Designing Researchmap: A Revolutionary Scholar Support Platform Achieved Through Human-AI Collaboration

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***Abstract*— Researchmap is a researcher support platform software-as-a-service (SaaS) that has successfully achieved the semi-automated construction of a comprehensive catalog of achievements for over 340,000 Japanese researchers through the collaboration of artificial intelligence (AI) and human expertise. Researchmap utilizes APIs from primary information providers such as Scopus to compile a substantial portion of researchers' achievement lists. This curated dataset then serves as training data for AI development. The AI model is iteratively refined by providing feedback to the users (i.e.researchers), allowing them to make corrections and improvements using a user-friendly interface. As a result of these efforts, Researchmap successfully captures information from more than 340,000 researchers within the Japanese academia, accumulating over 20 million research achievements in machine-readable formats. The F1 Score of AI in recommending discovered research achievements to the respective researchers exceeds 0.94.**

Keywords—Human-AI collaboration, API, scholar support system, SaaS

I. INTRODUCTION

In today's rapidly advancing world, the role of science and technology in shaping the prosperity and competitiveness of nations cannot be overstated. Governments and policymakers worldwide recognize the need for evidence-based science and technology policy to guide effective investments. Science and technology are key drivers of long-term economic growth, innovation, and societal advancements [1]. Consequently, understanding the most effective strategies for science and technology investments has become a top priority for governments seeking to harness the potential of scientific research [2].

Various factors come into play to evaluate the impact of science and technology investments. These include researchers' employment opportunities, research funding allocations, and acquisitions in research facilities, all of which contribute to the inputs required for scientific progress [3]. However, analyzing the outcomes and outputs of these investments is equally crucial: it entails assessing researchers' achievements, such as published research papers and patented inventions and developing skilled research personnel.

However, traditional measures like citation counts and h-index have been criticized for failing to adequately reflect a comprehensive picture of a researcher's contributions and impact [4]. For instance, pressing regional issues like Japan's rapidly aging population and declining birthrate may not necessarily correspond with high citation counts or h-index, despite being high-priority research areas for national policy. Therefore, it is crucial to establish a broader understanding of research productivity and influence by examining inputs and outputs, enabling policymakers to understand the effectiveness and outcomes of science and technology investments [5].

Access to machine-readable formats of researchers' professional trajectories, secured research funding, and documented contributions to the scientific community is necessary for more sophisticated analysis and informed decision-making in science and technology policy. However, achieving this without burdening researchers' valuable time necessitates the utilization of advanced technologies, such as artificial intelligence (AI).

Artificial intelligence can be pivotal in streamlining, automating, capturing, and organizing researchers' achievements. By leveraging AI algorithms and techniques, it becomes possible to automate compiling comprehensive lists of researchers' accomplishments partially. Nevertheless, the involvement of researchers themselves in verifying and refining AI-generated results remains crucial. Potential errors or inconsistencies can be identified and rectified only through their domain expertise and contextual understanding.

Hence, Researchmap, an innovative scholar support platform, emerges as a solution to address these challenges. By combining AI's power with researchers' active participation, Researchmap has achieved a significant milestone in constructing a comprehensive repository of achievements for over 340,000 Japanese researchers. This extraordinary endeavor has amassed over 20 million research outputs in machine-readable formats, enabling evidence-based science and technology policy decisions.

This paper delves into the background and development of Researchmap, emphasizing its vital role in advancing science and technology policy. We explore the significance of providing policymakers with reliable and comprehensive data-driven insights into the scientific landscape. By leveraging Researchmap's user-friendly interface and Human-AI collaboration, researchers can actively participate in refining their achievements, ensuring the accuracy and relevance of the compiled information.

The subsequent sections of this paper will delve deeper into the methodology and design considerations behind Researchmap, highlighting its potential to revolutionize scholarly support systems and enhance evidence-based decision-making in science and technology policy. By empowering policymakers and researchers alike, platforms like Researchmap offer a strategy for nations to optimize their own science and technology policies and pave the way for strategic investments that drive scientific progress, foster innovation, and shape the future of nations'.

