# Exploring financially sustainable initiatives to address out-of-area placements in psychiatric ICUs: a computer simulation study

Simon J Moss[1], Christos Vasilakis[2], Richard M Wood[1,2]

[1] Bristol, North Somerset and South Gloucestershire CCG, UK National Health Service.
[2] School of Management, University of Bath.

Correspondence to: Dr RM Wood; BNSSG CCG, South Plaza, Marlborough Street, Bristol, BS1 3NX, United Kingdom; richard.wood16@nhs.net.

Article accepted for publication by the Journal of Mental Health (4th May 2022)

# Exploring financially sustainable initiatives to address out-of-area placements in psychiatric ICUs: a computer simulation study


**Abstract**

**Background**: Transferring individuals for treatment outside their geographic area occurs when healthcare demand exceeds local supply. This can result in significant financial cost while impacting patient outcomes and experience.

**Aims**: The aim of this study was to assess initiatives to reduce psychiatric intensive care unit (PICU) out-of-area bed placements within a major healthcare system in South West England.

**Methods**: Discrete event computer simulation was used to model patient flow across the healthcare system's three PICUs. A scenario analysis was performed to estimate the impact of management plans to decrease admissions and length of stay. The amount of capacity required to minimise total cost was also considered.

**Results**: Without increasing in-area capacity, mean out-of-area bed requirement can be reduced by 25.6% and 19.1% respectively through plausible initiatives to decrease admissions and length of stay. Reductions of 34.7% are possible if both initiatives are employed. Adjusting the in-area bed capacity can also lead to aggregate cost savings.

**Conclusions**: This study supports the likely effectiveness of particular initiatives in reducing out-of-area placements for high-acuity bedded psychiatric care. This study also demonstrates the value of computer simulation in an area that has seen little such attention to date.



***Keywords:*** *Systems modelling; Computer simulation; Psychiatric intensive care*

## 1. Introduction

Many high-income countries can now attribute a substantial and increasing proportion of government healthcare funding to mental health. In recent years, this has been estimated at 7.8% in Australia (Australian Government, 2021), 7.2% and 8.2% in Canada and the USA respectively (Vigo et al, 2018), and 14.0% in the UK (National Health Service England, 2021). Despite this level of spending, mental health services have struggled to meet the needs of the population, with performance suffering across a range of metrics (Corscadden et al, 2019; Minichino et al, 2019; Moroz et al, 2020). One particular challenge is matching variable and unpredictable demand for admitted mental healthcare with local supply. Where this is not possible, patients may be sent for treatment outside the geographic area of their usual residence.

Out-of-area mental health placements result in worse patient outcomes and can be financially costly, particularly for the healthcare provider having to send the patient out of area (Healthcare Quality Improvement Partnership, 2015; Galante et al, 2019). A recent study estimated that out-of-area placements may cost up to 65% more than admitting those same individuals to local services (Brooker & Brown, 2015). As well as being disruptive to the patient and family, transport and travel can represent a significant additional cost to healthcare providers (Norfolk and Suffolk NHS Foundation Trust, 2019). As a result, the reduction in out-of-area mental health placements has been a priority for many healthcare systems, including England's National Health Service (NHS England, 2019) which has continued to see elevated use of out-of-area placements (BMJ, 2021) despite an earlier pledge to end the practice by April 2021 (UK Department of Health and Social Care, 2016). Other countries have attempted to reduce the need for out-of-area placements through considering reductions to the referral rate and length of stay of mental health placements (Paton & Tiffin, 2018), setting up temporary admission units (Mulder et al, 2007), and increasing permanent acute capacity (Allison et al, 2018).

The issue of sending patients for treatment outside their geographic area is particularly problematic for psychiatric intensive care, given the high acuity of patient need, the consequences for delayed transfer and admission to patient outcome, and significant resource costs (Dolan & Lawson, 2001; Haw et al, 2017; Pereira et al, 2005). Psychiatric Intensive Care Units (PICU) are low-capacity, highly-staffed, specialised wards, designed to treat acute challenging psychotic behaviour (Brown & Bass, 2004). Patients are typically referred into a PICU from adult acute mental health services. Within a PICU, service users are supported by multidisciplinary teams who manage a range of health and care needs and jointly assess risk (Dolan & Lawson, 2001; National Association of Psychiatric Intensive Care & Low Secure Units, 2018). Individuals being referred onward from PICU typically re-enter an adult acute mental health inpatient unit or similar setting, while others are referred to forensic mental health services, rehabilitation services, the criminal justice system or community mental health services (Dolan & Lawson, 2001).

In this study, we investigated the ability to reduce out-of-area PICU placements in a major healthcare system in South West England. Assuming no change to the in-area bed allocation, we sought to estimate the likely effect of reductions to PICU admissions and length of stay on the out-of-area bed requirement. Also of interest was the extent to which changes to the allocated PICU capacity could reduce the costlier out-of-area placements, and thus reduce net costs borne by the healthcare system.

Real-life implementation of such initiatives would require considerable system-wide coordination (e.g. additional specialist mental health capacity may be needed to reduce PICU demand) and would come at potentially significant risk (the possible effect on costs and performance would be largely unknown). Also, only a single intervention could be explored at a time, and it could take many months to gather and analyse data on its impact. In part for these reasons, we used computer modelling and simulation to estimate the possible effect of a range of scenarios, without having to implement any in real life. Specifically, we build a computer simulation model to appropriately account for existent variability in arrivals and lengths of stay, and to provide distributions as well as averages for key output metrics such as bed occupancy. Our aim was for the results of the scenario analysis to furnish managers with the necessary insights regarding the possible financial and operational effects on PICU, which in turn, would help assess viability and the need for further examination of any system-wide coordination and resources that may be necessary.

### *1.1 Modelling in healthcare*

In attempting to understand complex healthcare issues, weighing up competing interests of evidence-based practice, patient outcomes and fiscal constraints, systems modelling and computer simulation have increasingly been used by researchers and analysts (Noorain et al, 2019). These models allow analysts and decision makers to consider the likely impact of complex interactions between different components of a healthcare system or pathway (Pitt et al, 2016). Several reviews have explored the application of modelling and simulation in healthcare, with some studies noting the increasing volume of literature and the increasing specificity of healthcare applications (Fone et al, 2003).

Early literature related to modelling in healthcare focussed on patient flows in outpatient clinics and hospitals (Hearn & Bishop, 1970; Fries, 1979). This work also notes issues in relation to the implementation of simulation model outputs, as well as the applied use of modelling within healthcare (Günal & Pidd, 2010; Fone et al, 2003). However, recent literature has demonstrated a focus on the application of modelling and simulation and its outputs within healthcare. These include case studies relating to the application of simulation modelling in different areas of health care, such as critical care (Griffiths et al, 2010), emergency departments and outpatient clinics (Jun et al, 1998) to name a few. Existing literature also covers the adoption and implementation of simulation models and their outputs across a variety of healthcare systems (Brailsford et al, 2011), as well as improving stakeholder engagement in relation to simulation modelling in healthcare (Kotiadis, K., Tako, A. A., & Vasilakis, C. (2014)).

