The POWER of Ikigai: Optimizing Life Fulfillment with an Integrated User Simulator and Adaptive Hobby Recommender

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Abstract

Health and longevity are topics of great interest, leading to an exploration of the Japanese concept of *ikigai*, known for its impact on a fulfilling, extended life. *Ikigai* levels are dynamic, changing with personal growth and life situations, but traditional assessment methods are time-consuming, discouraging frequent tracking. In this paper, we propose *Personalized Optimization and Wellbeing Enhancement Recommendation* (*POWER*), which integrates an *ikigai* simulator to predict *ikigai* levels from profile information and a hobby recommender that uses reinforcement learning to adapt recommendations based on continuous user feedback. Our methods, validated through both offline data and an online user study, effectively capture and enhance *ikigai*.

Introduction

Health and longevity have long been enduring topics of interest. Japan, home to some of the world's longest-lived people, has attracted increasing attention from researchers, bringing the Japanese term "*ikigai*" into focus. *Ikigai*, which means "realizing the value of being alive" (Shinmura 1987), encapsulates the idea of finding purpose and joy in life, essential for both mental and physical well-being. As researchers delve deeper into the factors contributing to a long and healthy life, they have identified the principles of *ikigai*—such as living with purpose, maintaining social connections, and staying active—as crucial elements in promoting health and longevity (Alimujiang et al. 2019; Buettner 2012).

Having a stronger sense of *ikigai* often associates with a happier and longer life. There are two primary scales for evaluating an individual's level of *ikigai*: the *ikigai*-9 scale (Fido, Kotera, and Asano 2020) and the four-factor *ikigai* scale (Takeda 2000). The *ikigai*-9 scale (Fido, Kotera, and Asano 2020) offers a general assessment, capturing a wide range of feelings and attitudes contributing to an individual's sense of *ikigai*, and the four-factor scale (Takeda 2000) provides a detailed and structured analysis by breaking down into four specific and measurable components. Nonetheless, both approaches require respondents to actively complete a questionnaire. Given that *ikigai* is a dynamic concept that may change over time, continuously monitoring one's *ikigai* level necessitates frequent reassessment. This process can be tedious and time-consuming, posing challenges in accurately capturing the dynamic nature of *ikigai*.

Among all evaluation indicators of *ikigai*, aside from objective factors like age and gender, hobbies stand out as an important and modifiable factor. Hobbies play a significant role in enhancing one's sense of purpose and joy, which are core elements of *ikigai*. Unlike fixed attributes, hobbies are activities that individuals can freely choose and adapt according to their interests and circumstances. Engaging in hobbies benefits individuals in various ways, such as enhancing personal fulfillment, promoting mental well-being by reducing stress and anxiety, and encouraging active engagement for physical and cognitive health (Goodman, Geiger, and Wolf 2017; Santini et al. 2022).

A hobby recommender system emerges as an effective way to improve an individual's *ikigai* level. By modeling user preferences, it can identify hobbies that are most likely to resonate with each individual, promoting a higher level of engagement and satisfaction. Additionally, leveraging data-driven insights enables the recommender system to continuously adapt and refine its suggestions, thereby serving as a potent tool for fostering ongoing personal growth and improving overall well-being.

In this work, we focus on effectively evaluating and improving individuals' *ikigai* level. To evaluate an individual's *ikigai*, we propose a user simulator that considers both relatively stable indicators and indicators that fluctuate over time yet can be readily tracked. This approach enables us to automatically predict the user's ikigai level and apply appropriate intervention when needed. This will also prevent individuals from spending excessive time on questionnaires when most answers can be tracked automatically.

To improve an individual's *ikigai*, we propose *POWER*, a framework that trains a hobby recommender using reinforcement learning (RL). RL is particularly effective because it engages in continuous learning from user interactions, optimizing recommendations to align with the dynamic nature of an individual's *ikigai* level and interests. This adaptive approach ensures that the recommendations remain relevant and personalized over time.

