Methodological Evolution and Knowledge Management in a Displacement Modelling Project: From Research Prototype to UNHCR Policy Tool

Laura Marshall Harbach[1[0000−0001−7944−0292]], Diana Suleimenova[1[0000−0003−4474−0943]], Yani Xue[1[0000−0002−7526−9085]], Yehor Yudin[2[0000−0001−8867−3207]], Derek Groen[1,3[0000−0001−7463−3765]], Giorgia Tornieri[4], Ivan Cardona Landinez[4], Susanne Klink[4], and Konstantin Fastovets[4]

[1] Department of Computer Science, Brunel University of London, Kingston Lane, Uxbridge, Middlesex, UB8 3PH, United Kingdom
laura.harbach@brunel.ac.uk

[2] School of Computer Science and Engineering, Dean Street Building, Bangor University, Bangor, Gwynedd, LL57 1UT, United Kingdom

[3] Faculty of Science (Informatics Institute), University of Amsterdam, Science Park, 904 1098 XH, Amsterdam, Netherlands

[4] United Nations High Commissioner for Refugees (UNHCR), P.O. Box 2500, 1211 Geneva 2, Switzerland

Abstract. Integrating complex computational models into humanitarian policy requires structured knowledge management and stakeholder co-design. This paper focuses on the development of 'Homecoming', a high-fidelity agent-based model developed in partnership with the United Nations High Commissioner for Refugees to forecast displacement and return movements in Ukraine. We describe the project's evolution from its academic research roots through three distinct phases: initial prototyping, rapid adaptation following power grid attacks, and final maturation into a policy instrument. Our main contribution is our *Expert-Informed Knowledge Repository (EIKR)* methodology, which aligned academic research with the strict requirements of an international humanitarian policy model. Through weekly sessions, a structured GitHub Wiki, and a seven-category taxonomy, the EIKR translates qualitative expertise into quantitative simulation parameters via continuous human-in-the-loop refinement. The effectiveness of this approach is evidenced by the model's adoption across multiple high-level humanitarian and governmental forums. By documenting these experiences, we provide an evidence-informed roadmap for future high-fidelity computational science projects aimed at supporting humanitarian policy.

Keywords: Expert-Informed Knowledge Repository (EIKR)· Co-design · Humanitarian Policy · UNHCR · Agent-Based Modelling · Science-Policy Interface

ICCS Camera Ready Version 2026
To cite this paper please use the final published version:
DOI: 10.1007/978-3-032-29909-3_7

1 Introduction

The ongoing full-scale war in Ukraine is one of the fastest-moving and most complex displacement crises in recent history [1]. As of early 2025, the United Nations High Commissioner for Refugees (UNHCR) reports that over 5.8 million refugees from Ukraine have been recorded globally, with the vast majority, approximately 5.3 million, seeking refuge across Europe [2]. For humanitarian organisations, development actors and governments, planning for the eventual return and sustainable reintegration of these populations is a highly complex task. It involves a wide range of international organisations, local non-governmental organisations (NGOs), and state departments, each operating with different institutional focuses, budgetary constraints, and operational limits. This complexity is further compounded by a profound uncertainty regarding the total volume of returns, the shifting demographics of those returning, the specific geographic locations they will settle in, and the volatile timing of these movements.

To address these challenges, we developed 'Homecoming', a novel predictive solution in the form of a large-scale agent-based model (ABM). Unlike previous research prototypes, Homecoming was designed from the outset as an operational policy tool. This transition from research to policy presented a significant computer science challenge: how to manage the "knowledge gap" between humanitarian field experts and computational modellers.

Homecoming occupies a unique niche in the research landscape. While macro-level migration models typically focus on push-pull drivers [3], evidence suggests safety thresholds and home-country conditions are more decisive for conflict-displaced populations [4]. Unlike the daily, route-centric focus of Flee [5], Homecoming uses monthly, household-level utility optimisation across seven domains to better support policy analysis. Furthermore, other Ukraine-focused models, such as ABSCIM [6] provide daily estimates of conflict-induced outflows, whereas Homecoming focuses on monthly scenario-based return and relocation planning. It features configurable policy levers, such as legal changes, aid, and investment, with evidence-to-parameter traceability maintained via the Expert-Informed Knowledge Repository (EIKR).