The most common approach to computer simulation is Discrete Event Simulation. DES models the pathway or system as a series of ‘events’ that occur over time, assuming no change to the pathway or system between events (Gunal and Pidd, 2010). It has been used extensively, for example, to model emergency departments in the UK (Mohiuddin et al, 2017), improving the design and organisation of neonatal care networks (Allen et al, 2015), and evaluating strategies of red blood cell provision following mass casualty events (Glasgow et al, 2018)

### *1.2 Modelling mental health services*

Existing literature has noted that the gap between demand for mental health services and service delivery provides a ‘unique opportunity’ for the application of simulation modelling in supporting the provision of patient-centered and evidence-based mental health services (Long & Meadows, 2018). Despite this, modelling of mental health services has largely been overlooked when compared to modelling of physical health services (Günal & Pidd, 2010; Noorain et al, 2019). Previous literature related to mental health modelling has explored service operations at a prison and forensic facility, making use of the system dynamics modelling method (Smith et al, 2004) while other studies have modelled outpatient and inpatient services for an adult mental health centre (Smits, 2010; Murch et al, 2021).

Previous literature demonstrates the use of DES in modelling the treated course of schizophrenia (Heeg et al, 2005), as well as studying the flow of patients with serious mental health conditions between acute and residential bedded facilities (Kuno et al, 2005). A variety of benefits of applying DES to complex mental health pathways have also been noted, including model flexibility, the ability to capture relevant interdependencies, and enabling decision-makers to test and consider hypothetical scenarios or alternative solutions without the associated levels of risk (Jun et al, 1998, Heeg et al, 2008).

Paton and Tiffin (2018) modelled out-of-area admissions for mental health patients by using DES to create a ‘virtual mental health ward’. The impact of assuming different referral rates into the unit and different lengths of stay was evaluated, with both parameters being altered in order to determine whether the combined impact of reduced referrals and length-of-stay could plausibly achieve lower rates of out-of-area placements.

While there have been efforts to highlight the role of modelling and simulation in mental health services, literature detailing the modelling of PICUs is limited. Within detailed reviews in this area, such as that of Long & Meadows (2018), there is no consideration to PICUs. However, there is a body of literature relating to the modelling of other types of ICU. Reviews into the use of DES in healthcare (Günal & Pidd, 2010) have cited examples of studies related to nursing requirements in an ICU (Griffiths et al, 2005), patient flow in an ICU when bed allocation is reduced (Cahill & Render, 1999) and, more recently, capacity (Wood et al, 2020) and triage criteria considerations in the context of the pandemic (Wood et al, 2021). Meanwhile, there is also literature relating to the modelling of ICUs which share similar characteristics to PICU, such as neonatal intensive care units. System dynamics modelling has been utilised in attempting to understand patient flow through these units (Demir et al, 2014) as well as the impact of length of stay reduction on performance improvement (Lebcir & Atun, 2020). These high impact uses of simulation modelling in different intensive care and mental health settings demonstrate the potential of applied modelling and simulation in psychiatric mental health services.

## 2. Materials and methods

### *2.1 Study setting*

The setting of this study was a major healthcare system located in South West England, covering a one million resident population across a mixture of large metropolitan areas and rural and coastal locations. A higher proportion of younger individuals reside in the main city, which also has a more culturally and ethnically diverse demographic. Rural and coastal areas contain a greater proportion of older individuals and pockets of severe deprivation. Overall, the age profile is similar to that of England. The system has a single Clinical Commissioning Group (CCG) that oversees the organisation and procurement of taxpayer-funded healthcare activity. Within the area, there are approximately 80 general practices, two acute hospital trusts, a single community services provider, and a single specialist mental health provider.

Various types of mental health related care are available for meeting the different needs of the population. These range from community support, through primary care and voluntary services, to highly specialist care. The focus of this study is psychiatric intensive care, which is provided through three small but highly staffed psychiatric intensive care units (PICUs). PICU 1 has six beds available for male patients in the area, PICU 2 has eight beds available for female patients, and PICU 3 has 12 beds available for male patients. Service users are normally aged 18-65 and cannot typically be managed on acute inpatient wards due to the level of risk posed to themselves and/or to others. PICU referrals are typically from acute mental health services or the criminal justice system, with PICU discharges returning patients to these settings as well as to forensic mental health services, community mental health services, and rehabilitative care.

Consent for this study was granted by the CCG and the relevant system groups, who sponsored and supported the work. Given the use of suitably anonymised data (i.e. no NHS numbers or patient names, addresses, or dates of birth), no specific ethics approval was required for this study.

### *2.2 Computer simulation*

Computer simulation was used to model patient flow through each of the three PICUs. The study made use of a versatile open-source discrete event simulation tool developed within the authors' organisations and previously used to model acute stroke service centralisation and operation of a COVID-19 mass vaccination centre (BNSSG Analytics, 2019; Wood et al, 2021). The tool implements the established 'three phase' method to stochastic simulation (Pidd, 1998), whereby discrete events are generated according to a schedule in which the next unconditional event (referral arrival or patient discharge) is executed alongside any associated conditional events (admission of waiting patient, provided a bed is available).

In accounting for realistic conditions throughout the simulation period, each simulation starts following a warm-up period to ensure stability prior to the data collection period. This warm-up period was set to 100 days, based on the outputs of trial simulations suggesting such a duration was sufficient for steady state to be reached. The full simulation period, from which results were harvested, was set to 365 days. Full results were obtained by performing 10,000 replications of the simulation, each starting with a different random number seed used to generate the random timing of referral arrivals and patient lengths of stay at each PICU. Bed occupancy was not restricted within any of the simulations.

Each of the three PICUs were modelled separately through this approach. To perform each simulation, the only required inputs are the distribution of arrivals (admissions) at the PICU and the distribution of patient length of stay at the PICU – each of which is defined by the probability distribution and the corresponding parameters. Length of stay (LOS) is from the point of arrival (admission) until ultimate discharge (i.e. not readiness for discharge). For each PICU, the model requires a single LOS distribution and does not distinguish between in-area and out-of-area LOSs. As mentioned, bed occupancy is assumed unrestricted, meaning that a placement (in-area or out-of-area) will always be found for an arriving patient, and the patient will not have to wait for admission.