We evaluated our proposed methods using both an offline dataset and an online user study. The experimental results demonstrate the effectiveness of both the user simulator and the hobby recommender system. We successfully collected over 500 questionnaire responses to create the offline dataset and engaged 40 participants for a 30-day user study. The study revealed a significant improvement in participants' *ikigai* levels, with one group showing an average relative improvement of more than 9% after the study. Additionally, the qualitative analysis of the user study highlighted promising directions for future improvements.

The main contributions of this paper are as follows:

- We propose an *ikigai* simulator that tracks both stable and dynamic indicators, enabling seamless prediction and timely interventions while minimizing the need for extensive questionnaires. To the best of our knowledge, this is the first work that automatically evaluates an individual's *ikigai* level.
- To enhance an individual's *ikigai* level, we propose a hobby recommender system using reinforcement learning, which models user preferences and continuously adapts to user feedback.
- To evaluate the effectiveness of our proposed models, we collected comprehensive questionnaires from 514 users with diverse backgrounds, encompassing age, gender, physical and cognitive capabilities, hobbies and many more. We believe this dataset could be invaluable for future studies, not only in understanding people's *ikigai* levels but also in exploring potential correlations among age, employment status, mental and physical health, personalities, and other factors.

Related Work

The Japanese term *ikigai*, combining '*iki*' (life) and '*gai*' (worthwhile) (García and Miralles 2017), is often translated as 'the purpose of life' or 'the sense that life is worthwhile' (Kondo and Takano 1993; Mori et al. 2017; Watanabe et al. 2003). *Ikigai* is a multifaceted concept encompassing life's meaning, motivations, and values (Kumano 2012; Weiss et al. 2005). It can be measured using tools like the *ikigai*-9 scale (Fido, Kotera, and Asano 2020), which provides a general assessment by capturing a wide range of feelings and attitudes contributing to an individual's sense of *ikigai*, and the four-factor scale (Takeda 2000), which offers a detailed and structured analysis by breaking down *ikigai* into specific, measurable components: self-esteem, purpose in life, personal energy, and life satisfaction. Both scales use a 5-point Likert scale, with a person's *ikigai* level calculated as the sum of the ratings for each item.

Physical health, financial status, and social capital are key factors influencing *ikigai*. These elements contribute to life achievements, autonomy, and social engagement, all of which enhance *ikigai* (Fukuzawa et al. 2019; Kaneko 1987). Strong social networks, in particular, provide support during challenges and boost emotional well-being (Wilson and Musick 1997).

A strong sense of *ikigai* is associated with numerous mental and physical health benefits, including increased longevity and reduced risk of cardiovascular disease (Alimujiang et al. 2019; Buettner 2012). It also helps individuals cope with stress and protects against mental health issues like depression and anxiety (Freedland 2019; Kim, Strecher, and Ryff 2014).

Artificial Intelligence (AI) has increasingly been applied in mental health and well-being, with recent studies using AI to predict, monitor, and detect mental health conditions. For example, (Li et al. 2022) predicted happiness and identified key contributing factors, while deep learning models have been used to detect depression through social media content (Shen et al. 2017; Jia 2018). Additionally, AI models have been employed to detect and categorize stress using data from wearable devices (Jesmin, Kaiser, and Mahmud 2020), and a conversational agent has proven effective in improving well-being for individuals with self-reported symptoms of depression (Inkster et al. 2018). Recent advances in large language models (LLMs) have also shown significant potential in mental health, with fine-tuned models demonstrating effectiveness in mental health prediction and psychological counseling (Xu et al. 2024; Lai et al. 2023).

Despite these advances, many aspects of mental well-being, including the concept of *ikigai*, remain underexplored in the context of AI (Ziesche and Yampolskiy 2020). The potential for AI to support and enhance *ikigai* presents a promising avenue for future research and application.

Methodology

To enhance people's *ikigai*, hobbies—being more adaptable than inherent attributes like age—serve as a practical starting point. Before effectively recommending hobbies to enhance *ikigai*, it's essential to understand how *ikigai* varies among individuals and how different hobbies influence these levels.

