Social justice, governance, and citizen participation

Where will they settle? On the role of uncertainty and choice of algorithm for humanitarian decisions

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Abstract: Migration is among the most uncertain and contested topics for policymaking. The increasing number of migrants and refugees globally necessitates effective planning and management, particularly in addressing infrastructure needs such as access to healthcare. While efforts to accommodate a surge of refugees prioritise primary needs, improving structural access to essential infrastructure becomes imperative over time. However, the path-dependent nature of the expansion of refugee settlements poses challenges for infrastructure development. Existing facility location models for infrastructure planning overlook the interplay of infrastructure growth and human behaviour. This chapter presents a study on the interplay between the settling preferences of refugees (behaviour) and the location of healthcare facilities as essential infrastructure. We develop a data-based approach that combines an agent-based model representing decision behaviour with facility location optimisation models for infrastructure planning. Through a case study of Cox's Bazar, Bangladesh, home to over 1 million Rohingya refugees, we demonstrate the implications of different optimisation approaches and thereby explore how and in how far digital tools influence policymaking on one of the most contested and uncertain topics in the current policy landscape. Our findings underscore the importance of integrating uncertainty about human behaviour in infrastructure decisions.

Keywords: refugee settlement, healthcare, optimisation, complex systems, agent-based model, adaptation, digitalisation

1. Introduction

Migration is a substantial driver of population change and, thereby, policy change. It has been shown that the uncertainties associated with migration have a major impact on population forecasts and the assumptions underlying many policies (Azose et al., 2016). One of the most important drivers of migration is geopolitical conflicts and wars. The worldwide refugee crisis has reached unprecedented levels, with a record number of more than 108 million people who have been forced to flee their homes in 2022.[1] Sure enough, forced migration and refugee streams pose important challenges to host communities and countries. A surge of refugees owing to geopolitical conflict presents major uncertainty for planning and policymaking. For instance, the war in Ukraine has led to about 6 million refugees, mostly seeking protection in the EU.[2] Similarly, after more than a decade of conflict, more than 14 million Syrians have been forced to flee their homes.[3]

The example of refugee camps serves here to demonstrate the interplay of behavioural uncertainty and planning decisions, paradigmatic for many policy decisions in the migration space. By using the case study of the Rohingya refugee camps in Bangladesh, we show how digital tools can be used to conceptualise and capture behavioural uncertainty. Given the increasing push for digital tools and automated decisions, especially in highly complex and uncertain conditions, we also discuss how digital tools for planning and policymaking influence and drive the emergence of structural patterns in migration (crises) and how the different objectives that are embedded in the algorithm shape the emergence of different access conditions.

2. Case study: Rapidly expanding refugee camps

Today, about 23 million refugees live in camps, where refugees are provided with essential services and goods, including water, food, shelter, emergency relief items, and healthcare. Humanitarian responders and NGOs alike strive to address these primary needs but often face resource limitations, especially if there is a rapid and massive influx of refugees. Host states, especially developing countries with limited resources, struggle to provide essential services, leading to environmental degradation and strained infrastructure (Fransen et al., 2024).

Given the rapid influx of people in need, refugee settlements often emerge and grow ad-hoc, driven by the initial settlement choices of refugee groups. Several studies use remote sensing and satellite imagery to understand how camps grow (Bjorgo, 2000), including infrastructure growth

1 see UNHCR Global Trend Report 2023
2 https://data.unhcr.org/en/situations/ukraine
3 https://www.unrefugees.org/news/syria-refugee-crisis-explained/

(Tomaszewski et al., 2016). For instance, as refugees settle close to those with similar backgrounds, new settlements often emerge where they cluster together. Much less is known, however, about how planning algorithms and digital tools, combined with the accessibility of infrastructure, influence the growth of refugee settlements and how, in turn, this growth impacts the expansion of infrastructure, see Figure 1.