The Homecoming model has been developed in three distinct operational phases. In Phase 1, the team focused on model prototype development for refugee returns, establishing core movement logic. This led into Phase 2, where the model was urgently pivoted to simulate outward displacement only, driven by the anticipated escalation of attacks on Ukraine's energy grid. Finally, in Phase 3, the model matured into a long-term forecasting tool for returnees. This process resulted in two policy briefs [7,8], a chapter in an Organisation for Economic Co-operation and Development (OECD) report [9], discussion at the 4th Ukraine Recovery Conference [10] and more recently an opportunity provided by the Ministry of Foreign Affairs of Ukraine to brief the diplomatic corporations in Kyiv, including Ambassadors, UN experts and international institutions, as well as representatives from the Government of Ukraine [11].

In this paper, Section 2 discusses this evolution from exploratory research to UNHCR forecasts. In part, due to the ongoing full-scale war in Ukraine, the

ICCS Camera Ready Version 2026
To cite this paper please use the final published version:
DOI: 10.1007/978-3-032-29909-3_7

Homecoming model itself cannot yet be made open source. Instead, we provide an introduction to the model design in Section 3, while in Section 4 we present the EIKR, a system created to convert qualitative expertise into quantitative parameters. By detailing the Homecoming model and EIKR methodology, we show how structured knowledge management enables the deployment of high-fidelity simulations in humanitarian settings. Lastly, we conclude the paper in Section 5.

2 From Exploratory Research to the UNHCR Forecasts

A key research challenge is transitioning theoretical ideas into operational tools. This progression is measured by Technology Readiness Levels (TRLs), a nine-point scale ranging from basic principles (TRL 1) to validated deployment (TRL 9) [12]. The research underlying our policy tool actually began with an ICCS paper and ABM prototype [13] (TRL 1-3). This paper led to the development of an ABM model for conflict-driven displacement, namely Flee (TRL 4) [5]. As this topic was societally relevant and relatively underexplored in the simulation community, Flee became a particularly suitable pilot use case for showcasing advances in the EU-funded projects on High Performance Computing (HPC), as well as verification, validation and uncertainty quantification (VVUQ). It was through EU-funded projects, VECMA and HiDALGO, that we were able to establish a scalable version of the displacement model, and develop facilities for automated VVUQ and sensitivity analysis. Flee was developed further through a dedicated EU-funded migration project (ITFLOWS), where it was embedded along with two other models in a larger population movement forecasting framework called the EUMigraTool (TRL 5). Due to a large diversity in the context of use of the underlying models and a confusingly distributed ownership structure, the EUMigraTool never found uptake after conclusion of the project, but Flee persisted as a tool. It was subsequently used in small (and often voluntary) projects in collaboration with NGOs such as Save the Children (TRL 6) and World Watch Research, as well as with academic partnerships with e.g. Columbia University, the University of Amsterdam and Delft University of Technology.

Adaptation to emerging needs: When we took on the initial project with UNHCR on Return Modelling, we realised that, compared to conflict-driven displacement, returnee modelling had (i) a less acute time frame, (ii) involved a wider range of factors in human decision-making and (iii) was subject to a very different set of circumstances and scenarios. Because of these differences, we chose not to extend Flee, but instead build a new tool (Homecoming) from scratch. Due to our previous experience, we were able to take this tool from TRL 1 to TRL 7 within two years.

Project evolution in hindsight: Our experience with Flee and Homecoming brought us several insights. First, research ideas in the TRL 1-2 stage are likely to be criticised, but we argue it is particularly worthwhile to persist as long as there is a feasible societal (or industrial) use case for the proposed technology.

ICCS Camera Ready Version 2026
To cite this paper please use the final published version:
DOI: 10.1007/978-3-032-29909-3_7

Second, models that reside within the TRL 3-4 stage are ideal to function as pilots or application use cases within the context of other technological initiatives, such as research projects on emerging HPC or AI technologies. Third, a flexible approach to model building is extremely useful as the end user needs shifted multiple times during the evolution of both Flee and Homecoming. In light of this, we found that having a simulation approach that is easy to develop, adapt and scrutinise is more important than having an approach that is user-friendly. Finally, had we adopted an AI-based approach from the outset, we might not have made it to TRL 7 at all due to inherent constraints around AI in relation to explainability and data protection [14].

3 Overview of the Homecoming Model

Homecoming simulates Ukrainian refugee population at various scales, including 1 agent representing a refugee at a full resolution. Agents are initialised with socio-demographic attributes (such as age, gender, origin oblast) derived from survey data and available official statistics. They are grouped into households, creating hierarchical structures similar to those presented in [6]. The simulation environment includes 26 European host nations, 24 Ukrainian oblasts, the Autonomous Republic of Crimea, and the city of Kyiv. Typical simulations provide 2-3 year forecasts with agent attributes and migration movements tracked to provide disaggregate statistics.