Simulation output measures were chosen in close collaboration with the multidisciplinary project delivery group and stakeholders with responsibilities for reducing out-of-area PICU placements in the region. Specifically, these were the percentage of time at which at least one patient is placed out-of-area, the total mean bed occupancy for in-area and out-of-area placements, and the mean out-of-area bed requirement.

### *2.3 Baseline scenario and validation*

The *Baseline* scenario reflects the configuration of psychiatric intensive care services within the area at the time of the study. In order to avoid any non-recurrent effects of the COVID-19 pandemic, data from Financial Year 2019 was used to inform the *Baseline* scenario. Specifically, data for regional PICU admissions and out-of-area placements, taken from the local specialist mental health providers' Monthly Activity Report (MAR), were used to estimate the Poisson-distributed PICU arrival rates. Meanwhile, historical individual-level PICU admissions data – obtained via a specific request to the same provider – were used to estimate PICU LOS. Various statistical distributions (exponential, lognormal, gamma, Weibull) were fitted to the LOS data for each of the three PICUs, with a lognormal distribution found to offer the best fit (as assessed by the Akaike Information Criterion) for each of the three units (Table 1). Note that the estimated LOS is in line with observed in other PICUs, with Haw et al (2017) previously reporting a 22-day median LOS for two PICUs in the UK.

[Insert Table 1 near here]

Face validity was established through regular presentations of the model and its outputs to various healthcare system stakeholders working in psychiatric mental health services, including clinicians, managers and analysts from both the CCG and specialist mental health provider. Model parameters were established, revised and checked during this process, ultimately resulting in a consensus among the project delivery group that both inputs and outputs were of reasonable accuracy.

Additional validation was obtained through ascertaining that outputs of the model were reasonably aligned to other data not used in its calibration. Under the *Baseline* scenario, the model estimated that approximately 12 out-of-area beds would typically be required (Table 2). Bed occupancy data unseen by the model revealed that a mean of approximately 10 out-of-area beds was required at any time during Financial Year 2019 (i.e. the same period of time as the model inputs were sourced). This difference was determined to be tolerable by the project delivery group.

### *2.4 Other scenarios*

First, assuming no change to in-area PICU capacity, three scenarios were modelled to examine the effectiveness of initiatives to decrease the out-of-area bed requirement through reducing admissions and length of stay (Table 2). The scenarios were co-produced with operational and clinical stakeholders working within psychiatric intensive care services. In the initial phases of the study, during which the baseline position was established, regular meetings were held with data and business intelligence analysts and managers to identify appropriate data sources relevant to the model input parameters. After presenting the baseline model at a regional workshop, further multidisciplinary meetings were held to develop the additional scenarios.

Second, for measuring the possible cost implications associated with changes to the allocated in-area capacity, it was necessary to quantify the cost ratio for out-of-area vs in-area PICU placements. Given that no estimate could be found within the relevant literature and no local data was available, modelling was based upon the aforementioned 65% uplift found for acute (non-PICU) mental health placements (Brooker & Brown, 2015). However, to appreciate uncertainty in this figure upon application to PICU services, a range of values were considered (1.25, 1.45, 1.65, 1.85, 2.05). Relative total costs were calculated by summing the in-area cost, given by the number of allocated in-area beds, and the out-of-area cost, given by the product of 1.65 and the mean number of out-of-area beds required. Thus, high total costs would result when either the in-area allocation is too small, and there is an overreliance on costlier out-of-area placements, or when the allocation is set too high, and the paid-for in-area capacity is under-utilised. The precise balance will depend on the cost ratio and the distribution of (in- and out-of-area) bed occupancy.

## 3. Results

### *3.1 Modelling with constrained in-area PICU capacity*

The estimated performance measures are summarised in Table 2 for the baseline and three additional scenarios assuming no changes to in-area PICU capacity. The full bed occupancy distributions are provided in Figure 1. The *Baseline* scenario supports available data and understanding at the time of the study, with results showing that service occupancy exceeds in-area PICU capacity for a significant proportion of the time (64.5-77.4%). The total 12.1 mean out-of-area bed requirement represents a substantial (47%) addition to the 26-bed in-area capacity.

Modelling suggests that a reduction of two admissions per month (*Decreased Admissions* scenario) at each of the PICUs would reduce the total mean out-of-area bed requirement by 26% to 9.0 beds, and lessen the proportion of time utilising out-of-area capacity to between 41.3% and 54.8%. Gains were slightly lower when modelling a 20% reduction in length of stay for those discharged from PICU to acute mental health services (*Decreased LOS* scenario). Here, the mean out-of-area bed requirement is reduced to 9.8 beds with the PICUs utilising out-of-area capacity between 48.0% and 61.1% of the time.

Were both initiatives to be successfully implemented (*Combined* scenario), then the mean out-of-area bed requirement would reduce 35% to 7.9 beds and some amount of out-of-area capacity would be required 27.1 to 37.4% of the time. Note that results for additional scenarios considered during the project are reported in the Supplementary Material.

[Insert Table 2 near here]

[Insert Figure 1 near here]

### *3.2. Optimising the in-area capacity allocation*

For the *Baseline* scenario, the simulation results suggest that the optimal number of in-area beds is likely above that allocated at the time of the study (Figure 2 and Table 3). In relation to PICU 1, the estimated cost-optimal in-area allocation is seven beds when out-of-area bed costs are 1.65 times that of in-area costs. As would be expected, this figure increases as an out-of-area bed becomes increasingly costlier relative to an in-area bed, ranging from 6 beds at a 1.25 ratio to 8 beds at a 2.05 ratio. For PICUs 2 and 3, assuming a 65% uplift, the estimated cost-optimal in-area bed allocation is 10 and 13 respectively, which represents an additional two and one beds respectively.

In general, the considered initiatives to reduce PICU admissions and length of stay would result in a lower in-area capacity requirement, which is to be expected given the reduced operational demands put on the service. Under some circumstances, cost-optimal performance would be achievable with the levels of allocated in-area capacity at the time of the study. For instance, with a 65% uplift in costs, the optimal PICU 1 allocation would be equal to the 6 beds allocated at the time of the study were plans to reduce LOS successfully implemented (*Decreased LOS* scenario). An equivalent finding results for PICU 2 were admissions successfully reduced (*Decreased Admissions* scenario).

[Insert Figure 2 near here]

[Insert Table 3 near here]

## 4. Discussion

While previous studies have indicated the potential benefit of modelling and simulation for improving mental health service delivery, there has been a deficit of efforts relating specifically to high-acuity PICU care, despite the recognised importance of optimised patient flow in this setting (Turkington et al, 2020). In terms of contribution to the literature, this current study therefore offers particular novelty in regard of its detailed consideration of this matter. Our study builds upon that outlined by Paton and Tiffin (2018) through the use of empirical data from multiple real-world units, the use of additional experimental scenarios and by estimating the potential role of in-area and out-of-area capacity optimisation in improving service efficacy. While the specific findings and insights of this study will be somewhat transferrable to other health economies, free and ready availability of the model code offers those wishing to pursue their own bespoke modelling the means to do so (BNSSG Analytics, 2019).