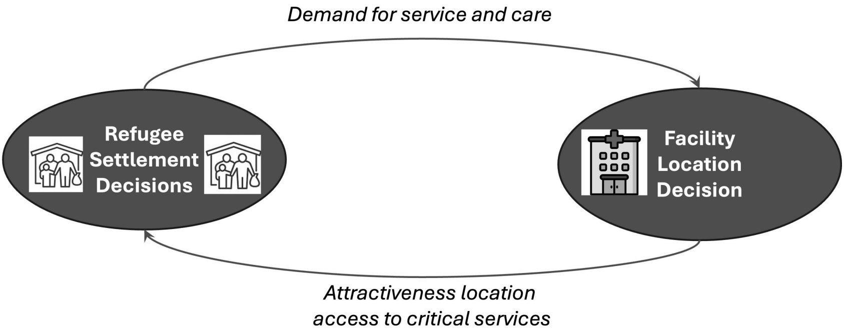

Figure 1. The interplay between settling decisions of refugees and facility location decisions

Traditionally, refugee camps have been viewed as temporary locations providing emergency shelter and services (Jahre et al., 2018). Standards such as the Sphere standards[4] provide guidance on the space requirements and service levels. However, many refugee camps are becoming permanent homes for their inhabitants (Hermans et al., 2017), and it has been argued that these settlements should rather be considered 'cities' instead of 'camps' (Montclos & Kagwanja, 2000). Nevertheless, because of the assumed short-term nature of the camps, the need for further growth or adaptation is neglected when camps are established. Initial efforts for camp design and management prioritise meeting urgent and primary needs. This is in line with other findings around crisis response (Comes et al., 2020) or resilient urban planning (Krishnan et al., 2024).

Over time, however, the demand for services and infrastructure has expanded. For example, in the Rohingya refugee camps in Cox's Bazar, Bangladesh, the percentage of refugees that indicated more attention should

4 https://www.spherestandards.org

primarily be given to healthcare increased from less than 6% in 2018[5] to 44% in 2019.[6] However, the high population density and limited space in camps limit the available locations for healthcare facilities. The lack of guidelines for long-term adaptation and the uncertain impacts of climate change further compound the challenges.

We argue that refugee settlements can be understood as complex adaptive systems in which the decisions of individual actors and the infrastructural decisions co-evolve (cf. Figure 1). In the following, we investigate the role of the digital tools and algorithms that are used to support the planning decisions in this interplay.

5 https://data.humdata.org/dataset/iom-bangladesh-needs-and-population-monitoring-npm-round-13-site-assessment

6 https://reliefweb.int/report/bangladesh/iscg-situation-report-rohingya-refugee-crisis-cox-s-bazar-10-january-2019-covering

Figure 2. The layout of camps 14, 15, and 16 in Cox's Bazar, including healthcare facilities. Data retrieved from IOM Geoportal (https://iom.maps.arcgis.com/home/index.html)

As one of the central infrastructures that exhibits a growing need, we focus on healthcare. To illustrate our approach, we develop a case study for the camps Hakimpara, Jamtoli, and Potibonia (camps 14, 15, and 16) in Cox's Bazar (see Figure 2), one of the world's largest refugee settlements. The camps appeared after the outbreak of the Rohingya crisis in August 2017, when the government of Bangladesh allocated undeveloped forest land for these camps in September 2017. Camps 14 and 15 were first mentioned in site assessments in September 2017, followed by camp 16 in October of the same year.[7] The two main camps (Kutupalong and Balukhali) already existed, and many NGOs had been providing healthcare in these camps for years before 2017. Therefore, by the time the situation reached emergency level 3, the necessary infrastructure was there to perform monthly needs assessments for the population in all camps. This also happened in the new camps 14, 15, and 16, resulting in regular situation reports. As camps 14 and 15 were first assessed in September 2017, this research uses data from September 2017 until June 2019.

3. Research approach and models

We start from the premise that migration and refugee settlements are both planning and social problems. To simulate the interplay of human settlement behaviour and infrastructure planning, we combine an agent-based simulation model to explain camp expansion patterns with optimisation models for facility location. Figure 3 provides an overview of three main modelled processes: camp expansion, healthcare use and the creation of new facilities (along with their location), and the interplay of behaviour and planning. The camp expansion and healthcare use cover refugee behaviour, whereas the facility creation falls under the realm of planning and policy problems. By connecting both realms, we can analyse how they interact. The source code of all models and the underlying datasets are available on GitHub: https://tinyurl.com/RefugeeSettlement.

The refugee decisions on shelter locations and healthcare provider decisions on healthcare facility locations are implemented in an agent-based model to study the emergent camp expansion. Various scholars acknowledge that the emergence of camps should be regarded as a process (Augustijn-Beckers et al., 2011; Ligmann-Zielinska & Sun, 2010). Therefore, the design of a camp should also be viewed as a process with no definite end state (Kennedy, 2008), which is reflected in the process diagram in Figure 3. Okyere et al. (2021) add that this process can be understood in terms of refugee settling choices. Hence, the emergence of the camp, resulting from the collective behaviour of all agents, can be researched through experiments in an agent-based model (Anderson et al., 2006). Our model follows earlier studies on the formation of informal settlements (Collins &

7 https://reliefweb.int/report/bangladesh/bangladesh-humanitarian-response-plan-september-2017-february-2018-rohingya

Frydenlund, 2016; Hofmann et al., 2015; Suleimenova et al., 2017). These models are effective in imitating settlement behaviour but neglect how the settlement choices were affected by the presence or lack of access to infrastructure, such as healthcare facilities (Hofmann et al., 2015).

