

An illustration of a RLHF-based model for research evaluation and strategic decision-making

António Correia¹, Benjamim Fonseca¹, Daniel Schneider², Pedro Antunes³, Shoaib Jameel⁴, and Andrea Grover⁵
¹ INESC TEC and University of Trás-os-Montes e Alto Douro, Vila Real, Portugal
² NCE and Federal University of Rio de Janeiro, Brazil
³ LASIGE and University of Lisbon, Portugal
⁴ University of Southampton, UK
⁵ University of Nebraska at Omaha, USA

Reinforcement Learning from Human Feedback

Modelling scientometric data through human-in-the-loop AI models leveraged by crowd-based processing

Building on research advances in human-computer interaction (HCI) and machine learning (ML), reinforcement learning from human feedback (RLHF) has emerged as an alignment technique where intelligent systems learn from human actionable insights and commands and are rewarded according to their correct decisions in an interactive fashion [1]. However, the potential uses and drawbacks of such models have not been extensively examined in scientometrics, a field with roots on citation indexing [2] that deals with the quantitative and qualitative aspects behind how scientists interact to produce intellectual outputs and how this knowledge is disseminated and reused by others. While the advances on large language models (LLMs) are being increasingly acknowledged worldwide, many challenges remain to be overcome when we transition from common sense reasoning to complex scientometric portraits characterized by volatile dynamics and heterogeneous semantic networks. Moreover, LLMs are reliant on the quality and availability of the foundational pre-trained data. As a result, problems like error propagation and hallucination have proven challenging to address in literature-based discovery.

This poster illustrates a revised model of crowd-based scientometric data processing for further evaluation and implementation into the SciCrowd system [3], a mixed-initiative human-AI teaming solution that interactively supports crowd-guided machine learning and enables to comprehend decision-making elements distinctly and in a coordinated manner. Figures 1 and 2 depict the refined workflow and underlying services of the proposed human-AI scientometric tool.

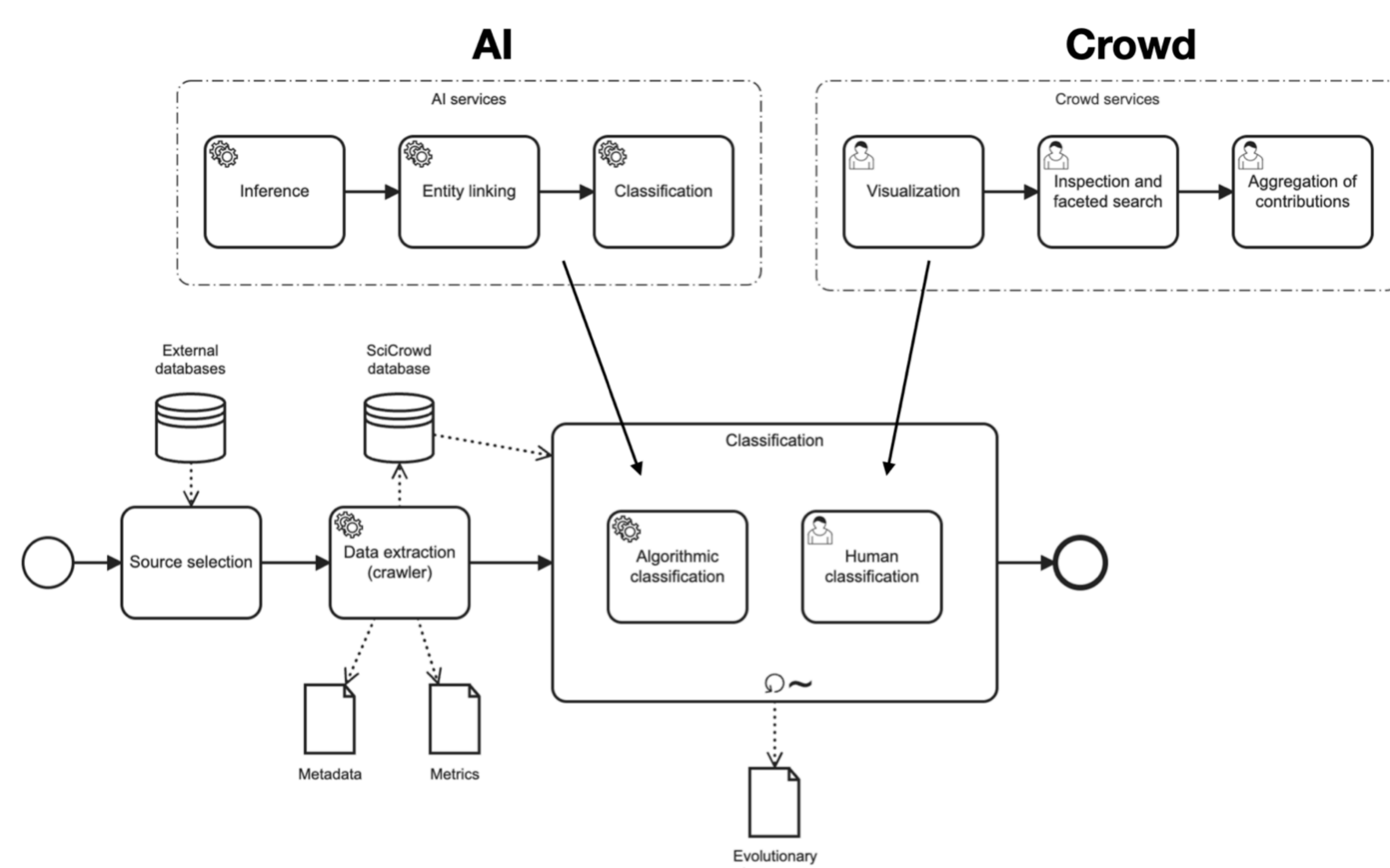


Figure 1. Human-AI scientometric system services.