In terms of practical implications for the healthcare system concerned, the study has been valuable primarily to those with responsibilities for reducing out-of-area PICU placements, with modelled outputs informing discussions regarding the likely impact of the various initiatives under consideration. Specifically, modelling has illustrated the possible scale of financial and operational benefits to the PICU service from initiatives to reduce admissions and/or LOS. This has allowed the project delivery group to move forward in considering their various enabling factors. For reducing admissions, consideration is being given to the wider system resource and coordination effort required, including through improved early intervention (which has been associated with reduced admissions, Glover et al, 2006). Consideration is also being given to the ability of early intervention to reduce LOS (McCrone et al, 2013), and the extent to which this can be achieved through greater involvement of community teams during the patient's admission (Paton & Tiffin, 2018). Additional attention is being given to reducing LOS through minimising any stays beyond the point of discharge readiness. This requires fluidity across the pathway, and is dependent on the service provided by other, downstream care providers. Although feedback from stakeholder meetings has acknowledged a lack of familiarity to computer modelling, there has been positive engagement with the project through its course, with evident enthusiasm from many colleagues eager to see new and improved approaches to operational management (particularly with regard to the cost curves of Figure 2).

Turning to limitations, the ability to explore and model the breadth of initiatives discussed at an early stage by the project delivery group was restricted by the practicalities of working within a fixed financial envelope: thus, first and foremost, no scenarios were considered involving changes to the in-area allocated capacity (Section 3.1). While this constraint was relaxed for subsequent analysis, with other in-area capacities considered (Section 3.2), the lack of reliable local financial data prohibited a more formal cost analysis of the calibre required to provide a basis for decision making. Another limiting factor in this regard was the assumption that any number of in-area beds could be allocated to each of the PICUs. In reality the wards have physical and spatial restrictions and can only be formed in blocks of a fixed number – that is, a single bed cannot always be simply added or removed, as considered in Section 3.2. Data limitations were also responsible for the inability to distinguish between cohorts treated in-area and out-of-area. Given that the more severe cases are handled in-area (local knowledge obtained through project delivery group), this lack of control for case mix could mean an overestimate of out-of-area LOS and thus of modelled out-of-area bed occupancy.

A particularly noteworthy point of discussion arising from this study is not the specific cost-optimal capacity allocations identified, nor the mechanics of the modelling used to derive them, but the wider context in which they should be understood. Simply put, the modelling results suggest that in order to be most cost-efficient then a good amount of out-of-area placements would still be required. For instance, under the cost-optimal PICU 2 bed allocation for the *Decreased Admissions* scenario with a 1.65 cost ratio, some amount of out-of-area bed capacity would still be required over half of the time (54.8%, Table 1). Ultimately, in a system with considerable variation in demand and length of stay, significantly reducing out-of-area placements would require uneconomical amounts of allocated in-area capacity, much of which would remain idle for a period of time. Faced with this, and in the absence of much higher financial penalties for out-of-area placements (perhaps better reflecting the 'hidden' costs for the patient and family), it is difficult to see how the government may succeed in its aims to eliminate such events (UK Department of Health and Social Care, 2016).

Future investigators may wish to examine this matter more fully in any further work, recognising that the credibility of any such analysis may necessitate a bespoke data collection or collaboration with healthcare system(s) known to possess sufficiently good quality data. Availability of such data may also facilitate wider coverage of the PICU pathway within the scope of the modelling, i.e. capturing the dynamic interactions between the PICU and the different upstream admissions sources and downstream discharge destinations. While the open-source tool used here has the necessary versatility to consider such interactions, the associated data requirements could not be met in the current study. Further work may also consider the wider patient and family impacts of out-of-area placements, in complementing the cost component within a more sophisticated and representative objective function. This could more effectively account for the negative implications to better dissuade the use of out-of-area placements.

**Acknowledgements**

The authors are grateful to the contributions of Simon Bailey, Simon Cole, Emma Gara, and Toby Rickard. The authors also acknowledge the comments and suggestions from the anonymous reviewers.

**Funding**

This work was partially supported by The Health Foundation in the UK (Evidence into Practice award).

**Data and material**

This study utilised a discrete event simulation tool purpose built for modelling patient pathways. Model code used for this study is freely available at https://github.com/nhs-bnssg-analytics/PathSimR.

**Declaration of interest**

The authors declare that they have no competing interests.

**References**


Allen, M. A., Spencer, A., Gibson, A., Matthews, J., Allwood, A., Prosser, S., & Pitt, M. (2015). Right cot, right place, right time: improving the design and organisation of neonatal care networks – a computer simulation study. *Health Services and Delivery Research*, 3(20). https://doi.org/10.3310/hsdr03200

Allison, S., Bastiampillai, T., Licinio, J. et al. (2018). When should governments increase the supply of psychiatric beds? *Molecular Psychiatry*, 23, 796-800. https://doi.org/10.1038/mp.2017.139

Australian Government (2021). *Mental health services in Australia*. https://www.aihw.gov.au/reports/mental-health-services/mental-health-services-in-australia/report-contents/expenditure-on-mental-health-related-services.

Bardsley, M., Steventon, A., & Fothergill, G. (2019). *Untapped potential: Investing in health and care data analytics*. The Health Foundation. https://www.health.org.uk/publications/reports/untapped-potential-investing-in-health-and-care-data-analytics

BNSSG Analytics (2019). Discrete event simulation of healthcare pathways in R. https://github.com/nhs-bnssg-analytics/PathSimR.