To understand the impact of digital tools for planning and decision support, two different optimisation approaches are tested as tools to support the location decision health facilities: facility location optimization problems, and p-median and maximum coverage problems. Increasingly, approaches to support or even automate decisions are introduced in crisis management and humanitarian crisis response (Comes, 2024; Coppi et al., 2021). While there is a discussion on the use of principles, trustworthy, transparent, or explainable tools or AI, the implications of using different optimisation approaches have barely been explored.

Determining the (best) location of healthcare facilities falls under the category of facility location problems (FLPs), optimisation problems that involve a location decision for a facility that serves a number of demand centres with a certain demand level for the lowest possible effort or cost (Melo et al., 2009). Facility location decisions can be used to assess the location of a camp as well as the specific location of separate facilities within a camp, such as medical or educational facilities (Cilali et al., 2021).

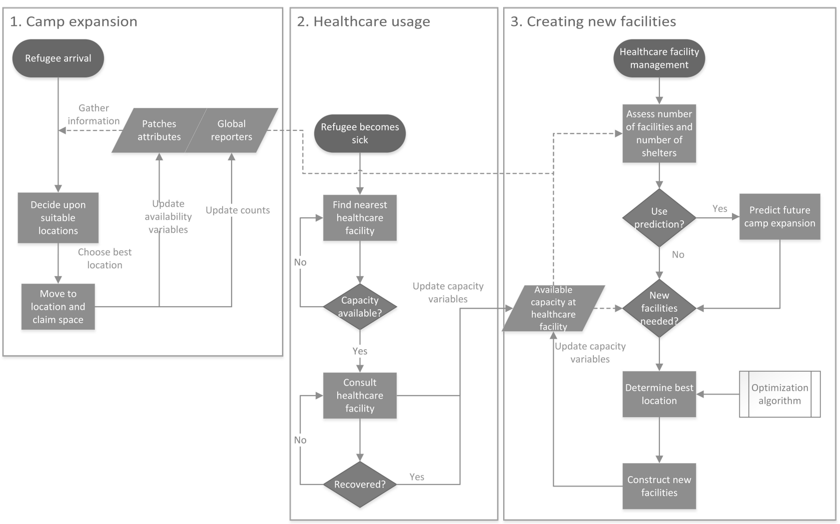

Figure 3. Flow diagram of the three main processes: camp expansion, healthcare usage, and creation of new healthcare facilities

To analyse the implications of using different digital tools, we here use the p-median and the maximum coverage problems, which are prominent approaches in location planning for humanitarian logistics (Ayudhya, 2020; Balcik & Beamon, 2008; İbrahim Miraç & Eren, 2020). For a recent review of humanitarian facility location problems under uncertainty, see Dönmez et al. (2021). Therefore, we investigate their implications to understand the choice of algorithm for infrastructure planning under uncertainty. The p-median approach aims to minimise the average demand-weighted travel distance, in our case, between shelters and healthcare facilities. The maximum coverage approach aims to maximise the number of shelters covered by the capacity of a healthcare facility. Here, we use a radius of 400 m.

To understand the influence of uncertainty, we test whether using predictions about future camp expansion based on the settling preferences of refugees improves the results of the planning algorithms. If future predictions are used, healthcare providers can adapt their location decisions to the settling preferences of refugees. Simultaneously, the placement of new facilities designed for expected camp expansion can affect the settling choices of refugees. This interplay is analysed in this research and applied in an approach for decision-making on healthcare facility locations.

The effect of location decisions is measured in the accessibility of healthcare facilities. While we acknowledge that there are many social, cultural, and financial factors that determine access to healthcare (Dawkins et al., 2021), we focus here primarily on physical factors: capacity of the facility and waiting and travel times as primary barriers that are especially relevant in refugee settlements (Aylett-Bullock et al., 2022). The accessibility is determined using four indicators: (i) the travel distance between shelters and healthcare facilities, (ii) the ratio of refugees allocated to a healthcare facility that has sufficient capacity to cover all allocated demand, (iii) capacity shortages across all facilities, and (iv) the ratio of patients who are waiting for treatment over the unused capacity. These first two indicators measure the accessibility of healthcare, and the latter two provide insight into the distribution of healthcare facilities throughout the camp.