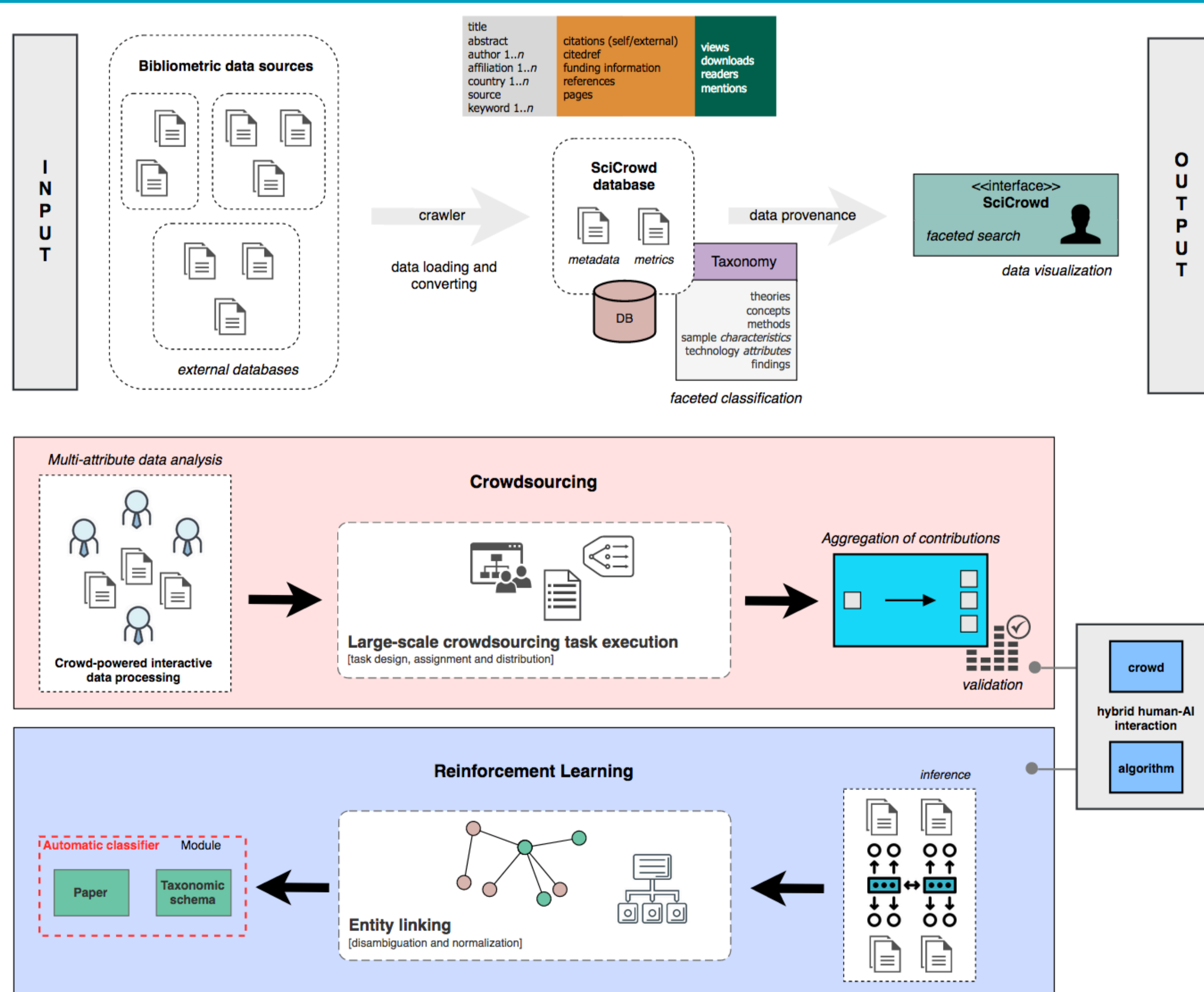


Figure 2. Overall working diagram of the RLHF model.

Challenges Ahead

The increasing volume, flux, and multidisciplinary of scientific endeavours and findings often make it challenging to identify and integrate multiple viewpoints when considering research evaluation pursuits. Despite the known benefits of crowd-machine supported research, engaging crowds in scientific discovery by linking disconnected findings and correcting errors across literatures can be difficult to achieve in practical terms since the sustained participation of their members is often affected by psychosocial conditions alongside other issues including familiarity and expertise.

Acknowledgements

We would like to thank Siân Lindley from Microsoft Research for all the support provided in the ideation stage that contributed to redesign the RLHF model. We would also like to acknowledge the researchers who participated in the previous stage of the SciCrowd project.