With these, we propose the *Personalized Optimization and Wellbeing Enhancement Recommendation* (*POWER*), which integrates an *ikigai* simulator with a hobby recommender to provide personalized suggestions aimed at boosting an individual's *ikigai*. *POWER* is illustrated in Figure 1, which can be described in three main steps:

1. **Hobby Recommender**. The user profile is first input into the hobby recommender, which recommends a hobby tailored to the user's specific characteristics. The goal of this recommendation is to propose a hobby that has the potential to enhance the user's *ikigai* level.
2. **User Simulator**. To introduce a realistic aspect to the simulation, the recommended hobby is passed through a probabilistic module that determines whether the user will accept the recommendation and, if accepted, how frequently the hobby will be practiced. If the hobby is accepted, the user's profile is updated to reflect this new hobby. The updated profile is then fed into the *ikigai* simulator, which predicts the new *ikigai* level.
3. **Optimization**. The predicted *ikigai* level can be used as the reward in optimizing the hobby recommender. This creates a feedback loop, where each iteration refines the recommender, making it increasingly effective at recommending hobbies that most enhance *ikigai*.

User Simulator

To effectively train the hobby recommender, a substantial amount of data is needed. However, gathering sufficient data

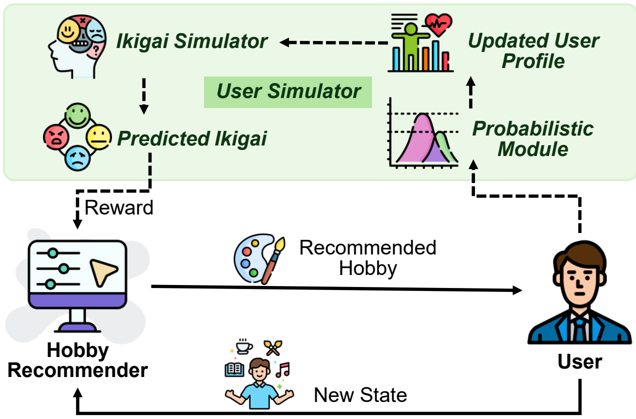

Figure 1: An overview of *POWER*, which utilizes reinforcement learning to train a hobby recommender.

is challenging, particularly for a recommender designed to enhance a person's *ikigai*. Thus, we trained a user simulator to create a realistic environment that closely mirrors actual user experiences, for the model to learn and adapt. A user simulator is necessary to help replicate the dynamic nature of *ikigai* and the variability in user behavior, which are critical for making effective hobby recommendations. To achieve this, we developed a user simulator that mimics real-world interactions by incorporating two key components: an *ikigai* simulator that predicts changes in a user's *ikigai* level, and a probabilistic module that estimates the likelihood of a recommended hobby being accepted.

Ikigai can be influenced by various factors in different ways. To estimate changes in a person's *ikigai* level, we trained the *ikigai* simulator I, which takes a user profile p as input and predicts the user's responses to a *ikigai* measurement questionnaire, such as the *ikigai*-9 or four-factor scale. A user profile includes demographic information, current hobbies, and personality traits. The *ikigai* simulator is a multi-layer perceptron trained to predict a person's answers to n questions. Thus, a person's *ikigai*, i, is estimated by summing the n predicted responses to each question, I_n:

$$i = \sum_{1}^{n} I_n(p). \tag{1}$$

People's behaviors can be unpredictable. To replicate the uncertainty regarding users' decisions to accept or reject recommended hobbies, the user simulator includes a probabilistic module P in addition to I. This probabilistic approach acknowledges that users do not always accept suggested activities and that their engagement levels can vary. The probabilistic module determines whether a hobby recommendation is accepted and, if so, how frequently the user will engage in the hobby. The probability of acceptance is influenced by factors such as the perceived difficulty of adopting the hobby, with more challenging hobbies being less likely to be accepted.

Hobby Recommender

Increasing a person's *ikigai* via hobby recommendations presents a level of uncertainty due to the person's evolving profile, including changes in their hobbies or preferences, and their decisions to accept or reject hobby recommendations. Therefore, we utilize RL to train the hobby recommender, as it can train models to handle such dynamic environments. Additionally, RL is particularly suited for this task because it allows us to directly train the recommender to maximize the user's *ikigai* by using it as the reward function. Through RL, the hobby recommender iteratively improves its recommendations, continuously refining its performance by maximizing the predicted *ikigai* levels. This approach enables the system to effectively learn which hobbies are most likely to enhance the user's well-being.