4. Results: The interplay of refugee behaviour and location decisions

Regarding the location decisions of healthcare providers, both location optimisation methods have been found to be effective in achieving accessible healthcare for the camp inhabitants in terms of Sphere standards. For the p-median problem, refugees are mostly not adapting their settlement choices successfully: their settling choice to the located healthcare facilities does not improve the overall accessibility of healthcare facilities. For the maximum coverage problem, adapting settling choices by refugees increases the accessibility of healthcare facilities.

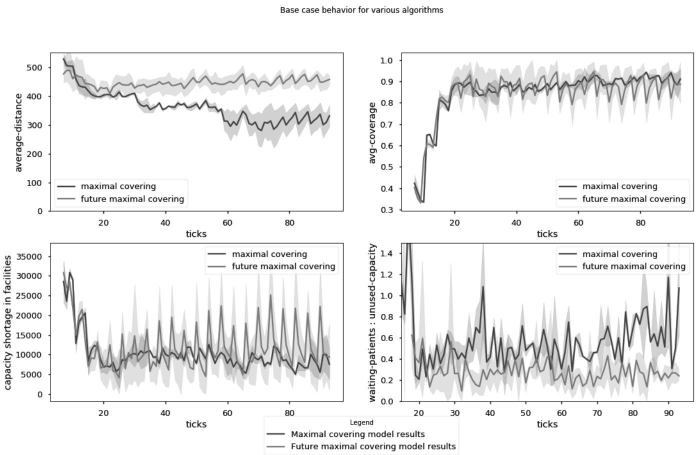

Figure 4. Impact of future predictions on KPIs when the focus lies on maximising equal allocation of healthcare for all shelters (max coverage problem)

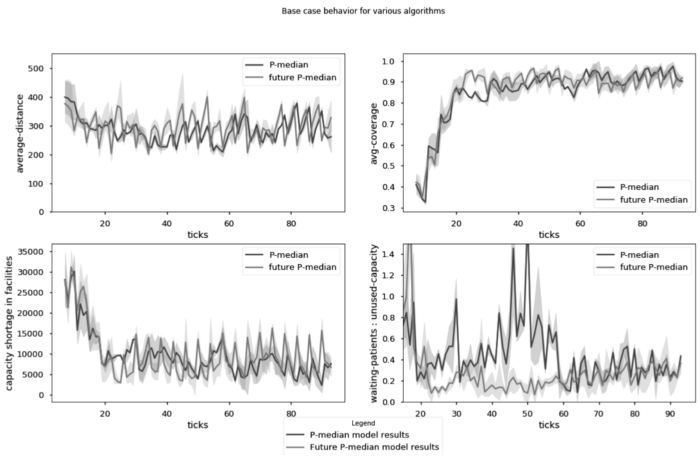

Figure 5. Impact of future predictions on KPIs when the focus lies on minimising the average travel distance to healthcare facilities (p-median problem)

Figures 4 and 5 show the difference between the results when distinguishing between the models that take future camp expansion into account while placing facilities (orange lines), the models that do not consider future expansion (blue lines) for the p-median problem (Figure 5), and the maximum coverage problem (Figure 4). For each algorithm, the indicator that is subject to the optimisation shows bigger fluctuations when future predictions are included. In Figure 5, this can be seen in the average distance results, and in Figure 4, this can be seen in the average coverage results.

Interestingly, including future predictions does not seem to lead to a significant improvement in the results. Moreover, the average distance between facilities and shelters is much higher with predictions for the p-median problem: the distance stabilises between 400 and 500 metres, while the model *without* future predictions returns results between 250 and 400 metres. For the maximum coverage problem, there is no such significant difference found.