In each monthly time step, every agent or household unit evaluates their current host European location against all other locations using a multi-criteria utility function. The core of this decision-making logic is the Location Score ($S_{location}$), calculated as,

$$S_{\text{location}} = \text{Base} + \sum_{i=1}^{7} (W_i \times F_i) + \text{Overrides}. \tag{1}$$

The 'Base' term represents the foundational utility value intrinsic to all locations before the variable primary factors are applied.

The model groups all relevant decision-making variables into seven weighted primary factors (F_i), each normalised to a discrete scale of 0 to 5. This normalisation simplifies the scrutinisation process and allows the model to ingest vastly different mechanisms and data types, such as conflict casualties or GDP growth rates, and translate them into a uniform influence on agent behaviour. The weights (W_i) serve as multipliers that reflect the relative importance of each factor as determined by expert consensus. These seven factors include Safety, Job Perspective, Living Standard, Education, Healthcare, Utilities and Social aspects. We also use numerical "overrides" for complex behaviours. For example, a Legal Multiplier simulates the expiration of Temporary Protection by reducing host-country security. Furthermore, we override pull factors when local safety falls below critical thresholds or to incorporate the dual push-pull effects of conscription for military-aged men. The seven factor categorisation has made it considerably easier for external experts to scrutinise the ABM rule set.

ICCS Camera Ready Version 2026
To cite this paper please use the final published version:
DOI: 10.1007/978-3-032-29909-3_7

Implementation-wise, Homecoming executes a monthly loop that updates location attributes, calculates individual seven-factor scores, aggregates household decisions with dependent weighting, and establishes a "stay" baseline influenced by inertia and legal factors. Migration is triggered only if a candidate destination's score exceeds this baseline, after which results are logged as time-series and movement records. This logic is driven by YAML configuration files that define scenario states, factor weights, and legal timing. To ensure reliability, extensive sensitivity analysis was conducted on the seven decision-factor weights, population aggregation levels, and stochastic run counts. These analyses identify influential assumptions, ensure result stability, and balance computational efficiency with statistical robustness.

4 The Expert-Informed Knowledge Repository (EIKR)

The EIKR is a structured and traceable knowledge management system developed for the Homecoming ABM. It connects raw external evidence with the concrete assumptions embedded in the simulation's source code and input data files. The EIKR is implemented as a GitHub Wiki and a curated collection of data files co-located within the project repository, enabling version-controlled, collaborative, and transparent documentation of every modelling decision. The core purpose of the EIKR is to ensure that every assumption in the model can be traced back to its evidential basis, whether that basis is strong quantitative data, survey findings, qualitative reports, or expert knowledge/judgement. This traceability is essential for accountability, reproducibility, and iterative model improvement.

4.1 Human-in-the-Loop Architecture

The EIKR is supported by a 'Human-in-the-Loop' architecture. In practice, policymakers co-design scenarios and select parameters alongside technical experts, who execute the simulations and provide structured CSV results (time series and movement logs) that policymakers then analyse for policy briefs. This iterative workflow uses continuous feedback to refine model mechanisms and weightings. The model was developed in close conjunction with a dedicated team of experts from UNHCR, who advised on refugee decision-making logic by providing vital context-specific knowledge regarding the drivers of return. Furthermore, the experts provided invaluable guidance on what was required for humanitarian experts and policy makers to fully understand, trust, and analyse the model's internal mechanisms and resulting forecasts. Work was further guided by the Informal Advisory Board (IAB), which met every two to three months to scrutinise the model development. Composed of representatives from UNHCR, development actors, International Financial Institutions, EU institutions, intergovernmental organisations, academia, and Ukrainian government officials, the IAB acted as a semantic bridge, translating high-level policy questions into computational scenarios. To mitigate expert-bias risks, we apply four safeguards: triangulation across independent quantitative and qualitative sources, explicit

ICCS Camera Ready Version 2026
To cite this paper please use the final published version:
DOI: 10.1007/978-3-032-29909-3_7

evidence-quality tagging, versioned provenance linking assumptions to sources, and periodic sensitivity checks on expert-informed parameters. We also record contested assumptions and revisit them when new data arrives, reducing lock-in to institutional priors.