Brailsford, S.C. et al. (2011) Overcoming the barriers: a qualitative study of simulation adoption in the NHS. *Journal of the Operational Research Society*, 64(2), 157-168. https://doi.org/10.1057/jors.2011.130

Brooker, G.D., & Brown, M. (2015). Out of Sight, Out of Mind, *The British Journal of Psychiatry*, 207(6), 474-475. https://doi.org/10.1192/bjp.bp.114.159566

Brown, S. & Bass, N. (2004). The psychiatric intensive care unit (PICU): Patient characteristics, treatment and outcome, *Journal of Mental Health*, 13(6), 601-609. 10.1080/09638230400017095

Cahill, W.T., & Render, M.T. (1999). Dynamic simulation modeling of ICU bed availability. *Proceedings of the 31st Winter Simulation Conference*, 1573-1576. https://doi.org/10.1145/324898.325327

Corscadden, L., et al. (2019) Who experiences unmet need for mental health services and what other barriers to accessing health care do they face? Findings from Australia and Canada. *The International Journal of Health Planning and Management,* 34(2), 761-772. https://doi.org/10.1002/hpm.2733

Demir, E., Lebcir, R., & Adeyemi, S. (2014). Modelling length of stay and patient flows: methodological case studies from the UK neonatal care services. *Journal of the Operational Research Society*, 65(4), 532-545. https://doi.org/10.1057/jors.2013.51

Dolan, M., & Lawson, A. (2001). A psychiatric intensive care unit in a medium-security unit, *Journal of Forensic Psychiatry*, 12(3), 684-693. https://doi.org/10.1080/09585180110057145

Fone, D., Hollinghurst, S., Temple, M., Round, A., Lester, N., Weightman, A., Roberts, K., Coyle, E., Bevan, G., & Palmer, S (2003). Systematic review of the use and value of computer simulation modelling in population health and health care delivery. *J Public Health Med*. 25(4), 325-35. https://doi.org/10.1093/pubmed/fdg075

Fries, B.E. (1979). Technical Note—Bibliography of Operations Research in Health-Care Systems: An Update. *Operations Research*, 27(2), 408-419. https://doi.org/10.1287/opre.27.2.408

Galante, J. et al. (2019). Out-of-area placements in acute mental health care: the outcomes, *Progress in Neurology and Psychiatry*, 23(1), 28-30. https://doi.org/10.1002/pnp.528

Glasgow, S. M., Perkins, Z. B., Tai, N. R., Brohi, K., & Vasilakis, C. (2018). Development of a discrete event simulation model for evaluating strategies of red blood cell provision following mass casualty events. *European Journal of Operational Research*, 270(1), 362-374. https://doi.org/10.1016/j.ejor.2018.03.008

Glover, G., Arts, G., & Babu, K. S. (2006). Crisis resolution/home treatment teams and psychiatric admission rates in England. The British Journal of Psychiatry, 189(5), 441-445. https://doi.org/10.1192/bjp.bp.105.020362.

Griffiths, J.D., Jones, M., Read, M.S., & Williams, J.E. (2010). A simulation model of bed-occupancy in a critical care unit. *Journal of Simulation*, 4(1), 52-59. https://doi.org/10.1057/jos.2009.22

Griffiths, J.D., Price-Lloyd, N., Smithies, M., & Williams, J.E. (2005). Modelling the requirement for supplementary nurses in an intensive care unit, *Journal of the Operational Research Society*, 56(2), 126-133. https://doi.org/10.1057/palgrave.jors.2601882

Günal, M. M., & Pidd, M. (2010). Discrete event simulation for performance modelling in healthcare: a review of the literature. *Journal of Simulation*, 4(1), 42–51. https://doi.org/10.1057/jos.2009.25

Haw, C., et al. (2017). Out of area admissions to two independent sector PICUs: patient characteristics, length of stay and delayed discharges, *Journal of Psychiatric Intensive Care*, 13(1), 27-36. https://doi.org/10.20299/jpi.2016.020

Healthcare Quality Improvement Partnership (2015). *The National Confidential Inquiry into Suicide and Homicide by People with Mental Illness Annual Report 2015: England, Northern Ireland, Scotland and Wales*. England: University of Manchester. https://www.hqip.org.uk/wpcontent/uploads/2018/02/national-confidential-inquiry-into-suicide-and-homicide-ncish-annualreport-2015.pdf

Hearn, C.R., Bishop, J.M., (1970). Computer Model Simulating Medical Care in Hospital, *British Medical Journal*, 3. https://doi.org/10.1136/bmj.3.5719.396

Heeg, B., Buskens, E., Knapp, M., van Aalst, G., Dries, P.J., de Haan, L., & van Hout, B.A. (2005). Modelling the treated course of schizophrenia: development of a discrete event simulation model. *Pharmacoeconomics*, 23, 17-33. https://doi.org/10.2165/00019053-200523001-00003

Heeg, B.M.S., Damen, J., Buskens, E., Caleo, S., de Charro, F., & van Hout, B.A. (2008). Modelling Approaches: The Case of Schizophrenia, *Pharmacoeconomics*, 26 (8), 633-648. https://doi.org/10.2165/00019053-200826080-00002

Jun, J.B., Jacobson, S.H., & Swisher, J.R. (1998). Application of discrete-event simulation in health care clinics: A survey. *Journal of the Operational Research Society*, 50(2), 109-123. https://doi.org/10.1057/palgrave.jors.2600669

Kotiadis, K., Tako, A. A., & Vasilakis, C. (2014). A participative and facilitative conceptual modelling framework for discrete event simulation studies in healthcare. *Journal of the Operational Research Society*, 65(2), 197-213. https://doi.org/10.1057/jors.2012.176

Kuno, E., Koizumi, N., Rothbard, A. B., & Greenwald, J. (2005). A service system planning model for individuals with serious mental illness. *Mental Health Services Research*, 7(3), 135-144. https://doi.org/10.1007/s11020-005-5782-5.

Lebcir, R., & Atun. R., (2020) Should doctors use their judgment? How a system dynamics model elicited knowledge in neonatal care services. *Journal of the Operational Research Society*, 71(7), 1113-1123. https://doi.org/10.1080/01605682.2020.1730252

Long, K. M., & Meadows, G. N. (2018). Simulation modelling in mental health: A systematic review. *Journal of Simulation*, 12(1), 76-85. https://doi.org/10.1057/s41273-017-0062-0.

Minichino, A., et al. (2019). Unmet needs in patients with brief psychotic disorders: Too ill for clinical high risk services and not ill enough for first episode services. *European Psychiatry*, 57, 26-32. https://doi.org/10.1016/j.eurpsy.2018.12.006

Mohiuddin, S., Busby, J., Savovic, J., Richards, A., Northstone, K., Hollingworth, W., Donovan, J., & Vasilakis, C. (2017). Patient flow within UK emergency departments: a systematic review of the use of computer simulation modelling methods. *BMJ Open*, 7, Article e015007. https://doi.org/10.1136/bmjopen-2016-015007

Moroz, N., Moroz, I., & D'Angelo, M.S. (2020). Mental health services in Canada: Barriers and cost-effective solutions to increase access. *Healthcare Management Forum*, 33(6), 282-287. https://doi.org/10.1177/0840470420933911

Mulder, W., et al (2007). Psychiatric emergency services in Amsterdam: experience of setting up a temporary admissions unit to manage acute admissions in a metropolitan area, *Journal of Psychiatric Intensive Care*, 2(2), 84–89. https://doi.org/10.1017/S1742646407000337

Murch, B. J., Cooper, J. A., Hodgett, T. J., Gara, E. L., Walker, J. S., & Wood, R. M. (2021). Modelling the effect of first-wave COVID-19 on mental health services. *Operations Research for Health Care*, 30, Article 100311. https://doi.org/10.1016/j.orhc.2021.100311.