This finding implies that when refugees can choose a location to settle upon arrival in a refugee camp, facility location optimisations improve when taking expected camp expansion into account. Thus, the expected camp expansion should be determined based on the settling preferences of refugees. However, if refugees *cannot* choose their settling location, the inclusion of expected camp expansion in the facility location optimisation does not improve the resulting accessibility of healthcare facilities. In other words, *if behavioural uncertainties exist and shape the expansion of the camp, the results improve when these uncertainties are integrated into the model.*

Naturally, behaviour is associated with uncertainty. Therefore, our next experiment explores the role of prediction accuracy in the results. Figure 6 shows the impact of predictions about future camp expansion with high or low prediction accuracy. The number of predicted shelters always equals 20 in these runs. It appears that a higher prediction accuracy can decrease the average distance in both algorithms. This effect is small for the p-median problem but is considerable (around 10%) for the maximum coverage problem. Simultaneously, the ratio of waiting patients over the unused capacity is slightly higher in the models with 100% prediction accuracy. This result means that the number of waiting patients is slightly higher or that the unused capacity is lower in these models.

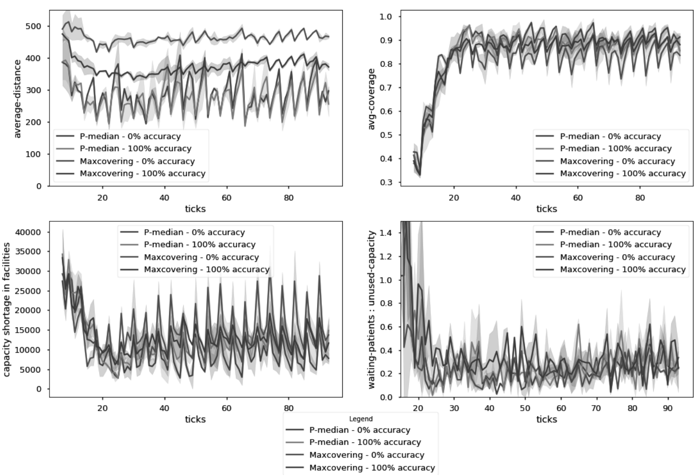

Figure 6. Effect of varying the prediction accuracy of new shelters while optimising facility locations for both algorithms and varying levels of accuracy and uncertainty

5. Conclusions

This research represents a first attempt to explore the interplay between refugee behaviour and health facility location decisions in refugee settlements and review the role of digital tools and planning algorithms and the impact of foresight. We first showed that the choice of algorithm, especially the ambitions and objectives that the algorithm represents, has a major impact on access to infrastructure and also on the expansion and growth of a settlement (Figures 4 and 5). Second, we show that taking into account behavioural uncertainty matters, especially if populations have freedom of choice. Third, Figure 6 shows that prediction accuracy has a significant influence, especially on travelling distances.

The findings directly highlight the importance of considering settlement choices made by refugees in optimising healthcare accessibility. By using two of the most popular facility location algorithms in humanitarian problems (p-median and maximum coverage), we also show that the choice of the specific optimisation algorithm has an important impact on performance. In sum, these results show that the digital tools (algorithm chosen and foresight accuracy) impact the quality of access and the emergence of camp infrastructures, as highlighted in Figure 7. This result is especially important given the current move in the humanitarian sector to increasingly use digital tools to support or fully automate decisions (Comes, 2024).

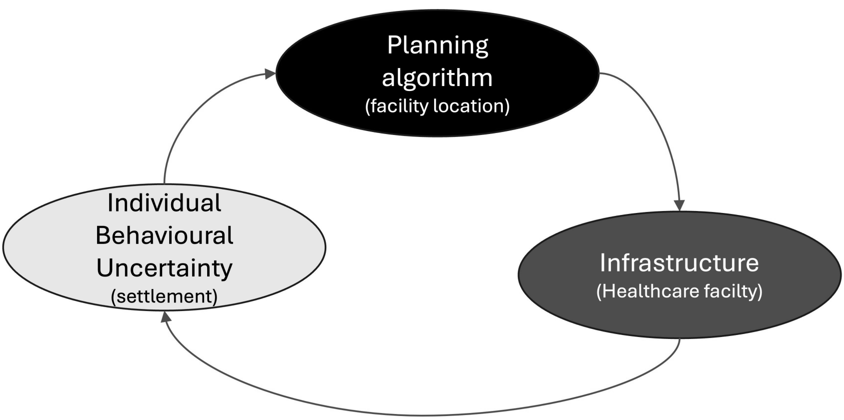

Figure 7. On the role of digital algorithms and planning tools in social-technical systems

This study has some limitations that warrant further investigation. Future work could explore scenarios and contexts and examine alternative strategies for healthcare facility location optimisation. Additionally, incorporating a broader range of healthcare quality and performance indicators, exploring dynamic capacity considerations, improving the accuracy and complexity of predictions for camp expansion, and adding additional vital infrastructures would enhance the modelling framework.

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