4.2 Four-Layer Architecture of the EIKR

As illustrated in Figure 1, the repository is organised into four interconnected layers, each serving a distinct role in the knowledge-to-model pipeline. This framework functions as a living knowledge system where the model can evolve as new evidence emerges. By using a wiki-based implementation, the system supports asynchronous updates and collaborative scrutiny from interdisciplinary team members. This ensures that every modelling decision is documented and version-controlled. An integrated quality tracking system ensures accountability by explicitly distinguishing well-supported logic from areas based on weaker proxies. While the principal pipeline is evidence-to-model (Layer 1-4), we operationally maintain iterative feedback loops from model behaviour back to assumptions (Layer 4 to Layer 3) and from assumption gaps back to evidence curation (Layer 3 to Layer 2).

Layer 1: External Data Sources The first layer, depicted in Figure 1, integrates raw data, reports, and expert knowledge through three channels. Firstly, there are continuously updated quantitative databases for essential indicators, such as Armed Conflict Location and Event Data (ACLED) Conflict Monitor for safety, Eurostat for protection beneficiaries, the World Bank for macroeconomic figures and IOM for displacement numbers inside Ukraine. Secondly, this is supplemented by periodic qualitative sources like the UNHCR "Lives on Hold" intention surveys and Socio-economic Insights Surveys (SEIS) to capture return intentions. Finally, expert knowledge synthesises these findings, filling data gaps and calibrating parameters to ensure the model reflects real-world expectations.

Layer 2: Knowledge Base and Key Findings The second layer systematically analyses external sources, extracting and curating key findings on dedicated GitHub Wiki pages. Each entry is documented by name, date, and URL to ensure a consistent format. This knowledge base organises regional reports, country assessments, and conflict map statistics while synthesising economic indicators like job vacancies and income levels.

Layer 3: Assumption Justifications The third layer maps extracted findings to model assumptions, structured by mirroring the model's seven-factor decision-making architecture. Each entry details the chosen rule or parameter, its evidential justification, technical implementation via code, and a quality assessment. Following the Qualitative Uncertainty Qualification (UQual) framework [15], the EIKR explicitly evaluates data source quality and qualitative uncertainty for each assumption.

Layer 4: Model Artefacts The fourth layer contains the simulation components encoding these assumptions. This includes YAML and CSV input files for monthly safety levels, oblast-level socio-economic scores, and demographic distributions for agent generation. Python modules support these inputs by managing movement logic, household aggregation, and simulation orchestration.

ICCS Camera Ready Version 2026
To cite this paper please use the final published version:
DOI: 10.1007/978-3-032-29909-3_7

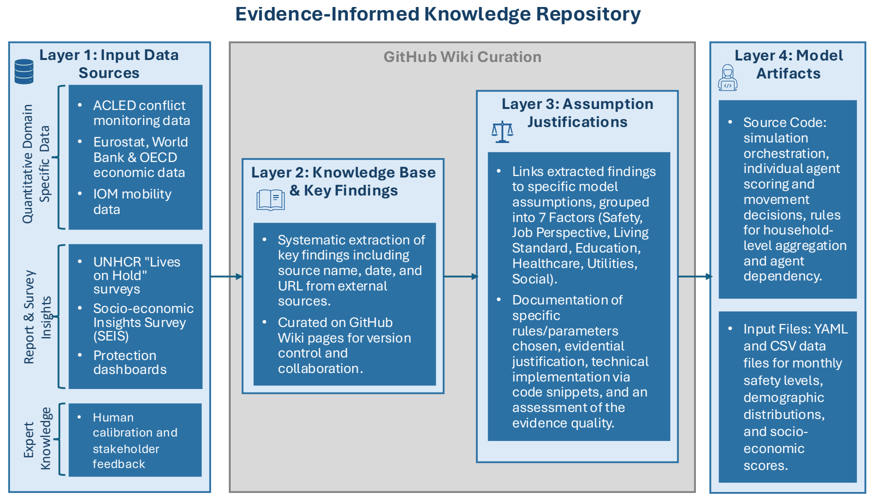

Fig. 1. The Four-Layer Architecture of EIKR. The primary forward flow of information is from raw external evidence (Layer 1) through systematic extraction and curation (Layer 2) and thematic justification of model parameters (Layer 3), culminating in the executable model artefacts (Layer 4). In operational use, this forward pipeline is complemented by iterative feedback from model behaviour and stakeholder review to update assumptions and evidence curation.

5 Conclusions

This paper presented the Expert-Informed Knowledge Repository (EIKR), a methodological framework designed to bridge the gap between academic agent-based modelling and operational humanitarian policy. By structuring the translation of qualitative expert knowledge into quantitative simulation parameters, we addressed the challenges of auditability, traceability, and trust that arise in high-stakes policy settings. In doing so, EIKR supported the evolution of the Homecoming model from a research prototype into a planning tool developed for UNHCR. While instantiated for Ukraine, this work is transferable and the EIKR serves as a general methodology for evidence curation and traceability. Future work will focus on further model refinement and on adapting the model for internal displacement.