McCrone, P., Singh, S. P., Knapp, M., Smith, J., Clark, M., Shiers, D., & Tiffin, P. A. (2013). The economic impact of early intervention in psychosis services for children and adolescents. Early intervention in psychiatry, 7(4), 368-373. https://doi.org/10.1111/eip.12024.

National Association of Psychiatric Intensive Care & Low Secure Units (2018). 'What are the roles in a multi-disciplinary team on a Psychiatric Intensive Care Unit (PICU)?' https://www.youtube.com/playlist?list=PLLetmiWVcWxjoujbuMLYalGkc2EHaU0E-

National Health Service England (2019). *NHS Long Term Plan – Adult Mental Health Services: Inpatient Care*. London: NHS England. https://www.longtermplan.nhs.uk/online-version/chapter-3-further-progress-on-care-quality-and-outcomes/better-care-for-major-health-conditions/adult-mental-health-services/

National Health Service England (2021). *Implementing the Mental Health Forward View: NHS Mental Health Dashboard*. London: NHS England. https://www.england.nhs.uk/mental-health/taskforce/imp/mh-dashboard/

Noorain, S., Kotiadis, K., & Scaparra, M. P. (2019). Application of discrete-event simulation for planning and operations issues in mental healthcare. *Proceedings of the 2019 Winter Simulation Conference*, 1184-1195. https://doi.org/10.1109/WSC40007.2019.9004749.

Norfolk and Suffolk National Health Service Foundation Trust (2019). *Inappropriate Out of Area Placements. England*: Norfolk and Suffolk National Health Service Foundation Trust. https://www.norfolk.gov.uk/-/media/norfolk/downloads/what-we-do-and-how-we-work/policy-performance-and-partnerships/partnerships/health-and-wellbeing-board/reports-to-the-health-and-wellbeing-board/inappropriate-out-of-area-placements-presentation-30-october-2019.pdf

Paton, L., & Tiffin, P. (2018). Modelling out-of-area admissions, *The British Journal of Psychiatry*, 213(4), 615 - 616. https://doi.org/10.1192/bjp.2018.119

Pereira, S., Sarsam, M., Bhui, K., & Paton, C. (2005). The London Survey of Psychiatric Intensive Care Units: psychiatric intensive care; patient characteristics and pathways for admission and discharge, Journal of Psychiatric Intensive Care, 1(1), 17-24. https://doi.org/10.1017/S174264640500004X

Pidd, M. (1998). *Computer Simulation in Management Science*. 4th edn, John Wiley and Sons Ltd, Chichester

Pitt, M., Monks, T., Crowe, S., Vasilakis. C. (2016). Systems modelling and simulation in health service design, delivery and decision making. *BMJ Qual Saf*. 25(1), 38-45. https://doi.org/10.1136/bmjqs-2015-004430.

Smith, G., Wolstenholme, E. F., McKelvie, D., & Monk, D. (2004). Using system dynamics in modelling mental health issues in the UK. *22nd International Conference of the System Dynamics Society*, 25-29.

Smits, M. (2010). Impact of policy and process design on the performance of intake and treatment processes in mental health care: a system dynamics case study. *Journal of the Operational Research Society*, 61(10), 1437-1445. https://doi.org/10.1057/jors.2009.110.

Turkington, D., Moorhead, S., Turkington, G. D., King, C., Bell, L., & Pickersgill, D. (2020). Improving patient flow in acute psychiatric wards: enhanced bed management and trusted assessment. *BJPsych Bulletin*, 44(4), 159-162. https://doi.org/10.1192/bjb.2020.12.

United Kingdom Department of Health and Social Care (2016). Out of area placements in mental health services for adults in acute inpatient care. London: Department of Health and Social Care. www.gov.uk/government/publications/oaps-in-mental-health-services-for-adults-in-acute-inpatient-care/out-of-area-placements-in-mental-health-services-for-adults-in-acute-inpatient-care

Vigo, D.V., Kester, D., Pendakur, K., Thornicroft, G., Atun, R. (2018). Disease burden and government spending on mental, neurological, and substance use disorders, and self-harm: cross-sectional, ecological study of health system response in the Americas. *The Lancet Public Health*, 4(2), E89-E96. https://doi.org/10.1016/S2468-2667(18)30203-2

Wood, R., McWilliams, C., Thomas, M. J., Bourdeaux, C., & Vasilakis, C. (2020). COVID-19 scenario modelling for the mitigation of capacity-dependent deaths in intensive care. *Health Care Management Science*, 23(3), 315-324. https://doi.org/10.1007/s10729-020-09511-7

Wood, R., Pratt, A., Kenward, C., McWilliams, C., Booton, R., Thomas, M. J., Bourdeaux, C., & Vasilakis, C. (2021). The value of triage during periods of intense COVID-19 demand: simulation modelling study. *Medical Decision Making*, 41(4), 393-407. https://doi.org/10.1177/0272989X21994035