II. Evolution of Researchmap: From Conception to Realization

Researchmap, a pioneering platform for publishing researcher CVs and achievements, debuted in 2008 as a service tailored to researchers [6]. The availability of APIs for paper information from external providers like PubMed and DBLP, replacing manual entry, catalyzed the emergence of this service. Once onboard with Researchmap, researchers could sift through achievements under their names from these providers, cherry-pick their papers, and feed them into the system. It drastically cut the time required to generate an achievement list by over a tenth.

In 2013, Researchmap began offering institutions the researchers' information through an API, allowing universities to construct and publicize overviews of their researchers without additional expenses [7]. Nevertheless, the incentive for researchers to build and publicize a comprehensive list of achievements through Researchmap varied, resulting in data that were often insufficient for reliable 'science for science and technology policy-making.

To tackle this challenge, we utilized the accumulated information as the initial training data to develop AI for paper deduplication, entity resolution, author disambiguation, and research output recommendation. Unfortunately, the 'research achievements of researchers affiliated with Japanese research institutions,' sourced from Scopus, were assigned to researchers registered with Researchmap to check their accuracy, suggesting that AI's full automation entails significant risks.

Leveraging insights from social psychology and user interface design, we have created and included in Researchmap a navigation system that helps researchers collaborate on a complete list of their accomplishments with the help of AI. We released this system in 2020 as Researchmap v.2. This revision of the user interface was a great success, drastically reducing the error rate of AI-recommended performance.

III. Development of AI systems for Researchmap

We developed mainly three AI systems for Researchmap: entity resolution, author disambiguation, and research output recommendation. The three AI systems we developed each uniquely influence Researchmap's functionality.

The Entity Resolution system aims to identify when two or more records correspond to the same real-world entity, such as a research paper. This capability is essential to maintaining data integrity and eliminating duplications, leading to a more reliable and consistent dataset. Our Entity Resolution system was developed after careful consideration of various factors. We ultimately decided on a relatively simple implementation emphasizing publication years and the titles' vector similarity [8]. Our choice was made based on the dual advantages of accuracy and ease of maintenance.

Next, we have the Author Disambiguation system, which targets the challenge of distinguishing between authors who share the same or similar names. The system accurately disambiguates authors by evaluating factors such as co-authors, affiliations, field of study, and other relevant indicators. It significantly reduces confusion and enhances the overall accuracy of our database. Author disambiguation presents unique challenges in the context of Japanese researchers, mainly when these researchers publish in languages other than Japanese, most notably in English. These challenges are mainly centered around variations in the representation of Japanese names in non-Japanese languages. To tackle this issue, we implemented a solution where researchers are prompted to enter their basic information before using the service. It is a strategy we will explore further in the next section. This method helps the system understand the range of name representations each researcher may use across different publications, significantly enhancing the disambiguation process's precision. By allowing researchers to provide their data, including variations of their names, we ensure a comprehensive and accurate association of their research outputs.

Finally, the Research Output Recommendation system is designed to propose potential research outputs that belong to individual researchers. This system uses AI algorithms to analyze researchers' past publications, co-author names, affiliations, etc., suggesting relevant papers and other research achievements. Not only does this significantly reduce the time researchers spend manually inputting their works, but it also helps build a more exhaustive and precise record of their research contribution. Table 1 shows the initial performance of AI recommendation using 3/4 of the Researchmap data in 2018 as training data and the rest as test data. We ran five tests with different parameters, and the average precision was 0.946, and F1-Score was 0.945.

While our initial models showed promising precision scores, we encountered a significant challenge when we conducted further tests using real-world data. We randomly selected 100 papers by Japanese authors provided by Scopus and assigned authors using our model. Table 2 shows the result: the precision was a respectable 0.953, but Recall and F1 Score remained at a suboptimal 0.788 and 0.863, respectively.