In *POWER*, the user simulator functions as the environment in which the hobby recommender operates. The recommender interacts with the simulator by recommending hobbies, and in turn, receives feedback based on the user's response. The reward given to the recommender is calculated by the change in the user's *ikigai* level. Formally, the reward is defined as:

$$r = \begin{cases} i_{t+1} - i_t & \text{if accepted} \\ 0 & \text{otherwise} \end{cases}, \tag{2}$$

where i_t is the *ikigai* level at time t and i_{t+1} is the new *ikigai* level after accepting a hobby recommendation, updating the user's profile, and predicting the new *ikigai* level using the *ikigai* simulator I.

We use Advantage Actor Critic (A2C) (Mnih et al. 2016) to train our recommender. A2C is a policy gradient method that aims to maximize the rewards obtained by a policy π by updating its weights θ using gradient ascent with the following gradient:

$$\nabla_\theta J(\theta) = \mathbb{E}[\sum_{t=0}^{T-1} \nabla_\theta \log \pi_\theta(a_t|s_t) A(s_t)], \tag{3}$$

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

$$A(s_t) = r_t + \gamma V(s_{t+1}) - V(s_t), \tag{4}$$

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

$$V(s_t) = \begin{cases} r_t & \text{if } s_t \text{ is terminal} \\ r_t + \gamma V(s_{t+1}) & \text{otherwise} \end{cases}. \tag{5}$$

Experimental Settings

To evaluate the effectiveness of our proposed approaches, we conducted both offline and online experiments. In the offline experiments, we collected data from over 500 participants to assess the accuracy of our *ikigai* simulator in estimating a user's ikigai based on their personal information and traits. We also evaluated how effectively *POWER*

Category	Variable/Dimension
Demographic Information	Age Gender Educational Level Living Arrangement Employment Status
Health Condition	Physical Capabilities Cognitive Condition Mental Status Medical History
Personality	Neuroticism Extraversion Openness Conscientiousness
Hobbies	Frequency Perceived Difficulty
Ikigai Level	Ikigai-9 Score Four Factor Ikigai Score
Others	Perceived Financial Status Smoking Frequency Drinking Frequency

Table 1: Information collected from the questionnaire.

enhances users' ikigai levels. For the online experiments, we conducted a 30-day user study to test the efficacy of *POWER* in recommending hobbies that not only engage users but also improve their *ikigai* levels.

Data Collection

To train the user simulator, we first collected data from participants using questionnaires that included comprehensive user profiles and two widely recognized *ikigai* measurements, the *ikigai*-9 scale (Fido, Kotera, and Asano 2020) and the four-factor *ikigai* scale (Takeda 2000), as summarized in Table 1. The questionnaire captured both objective factors, such as age and gender, and subjective perceptions, such as perceived financial status. The *ikigai* measurements employed were the *ikigai*-9 scale (Fido, Kotera, and Asano 2020) and the four-factor *ikigai* scale (Takeda 2000). In total, we collected 514 valid responses. Figure 2 illustrates the distribution of demographic variables among the respondents. Most respondents are female, live with family members, have tertiary education, and are employed. Additionally, some participants are over the age of 85, adding further diversity to the dataset.

The dataset's diversity allows for a broader understanding of *ikigai* across different population segments. Additionally, data on hobbies and the perceived difficulty of adopting new hobbies offer valuable insights for tailoring personalized recommendations to enhance *ikigai*. This rich dataset supports the current work and provides a valuable resource for future research on the relationships between lifestyle factors, well-being, and *ikigai*.