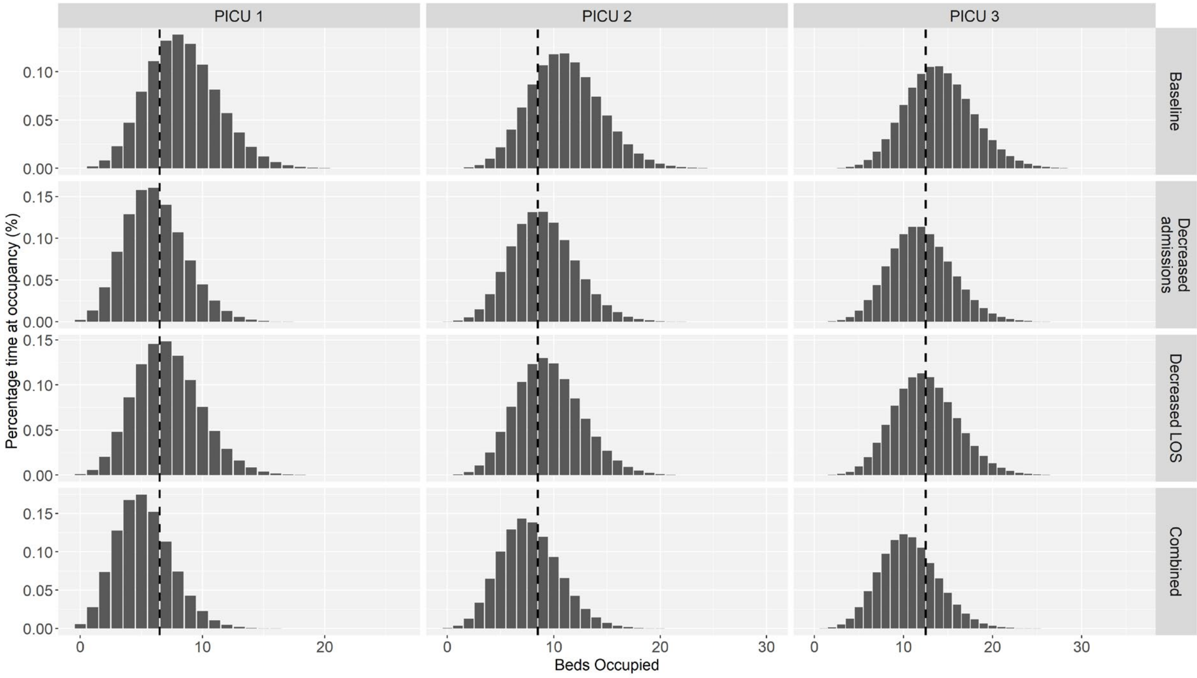


**Figure 1.** Full bed occupancy distributions for the baseline position and various initiatives considered in this study. The dashed vertical lines represent the number of allocated in-area beds at the time of the study. Results show that service occupancy frequently exceeds the available in-area capacity, with out-of-area placements required for a substantial amount of time.

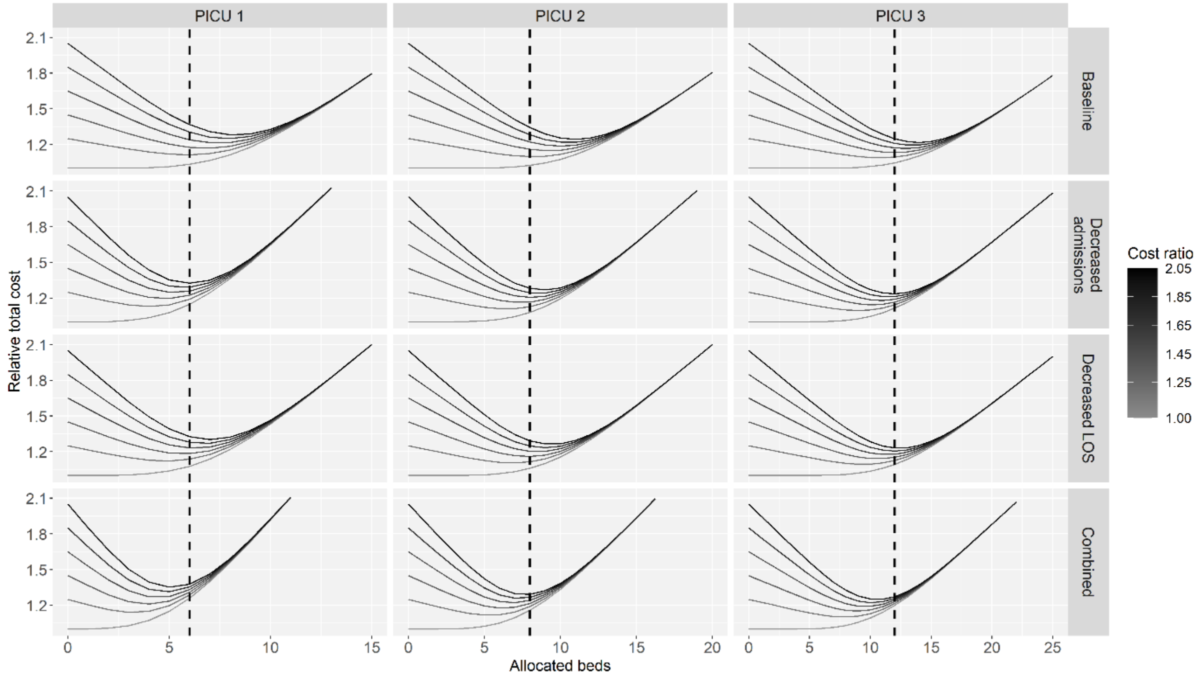


**Figure 2.** Comparison of relative total costs for different amounts of in-area capacity allocations, as determined for various out-of-area to in-area cost ratios considered. The 1.0 cost ratio is also included. The dashed vertical lines represent the number of allocated in-area beds at the time of the study.

| PICU unit | Sample size (patient admissions) | Arrival rate (mean, daily) | Length of stay (days) | | Best fitting distribution |
|---|---|---|---|---|---|
| | | | Median | Mean | |
| 1 | 346 | 0.26 | 19.6 | 33.1 | Lognormal ($\mu$=2.97, $\sigma^2$=1.02) |
| 2 | 412 | 0.38 | 18.1 | 29.7 | Lognormal ($\mu$=2.90, $\sigma^2$=0.99) |
| 3 | 578 | 0.47 | 17.3 | 30.9 | Lognormal ($\mu$=2.85, $\sigma^2$=1.08) |

**Table 1.** Summary of empirical data for length of stay (Financial Year 2019) and fitted statistical distributions for the three psychiatric intensive care units (PICUs) considered in this study.

| Scenario | Description | PICU unit | Allocated capacity (in-area beds) | Time at which at least one patient is out-of-area (%) | Mean occupancy (in-area and out-of-area) | Out-of-area bed requirement (mean) |
|---|---|---|---|---|---|---|
| Baseline | Configuration at the time of the study | 1 | 6 | 73.0 | 8.4 | 3.6 |
| | | 2 | 8 | 77.4 | 11.1 | 4.3 |
| | | 3 | 12 | 64.5 | 14.0 | 4.2 |
| Decreased Admissions | Decrease of two admissions per month per PICU | 1 | 6 | 41.3 | 6.1 | 2.5 |
| | | 2 | 8 | 54.8 | 9.0 | 3.2 |
| | | 3 | 12 | 42.3 | 12.0 | 3.3 |
| Decreased LOS | 20% decreased LOS for discharges to acute mental health services | 1 | 6 | 57.1 | 7.1 | 3.0 |
| | | 2 | 8 | 61.1 | 9.5 | 3.4 |
| | | 3 | 12 | 48.0 | 12.5 | 3.4 |
| Combined | Both initiatives | 1 | 6 | 27.1 | 5.2 | 2.2 |
| | | 2 | 8 | 37.4 | 7.8 | 2.9 |
| | | 3 | 12 | 27.2 | 10.6 | 2.8 |

**Table 2.** Summary of modelled results for the various initiatives considered in this study, alongside the baseline position representing operational performance at the time of the study.