Acknowledgments. This research was led by the Department of Computer Science, Brunel University of London, and supported by the UNHCR. The authors thank the Informal Advisory Board for their guidance and the University of Edinburgh's EPCC for providing ARCHER2 supercomputing resources and a vital technical audit. We are also grateful to the scientific reviewer for feedback that sharpened our methodology, and we acknowledge the SEAVEA toolkit for its role in managing large-scale simulations and uncertainty quantification.

Disclosure of Interests. The authors have no competing interests to declare.

ICCS Camera Ready Version 2026
To cite this paper please use the final published version:
DOI: 10.1007/978-3-032-29909-3_7

References

1. UNHCR: Global report 2022. Annual report, United Nations High Commissioner for Refugees, Geneva, Switzerland (2023), https://www.unhcr.org/sites/default/files/2023-07/2305336E_UNHCR-AR-2022_web_V3.pdf
2. UNHCR: Ukraine refugee situation: Operational data portal. https://data.unhcr.org/en/situations/ukraine (2024), accessed: 2024-05-22
3. Rahmati, S.H., Tularam, G.A.: A critical review of human migration models. Climate Change **3**(12), 924–952 (2017)
4. Alrababah, A., Masterson, D., Casalis, M., Hangartner, D., Weinstein, J.: The dynamics of refugee return: Syrian refugees and their migration intentions. British Journal of Political Science **53**(4), 1108–1131 (2023). https://doi.org/10.1017/S0007123422000667
5. Suleimenova, D., Bell, D.K., Groen, D.: A generalized simulation development approach for predicting refugee destinations. Scientific Reports **7**(1), 13377 (Oct 2017). https://doi.org/10.1038/s41598-017-13828-9, https://www.nature.com/articles/s41598-017-13828-9
6. Mehrab, Z., Stundal, L., Venkatramanan, S., Swarup, S., Lewis, B., Mortveit, H.S., Barrett, C.L., Pandey, A., Wells, C.R., Galvani, A.P., et al.: An agent-based framework to study forced migration: A case study of ukraine. PNAS nexus **3**(3) (2024)
7. United Nations High Commissioner for Refugees: Policy brief i forecasting refugee return to ukraine amid ongoing war and uncertainty. Reports and policy papers, UNHCR, Geneva, Switzerland (July 2025), https://data.unhcr.org/en/documents/details/117421
8. United Nations High Commissioner for Refugees: Policy brief no. 2: Forecasting refugee return to ukraine amid ongoing war and uncertainty. Reports and policy papers, UNHCR, Geneva, Switzerland (February 2026), https://data.unhcr.org/en/documents/details/120890
9. OECD: Ukraine's strategic response to the displacement crisis: Return, reintegrate, reconnect (2026). https://doi.org/10.1787/9b773da4-en, https://doi.org/10.1787/9b773da4-en
10. United Nations High Commissioner for Refugees: Ahead of the 4th Ukraine Recovery Conference, UNHCR shares new forecasting model and policy brief on future returns of Ukrainian refugees. UNHCR Ukraine Press Release (July 2025), https://www.unhcr.org/ua/en/news/press-releases/ahead-4th-ukraine-recovery-conference-unhcr-shares-new-forecasting-model-and, accessed: 2026-02-16
11. Ministry of Foreign Affairs of Ukraine, UNHCR: Joint briefing for the diplomatic community: Forecasting refugee returns and implications for Ukraine's recovery (February 2026), https://mfa.gov.ua/en/news/mzs-ta-uvkb-oon-proveli-spilnij-brifing-dlya-diplomatichnogo-korpusu
12. Mankins, J.C., et al.: Technology readiness levels (1995)
13. Groen, D.: Simulating refugee movements: Where would you go? Procedia Computer Science **80**, 2251–2255 (2016)
14. Tschalär, M., Xanthaki, A., Xanthopoulou, E.: Human rights risks of migration flow predictions and policy implications within the eu. Human Rights Quarterly **47**(1), 87–114 (2025)
15. Groen, D., Harbach, L.M.: On qualitative uncertainty in modelling assumptions. Journal of Computational Science **94**, 102782 (2026). https://doi.org/10.1016/j.jocs.2025.102782, https://doi.org/10.1016/j.jocs.2025.102782

ICCS Camera Ready Version 2026
To cite this paper please use the final published version:
DOI: 10.1007/978-3-032-29909-3_7