hobby, with the probabilistic module deciding its acceptance. If accepted, the user profile is updated, and the new ikigai level is predicted. The recommender's reward is based on the change in the ikigai level. More formally, the reward given to the agent is defined as:

$$r = \begin{cases} \text{new\_ikigai} - \text{init\_ikigai} & \text{if accepted} \\ 0 & \text{otherwise} \end{cases}, \tag{1}$$

where init_ikigai is the initial ikigai level from the user's profile calculated by summing the answers to the ikigai-9 scale, and new_ikigai is the new ikigai after accepting a hobby recommendation,

Table 1 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

updating the user's profile, and predicting the new ikigai level using the ikigai simulator.

We employed the Advantage Actor Critic (A2C) algorithm [14] for RL training. A2C optimizes the policy to maximize rewards, updating weights using gradient ascent.

IV. Experiments

In order to evaluate the effectiveness of our proposed approaches, we conducted an experimental study on the data that we collected.

A. *Ikigai Simulator*

Our ikigai simulator, designed to output answers for the ikigai-9 scale, was tested with three models: a random model, a probabilistic model, and a supervised learning model. The random model arbitrarily selects answers, while the probabilistic model uses a dataset-derived probability distribution for each question. The supervised learning model, a multi-layer perceptron trained with cross-entropy loss, predicts answers based on user profiles.

We evaluated these models based on how closely their answers matched the ground truth, considering the Likert scale nature of the questionnaire responses. A closer numerical match indicates greater accuracy. Results shown in Table 1 show that the supervised learning model outperformed the others, suggesting a significant correlation between user profiles and their ikigai-9 responses.

Table 2 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 ± 0.876	89.90%
Supervised	1.481 ± 1.063	88.63%
RL	1.771 ± 0.950	88.33%

B. Hobby Recommender

Our hobby recommender is designed to suggest hobbies that maximize ikigai gains. In training and evaluation, each model has five attempts for an accepted recommendation. We assessed three models: random, supervised learning, and reinforcement learning (RL). The random model suggests arbitrarily, while the supervised model, trained with a dataset we collected, learns through cross-entropy loss. During validation, this model also gets five recommendation attempts, with the best performer on validation proceeding to test evaluation. The RL model's selection follows a similar approach.

Results shown in Table 2 indicate the RL model achieves the highest average ikigai increase. Its advantage likely stems from interactive learning with the user simulator, understanding likely hobby rejections and exploring varied recommendations, unlike the more static supervised model. The superior performance of both supervised and RL models over the random approach suggests a correlation between user profiles and ikigai-enhancing hobbies.

V. Conclusion

This paper introduced machine learning methods to predict and enhance people's ikigai through hobby recommendations. We developed an ikigai simulator and trained two hobby recommenders using supervised and reinforcement learning. Experiments confirm the effectiveness of these approaches in improving ikigai. Our experimental results validate the efficacy of these methods in enhancing ikigai. Future work includes conducting a user study to assess the impact of these recommendations and exploring recommendations of existing hobbies to promote regular involvement, especially among older adults. This research paves the way for integrating computer science with the philosophical concept of ikigai.

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