| PICU unit | In-area allocation at time of study | Scenario | Cost-optimal bed allocation (for different cost ratios) | | | | |
|---|---|---|---|---|---|---|---|
| | | | *1.25* | *1.45* | *1.65* | *1.85* | *2.05* |
| 1 | 6 | Baseline | 6 | 7 | 7 | 8 | 8 |
| | | Decreased Admissions | 4 | 5 | 5 | 6 | 6 |
| | | Decreased LOS | 5 | 6 | 6 | 7 | 7 |
| | | Combined | 3 | 4 | 4 | 5 | 5 |
| 2 | 8 | Baseline | 8 | 9 | 10 | 11 | 11 |
| | | Decreased Admissions | 6 | 7 | 8 | 9 | 9 |
| | | Decreased LOS | 7 | 8 | 9 | 9 | 9 |
| | | Combined | 5 | 6 | 7 | 7 | 8 |
| 3 | 12 | Baseline | 11 | 12 | 13 | 13 | 14 |
| | | Decreased Admissions | 9 | 10 | 11 | 11 | 12 |
| | | Decreased LOS | 9 | 11 | 11 | 12 | 12 |
| | | Combined | 8 | 9 | 10 | 10 | 11 |

**Table 3**. Cost-optimal in-area capacity allocations for the baseline position and various initiatives considered, as determined for various out-of-area to in-area cost ratios considered.

**Supplementary Material**

This section consists of four parts. Parts A to D contain the results associated with various perturbations to the model parameters, conducted as part of the sensitivity analysis performed.

**Part A: Baseline results**

| Scenario | Unit | Allocated capacity (in-area beds) | Time at which at least one patient is out-of-area (%) | Mean occupancy (in-area plus out-of-area) | Out-of-area bed requirement (mean) |
|---|---|---|---|---|---|
| Baseline | PICU 1 | 6 | 73 | 8.4 | 3.6 |
| Baseline | PICU 2 | 8 | 77.4 | 11.1 | 4.3 |
| Baseline | PICU 3 | 12 | 64.5 | 14 | 4.2 |

**Part B: Variations to the modelled admission rate into psychiatric intensive care units (PICUs) 1-3 (baseline = 0.26 admissions per day - PICU 1, 0.38 - PICU 2, 0.47 - PICU 3)**

| Scenario | Unit | Allocated capacity (in-area beds) | Time at which at least one patient is out-of-area (%) | Mean occupancy (in-area plus out-of-area) | Out-of-area bed requirement (mean) |
|---|---|---|---|---|---|
| Admissions decrease (two per month) | PICU 1 | 6 | 41.3 | 6.1 | 2.5 |
| | PICU 2 | 8 | 54.8 | 9 | 3.2 |
| | PICU 3 | 12 | 42.3 | 12 | 3.3 |
| Admissions decrease (four per month) | PICU 1 | 6 | 13.3 | 4.2 | 1.8 |
| | PICU 2 | 8 | 30.9 | 7.3 | 2.5 |
| | PICU 3 | 12 | 22.5 | 10.2 | 2.6 |
| Admissions decrease (six per month) | PICU 1 | 6 | 0.4 | 1.9 | 1.3 |
| | PICU 2 | 8 | 8.4 | 5.2 | 1.9 |
| | PICU 3 | 12 | 6.8 | 8.1 | 2.1 |

**Part C: Variations to the PICU length of stay (LOS) assumed for patients admitted to acute mental health services from PICU (baseline = 29.7 days for PICU 1, 28.1 days for PICU 2, 31.1 days for PICU 3)**

| Scenario | Unit | Allocated capacity (in-area beds) | Time at which at least one patient is out-of-area (%) | Mean occupancy (in-area plus out-of-area) | Out-of-area bed requirement (mean) |
|---|---|---|---|---|---|
| Length of stay decrease for those admitted to acute mental health services from PICU (8%) | PICU 1 | 6 | 67 | 7.9 | 3.4 |
| | PICU 2 | 8 | 71.2 | 10.4 | 3.9 |
| | PICU 3 | 12 | 58.2 | 13.4 | 3.9 |
| Length of stay decrease for those admitted to acute mental health services from PICU (12%) | PICU 1 | 6 | 64.5 | 7.7 | 3.2 |
| | PICU 2 | 8 | 67.8 | 10.1 | 3.8 |
| | PICU 3 | 12 | 54.5 | 13.1 | 3.7 |
| Length of stay decrease for those admitted to acute | PICU 1 | 6 | 61.3 | 7.4 | 3.1 |
| | PICU 2 | 8 | 64.3 | 9.8 | 3.6 |

| | | | | | |
|---|---|---|---|---|---|
| mental health services from PICU (16%) | PICU 3 | 12 | 51.8 | 12.8 | 3.6 |
| Length of stay decrease for those admitted to acute mental health services from PICU (20%) | PICU 1 | 6 | 57.1 | 7.1 | 3 |
| | PICU 2 | 8 | 61.1 | 9.5 | 3.4 |
| | PICU 3 | 12 | 48 | 12.5 | 3.4 |

**Part D: Variations to the PICU length of stay (LOS) assumed for patients admitted to forensic mental health services from PICU (baseline = 29.7 days (PICU 1), 28.1 days (PICU 2), 31.1 days (PICU 3))**

| Scenario | Unit | Allocated capacity (in-area beds) | Time at which at least one patient is out-of-area (%) | Mean occupancy (in-area plus out-of-area) | Out-of-area bed requirement (mean) |
|---|---|---|---|---|---|
| Length of stay decrease for those admitted to forensic mental health services from PICU (5%) | PICU 1 | 6 | 72.6 | 8.3 | 3.6 |
| | PICU 2 | 8 | 77 | 11 | 4.3 |
| | PICU 3 | 12 | 64.2 | 14 | 4.2 |
| Length of stay decrease for those admitted to forensic mental health services from PICU (10%) | PICU 1 | 6 | 72.3 | 8.3 | 3.6 |
| | PICU 2 | 8 | 77 | 11 | 4.3 |
| | PICU 3 | 12 | 63.6 | 14 | 4.1 |
| Length of stay decrease for those admitted to forensic mental health services from PICU (15%) | PICU 1 | 6 | 71.8 | 8.3 | 3.6 |
| | PICU 2 | 8 | 77.1 | 11 | 4.3 |
| | PICU 3 | 12 | 62.7 | 13.9 | 4.1 |
| Length of stay decrease for those admitted to forensic mental health services from PICU (20%) | PICU 1 | 6 | 71.7 | 8.3 | 3.6 |
| | PICU 2 | 8 | 76.6 | 11 | 4.3 |
| | PICU 3 | 12 | 62.2 | 13.8 | 4.1 |