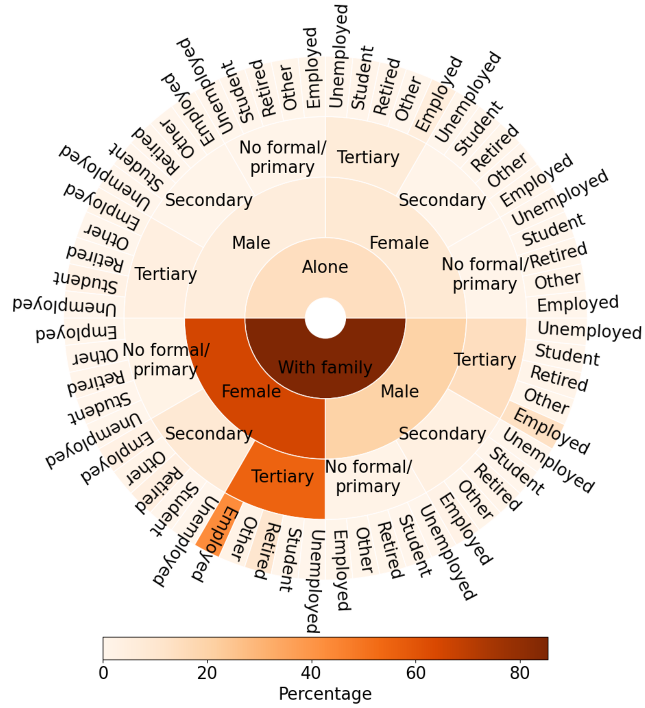

Figure 2: Demographic breakdown of questionnaire respondents across various categories, including living arrangement, gender, educational background, employment status, and age (from inner ring to outer ring).

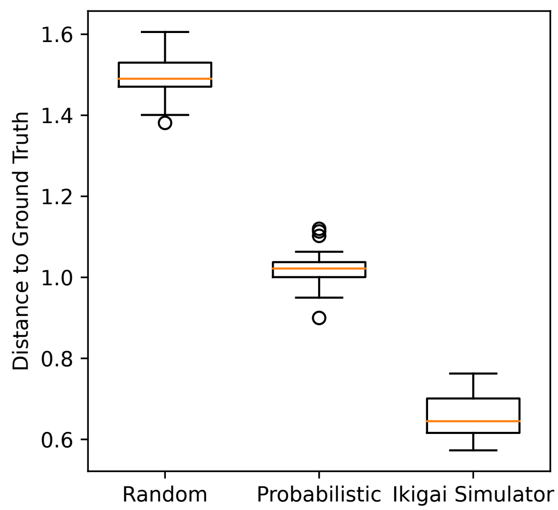

Figure 3: Results for the *ikigai* simulator. Performance is measured as the distance from the ground truth, therefore a lower number is better.

Offline Evaluation

***Ikigai* Simulator** To evaluate the effectiveness of our proposed *ikigai* simulator, we compare to the below baselines:

- **Random**, which randomly outputs ratings regardless of the user profile.

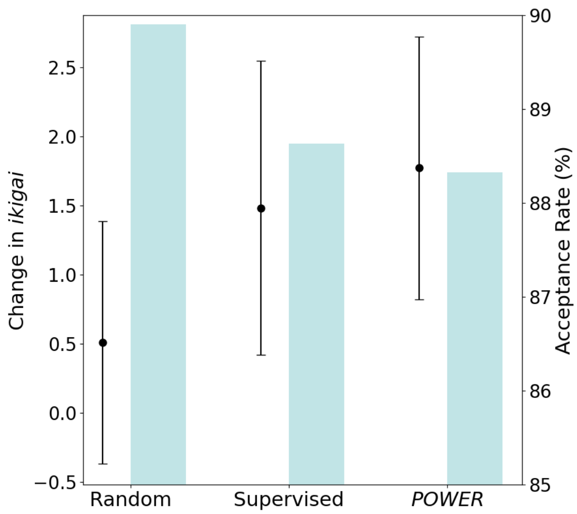

Figure 4: Average change in *ikigai*, standard deviation, and acceptance rate across recommendation models.

- **Probabilistic**, which outputs ratings according to their frequency of occurrence in the dataset. More frequent ratings are therefore more likely to be output.

