

¹ patientflow: a Python package for real-time prediction
² of hospital bed demand from current and incoming
³ patients

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DOI: [10.xxxxxx/draft](https://doi.org/10.xxxxxx/draft)

Software

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⁹ patientflow: a Python package for real-time predictions of hospital
¹⁰ bed demand from current and incoming patients

¹¹ Summary

Editor: [Open Journals](#) 

Reviewers:

- [@openjournals](#)

Submitted: 01 January 1970

Published: unpublished

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²² Statement of need

Hospital bed managers monitor whether they have sufficient beds to meet demand. At specific points during the day they predict numbers of inpatients likely to leave and numbers of new admissions. These predictions are important because, if bed managers anticipate a shortage of beds, they must take swift action to mitigate the situation. Commonly, bed managers use simple heuristics based on past admission and discharge patterns. Electronic Health Record (EHR) systems can offer superior predictions, grounded in real-time knowledge about patients currently in the hospital.

Many studies demonstrate the use of EHR data to predict individual patient outcomes, but few harness such predictive models to methods for estimating aggregate outcomes for cohorts of patients. In the context of predicting bed demand, it is this aggregate level that is most meaningful for bed managers (King et al., 2022). Note that by design, we provide methods to estimate unfettered demand for beds to inform decision-making (Worthington et al., 2019).

This package is intended to make it easier for researchers to create such predictions. Its central tenet is the structuring of data into ‘snapshots’ of a hospital, where a patient snapshot captures what data are available on a current patient’s state at a specific moment, and a cohort snapshot represents a collection of patient snapshots, for aggregate predictions. Notebooks

39 in the Github repository demonstrate how to use the package to create patient and group
40 snapshots from EHR data. Once data is structured into snapshots, researchers can use their
41 own patient-level models with our analytical methods to produce cohort-level predictions. The
42 package provides tools to compare predicted distributions against observations.

43 Our intention is that the patientflow package will help researchers demonstrate the practical
44 value of their predictive models for hospital management. Notebooks in the accompanying
45 repository show examples based on fake and synthetic data (King et al., 2024b). Researchers
46 also have the option to download real patient data from Zenodo to use with the notebooks
47 (King & Crowe, 2025). The repository includes a fully worked example of how the package
48 has been used in a live application at University College London Hospital to predict demand
49 for emergency beds. Detailed examples illustrating the features of the package applied to
50 predicting demand for emergency beds are available in a series of Jupyter notebooks (King et
51 al., 2024a).

52 Related software

53 Simulation is a common approach for modelling patient flow, and there are various packages
54 to support that, such as PathSimR for R (Tyler et al., 2022) and sim-tools (Monks & Harper,
55 2023) and ActaPatientFlow (Szabó et al., 2024) for Python.

56 To our knowledge, there are no packages that support the use of real-time patient data with
57 a specific focus on output that can help healthcare managers respond to changes as they
58 arise. Our intention for patientflow is to support the development of patient level predictive
59 models and the use of real-time data, combined with a mathematical approach to calculating
60 distributions of aggregate demand. Taking a mathematical approach provides quicker and
61 more accurate results than deploying simulation for the same task.

62 Acknowledgements

63 The PyPi template developed by Tom Monks inspired us to create a Python package. This
64 repository is based on a template developed by the Centre for Advanced Research Computing,
65 University College London. We are grateful to Lawrence Lai for creation of the synthetic
66 dataset.

67 The development of this repository/package was funded by UCL's QR Policy Support Fund,
68 which is funded by Research England.

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