The primary cause we identified for this discrepancy was the significant missing data in the records accumulated on Researchmap. Despite the AI's advanced capabilities, it was evident that a critical component was missing - human input. The shortcomings of a purely AI-driven system underlined the necessity for a harmonious collaboration between humans and AI.

TABLE I. The initial performance of AI recommendation

Index						**Average**
Precision	0.946	0.948	0.952	0.933	0.953	0.946
Recall	0.838	0.867	0.837	0.845	0.841	0.845
Accuracy	0.995	0.996	0.995	0.995	0.995	0.995
F1-Score	0.943	0.952	0.944	0.942	0.945	0.945

TABLE II. The Initial Performance of AI on Scopus Data

Index	**Score**
Precision	0.953
Recall	0.788
Accuracy	0.869
F1-Score	0.863

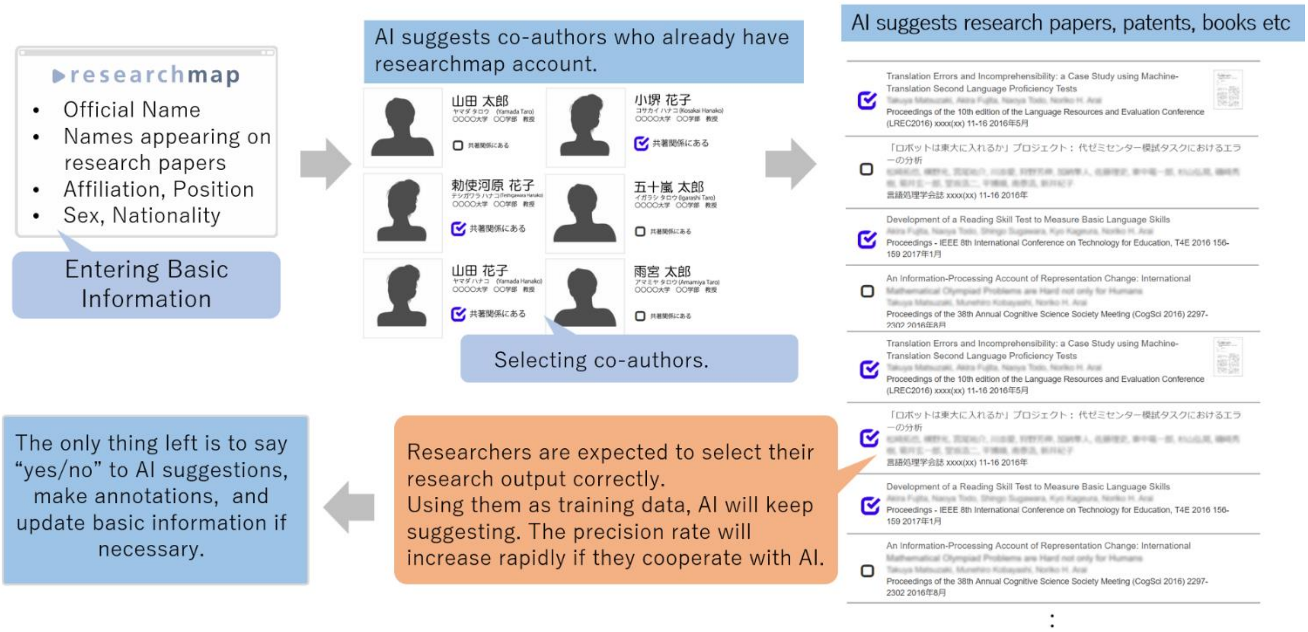

Fig. 1. The Human-AI Collaboration Cycle in Researchmap.

These findings led us to the critical realization that to fully complete and refine the dataset, the development of a user interface facilitating active collaboration between AI and researchers was indispensable. The narrative of this initiative, its design, and its impact on enhancing the Researchmap accuracy form the following section's crux.