We train the *ikigai* simulator to predict responses to the *ikigai*-9 questionnaire and measure performance in terms of the distance of the models' answers to the ground truth. In the context of the *ikigai*-9 scale, which utilizes a Likert scale, a smaller numerical distance between the response and the ground truth signifies a higher accuracy. 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.

Hobby Recommender To evaluate the hobby recommender, we compare our RL model to two baseline models:

- **Random**, which randomly makes recommendations without considering user profiles.
- **Supervised**, which is trained using a dataset generated by the *ikigai* simulator.

We ran experiments 20 times to ensure robustness and reproducibility.

User Study

To further evaluate *POWER*'s effectiveness in enhancing *ikigai*, we conducted a 30-day user study.

Participants In this user study, we recruited 45 participants, though 5 dropped out during the study. All participants were ethnically Chinese, with 17 males and 23 females. The study included a broad range of age groups, from 18-24 years old to 65-74 years old, with the majority falling within the 45-64 age range.

Experiment Procedure Before the experiment, all participants completed a questionnaire that included the 9-item *ikigai*-9 scale, rated on a 5-point scale (Fido, Kotera, and Asano 2020). Additionally, a 28-item four-factor scale (Takeda 2000), also rated on a 5-point scale, was used to validate changes in participants' *ikigai* levels. Participants were divided into three groups, and their initial responses served as benchmarks for assessing their *ikigai* levels.

During the 30-day study, participants received a hobby recommendation every six days. For the next five days, they were asked if they had acted on it. For example, a participant might receive a message like, *"Based on your responses, we recommend hobbies related to photography."* If rejected, a new hobby was recommended on day seven, with up to five recommendations given during the study.

Participants were split into three groups randomly. Group I (n=13) received hobby recommendations from a supervised model, while Groups II (n=14) and III (n=13) received recommendations from the proposed *POWER*. Group III also received daily messages encouraging hobby development, such as, *'Photography is a good way to preserve your family's history and memories.'* Participants' responses and actions were recorded for analysis.

After the study, participants completed the *ikigai*-9 and four-factor scales again, followed by semi-structured interviews to gather insights into their experiences.

Results and Discussion

Offline Evaluation

Ikigai simulator Figure 3 shows the experimental results. Our results show that the proposed *ikigai* simulator outperforms other models, suggesting a tangible correlation between a user's profile and their responses to the *ikigai*-9 questionnaire. This indicates the potential to accurately predict an individual's *ikigai* level, offering valuable insights into the dynamics of *ikigai*. These insights could, in turn, lead to personalized interventions aimed at enhancing and sustaining higher *ikigai* levels.

Hobby recommender Based on our results, shown in Figure 4, both the supervised learning model and *POWER* significantly outperformed the random model. This suggests that there is a correlation between a user's profile and hobbies that can lead to greater *ikigai* gain. In addition, *POWER* can give the highest average increase in *ikigai* through a hobby recommendation. One reason that *POWER* 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, *POWER* can explore other hobby recommendations, whereas the supervised model is fixed in its training. This highlights the potential of *POWER* as a robust solution for personalized hobby recommendations aimed at enhancing users' *ikigai*.

One interesting result is that the acceptance rate for *POWER* is slightly lower than the supervised model, and both *POWER* and supervised models are slightly lower than randomly recommending a hobby. This is likely due to the fact that *POWER* 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 hobby acceptance rate.

		Group I	Group II	Group III
Ikigai-9 Scale	Curr. Accept	1.333	2.875	1.857
	Fut. Accept	2.600	1.500	1.333
	Reject	-1.600	1.000	1.000
	p-values	0.278	0.033	0.017
	Relative Imp.	2.089%	9.114%	4.117%
Four-Factor Scale	Curr. Accept	-0.333	2.500	10.857
	Fut. Accept	-0.600	6.500	9.000
	Reject	-3.400	-0.500	-2.667
	p-values	0.843	0.082	0.012
	Relative Imp.	-1.301%	3.633%	6.583%

Table 2: User study results for average changes in *ikigai* for different groups as measured by *ikigai*-9 scale and the four-factor *ikigai* scale, paired t-test between before and after-study *ikigai* scores and average relative improvement in *ikigai* scores.

Online Evaluation

Both quantitative and qualitative analyses were conducted. To explore how individuals experience phenomena differently, we used phenomenography, one of the most widely used qualitative methods that distills common features and meanings from individual experiences (Starks and Brown Trinidad 2007).

Quantitative Analysis Table 2 shows the changes in participants' *ikigai* levels across different groups, measured by the *ikigai*-9 and four-factor scales. "Curr. Accept" represents participants who acted during the study, "Fut. Accept" those who plan to act later, and "Reject" those who rejected all recommended hobbies. Positive numbers indicate *ikigai* increases, while negative numbers show declines.

Participants in Groups II and III, who received hobby recommendations through *POWER*, showed consistent increases in *ikigai* levels on both scales. However, Group I participants, who received recommendations from a supervised model, did not show consistent improvements across the two scales. Those who rejected all recommendations saw minimal or decreased *ikigai* levels.

Upper-tailed paired t-tests were used to determine whether the mean post-study *ikigai* score was higher than the pre-study score, regardless of whether participants accepted the hobby recommendations. Results reveal significant *ikigai* improvements in Group III (*ikigai*-9: $p = .017 < .05$; four-factor: $p = .012 < .05$) and in Group II (*ikigai*-9: $p = .033 < .05$). Group I did not show significant changes.

Table 2 also indicates that Groups II and III had higher relative improvements in *ikigai* levels across both scales, while Group I showed smaller or negative changes. This suggests that *POWER* is more effective at recommending hobbies that enhance *ikigai* compared to the supervised model.

Qualitative Analysis To evaluate *POWER*'s effectiveness in enhancing *ikigai*, we employed a phenomenographic approach to explore how participants perceived the recommended hobbies differently (Marton 1986). Participants were divided into two groups: Group A (29 participants), who showed an increase in *ikigai*, and Group B (11 participants), who showed no increase. A larger proportion of Group A (24 out of 29) took or planned to act on the recommended hobbies, compared to Group B (6 out of 11). We identified key behavioral differences between the groups:

- **Willingness to Share:** Participants in Group A were more communicative, expressing interest in suggested hobbies and elaborating on their actions or plans, while Group B participants were less responsive.
- **Engagement with the Researcher:** Group A actively interacted with the researcher, sharing progress and photos, unlike Group B.
- **Having Concrete Plans:** Group A participants often shared specific future plans related to the hobbies, whereas Group B gave vague responses.
- **Reflecting on Experiences:** Group A participants reflected on past experiences and related them to the recommended hobbies, a behavior not observed in Group B.

Although the additional persuasive messages didn't necessarily increase hobby acceptance, they did prompt participants to think more deeply, with many offering detailed feedback, expressing their agreement or disagreement. During the interview, participants noted that the hobbies provided new goals and made life more enjoyable, with several praising the personalized recommendations for their accuracy and appeal. Overall, the hobby recommendations were effective in enhancing *ikigai*.

Conclusion and Impacts

This paper introduced *POWER*, a novel approach to evaluate and enhance *ikigai* levels. By predicting *ikigai* from profile data and adapting hobby recommendations through reinforcement learning, our method was validated through both an offline dataset and a 30-day user study, showing significant improvements, with some participants experiencing over a 9% increase in *ikigai*. The identified phenomenographic categories can guide future research and inform the integration of relevant features in the deployed product.

Looking ahead, *POWER* has the potential to transform personalized well-being recommendations, particularly through *ikigai*. By demonstrating that tailored hobby suggestions can enhance purpose and satisfaction, this approach paves the way for practical applications in mental health and wellness programs. With over 300 million people globally affected by depression (Friedrich 2017), costing the global economy $1 trillion annually in lost productivity (Health 2020), solutions like *POWER* are increasingly vital.

POWER could be integrated into digital health services, providing real-time, personalized recommendations and improving well-being across diverse populations. Ultimately, *POWER* offers a scalable and effective method for enhancing quality of life, with broad applications in personal health and wellness.

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