IV. Human-AI Collaboration in Researchmap

In this section, we unveil Researchmap's unique design that synergizes human researchers and artificial intelligence (AI) to amplify the precision of our three AI systems. Fig. 1. offers a schematic depiction of this unique workflow. Each time researchers log in to Researchmap, they are presented with new co-authors and academic papers AI recommends. The researchers, as needed, update their basic information and accurately respond to these AI recommendations. This process, in turn, enhances the precision of the AI recommendations. Gradually, researchers can fully entrust the maintenance of their Curriculum Vitae (CV) to the AI, as it continually learns and adapts to their research profile, making CV maintenance a more efficient and accurate process. By engaging the researchers themselves in the disambiguation process, Researchmap ensures a more precise and reliable representation of an author's work, fostering a more robust scientific information ecosystem.

A. *The Basic Information*

To augment the performance of our Author Disambiguation system, we have made it a requirement for researchers registered on Researchmap to provide not only their names but also potential variations of their names that may appear in their publications. For instance, a Japanese name like Shin-ichi Matsuda may be alternatively represented using different characters as Shin-ichi Matuda, Shin'ichi Matuzaki, or even abbreviated as S. Matsuzaki. By having these variations fed into the system; we can significantly enhance the precision of the Author Disambiguation system. We also encourage researchers to provide identification numbers such as researcher numbers or ORCID IDs.

Additionally, inputting the researchers' date of birth facilitates narrowing down the likely time frame during which they might have been actively publishing - presumably between the ages of 20 and 100. Moreover, providing information about their current employment status, such as their institution and job rank, and gender, among other data, also plays a crucial role in the process.

Such 'basic information,' when obtained in detail, not only improves the accuracy of AI but also significantly contributes to the science of policy-making. However, soliciting too much information at once may deter researchers and lead to their reluctance to provide data. Therefore, we had to be selective in determining the mandatory fields, a process we arrived at through a careful trial-and-error approach. This balance between the depth of information and user engagement has been an essential aspect of designing our user interface, and it reflects our commitment to creating a system that prioritizes ease of use and accuracy.

B. *The Co-Authors Recommendation*

As we delved deeper into the feature importance of the AI model, it suggested the significance of co-author names. Therefore, right after the researchers had input their basic information, we decided to display a list of co-authors as determined by the AI. One of the most distinguishing features of Researchmap that sets it apart from other platforms, such as Google Scholar or Orcid, is the co-author recommendation interface before paper recommendations. The co-author recommendation step provides a unique layer of precision that assists in identifying papers authored by researchers with common names, mitigating potential errors in paper attribution. We conveyed to the researchers that correctly choosing the co-authors could enhance the accuracy of the AI's advice. We implemented these measures to ensure the researchers could complete this task effectively. This interaction, where researchers verify or correct the co-author list suggested by the AI, forms a critical feedback loop, enhancing the AI's future performance.

C. *The Research Paper Recommendation*

After selecting the co-authors, the next step involves AI recommending research papers. The researchers choose their papers from this list, further refining the accuracy of the AI's recommendations. This process of selection and validation forms another critical feedback loop, which iteratively enhances the AI's performance. Each interaction allows AI to learn and improve its understanding of the researcher's work, making subsequent recommendations more precise.

V. Performance Improvement and User Engagement with Human-AI Collaboration

The accuracy of AI in recommending papers improved in all metrics, as shown in Table 3. In particular, Recall significantly improved from 0.788 to 0.918. The F1 Score also considerably improved from 0.863 to 0.944. It reaffirms the success of our Human-AI Collaboration design, as described in the previous section. Upon error analysis, the primary errors were concentrated among researchers who (1) have not registered a single paper on Researchmap, (2) have no co-authors, and (3) have not logged into Researchmap after the introduction of AI.

The accuracy is already so high that further improvements can only be expected if registration on Researchmap is mandated. Figure 1 presents the growth in the number of registrants to Researchmap and the number of registered publications. As shown in Figure 1, while the number of registered researchers increases at the same rate yearly, the number of publications sharply increased from 2019 to 2020, when AI was introduced. This increase is likely due to the impact of AI recommendations.

TABLE III. The Current Performance of AI on Scopus Data

Index	Score
Precision	0.971
Recall	0.918
Accuracy	0.919
F1-Score	0.944

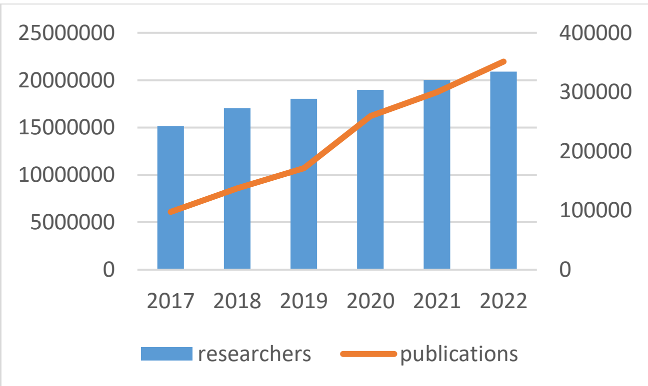

Fig. 2. Growth in the Number of Researchers and Publications Registered on Researchmap.

VI. Policy Implications and Contributions of Researchmap

Currently, over 340,000 researchers use researchmap. Given that the total number of researchers across academia, industry, and government in Japan is not precisely known, and has been estimated by the Ministry of Education, Culture, Sports, Science and Technology (MEXT) to range from 300,000 to 500,000. Considering that this number includes retired researchers and those who do not produce publications, it can be inferred that Researchmap has captured a significant proportion of the research output, including publications and patents.

In light of this, Japan's two major funding agencies, the Japan Society for the Promotion of Science (JSPS) and the Japan Science and Technology Agency (JST), have announced using Researchmap data to review competitive research funding: it was the first instance of Researchmap data being utilized for science policy, which further incentivized researchers to maintain their CVs on Researchmap.

As a result, researchers have started maintaining information that AI cannot obtain, such as award history, patents, and media coverage. Using these data, we have reached a step where we can promote more refined science for policy.

Researchmap has accumulated a large amount of data that allows for extensive analysis. For example, we can automatically generate a list of outputs for research projects funded by competitive funds by creating a simple interface linking competitive funds and their outcomes. If JSPS and JST, Japan's major funding agencies, accept this list as an output of each research project, researchers will be motivated to link their achievements to competitive funds. In turn, it will enable JSPS and JST to understand the short-term and long-term outputs of competitive funding. Once this cycle functions smoothly, we can examine which competitive funds (in terms of amount, research duration, size of the research team, etc.) yield good returns on investment for different purposes.

Furthermore, it becomes possible to measure how the diversity of research teams influences research productivity. We can also quantitatively analyze the support needed for research teams with low productivity efficiency. These developments represent the future directions for Researchmap, which is expected to contribute more and more to policy-making based on science.

VII. Conclusion

We developed a researcher support platform called Researchmap as a Software-as-a-Service (SaaS). This platform, designed to assist researchers in maintaining and updating their CVs, utilizes an innovative Human-AI Collaboration system. This system uses AI to recommend potential co-authors and papers to the researchers, who provide feedback to the system, improving its accuracy over time.

Through this collaboration, we significantly improved the accuracy of the AI recommendation system. As demonstrated, the Recall increased from 0.788 to 0.918, and the F1 Score improved from 0.863 to 0.944. This success is further evidenced by the rapid increase in registered achievements following the introduction of the AI system.

Researchmap, with its evolving AI capabilities and strong user engagement, has now reached a point where it has almost captured the active researcher population in Japan and a significant proportion of its research outputs. This success story suggests that the approach taken by Researchmap – integrating AI and human intelligence – offers a promising model for developing intelligent systems that can provide valuable services to users while continuously improving through user feedback.

As we move forward, we will continue to enhance Researchmap by incorporating new features and functionalities. These improvements will make the platform more effective in supporting researchers and offer new possibilities for utilizing the accumulated data for policy-making and research management. The future holds a wealth of opportunities for Researchmap as it continues to evolve, driven by technological advancements and the needs of its users.

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