



Quantitative metrics for evaluating the phased roll-out of clinical information systems



David Wong^{a,*}, Nicolas Wu^b, Peter Watkinson^c

^a Yorkshire Centre for Health Informatics, Leeds Institute of Health Sciences, Worsley Building, University of Leeds, LS2 9JT, United Kingdom

^b Department of Computer Science, Merchant Venturers Building, University of Bristol, BS8 1UB, United Kingdom

^c Kadoorie Centre for Critical Care Research and Education, University of Oxford, Level 3, John Radcliffe Hospital, Headley Way, Oxford, OX3 9DU, United Kingdom

ARTICLE INFO

Keywords:

Clinical information systems
Algorithms
Information systems
Implementation

ABSTRACT

Objectives: We introduce a novel quantitative approach for evaluating the order of roll-out during phased introduction of clinical information systems. Such roll-outs are associated with unavoidable risk due to patients transferring between clinical areas using both the old and new systems.

Methods: We proposed a simple graphical model of patient flow through a hospital. Using a simple instance of the model, we showed how a roll-out order can be generated by minimising the flow of patients from the new system to the old system.

Results: The model was applied to admission and discharge data acquired from 37,080 patient journeys at the Churchill Hospital, Oxford between April 2013 and April 2014. The resulting order was evaluated empirically and produced acceptable orders.

Discussion: The development of data-driven approaches to clinical Information system roll-out provides insights that may not necessarily be ascertained through clinical judgment alone. Such methods could make a significant contribution to the smooth running of an organisation during the roll-out of a potentially disruptive technology.

Conclusion: Unlike previous approaches, which are based on clinical opinion, the approach described here quantitatively assesses the appropriateness of competing roll-out strategies. The data-driven approach was shown to produce strategies that matched clinical intuition and provides a flexible framework that may be used to plan and monitor Clinical Information System roll-out

1. Introduction

The implementation of hospital Clinical Information Systems (CISs) is known to be complex. Poor implementation has previously led to delays in full functionality, and in the worst cases, systems remaining partially deployed for long periods [1–3]. In many instances, poor performance following the introduction of a CIS may be attributed to the system not functioning as intended. For instance, Darbyshire reported how one such CIS was considered unsuitable by clinical end users [4]. In contrast, Huerta et al. showed that the effect of a CIS on hospital productivity depended on the rollout strategy, which suggests an effect due to the implementation process itself [5].

One key decision during CIS implementation is the roll-out strategy used to determine how the system is introduced into each clinical area. CISs can be rolled-out according to one of two broad approaches. In a big-bang approach, the whole system is adopted over a very short period of time for a whole hospital site. Alternatively, in a phased approach, subsections of the hospital are moved to the new system over an

extended period of time. The phased approach may also refer to the gradual release of system functionality, such that users are not immediately exposed to a system's full capabilities.

Big-bang implementations have previously been recommended for stable systems that do not contain critical functionality [6]. In practice, technical constraints mean that a big-bang approach is often appealing [7]. For instance, in the case of Computerised Physician Order Entry (or e-Prescribing) systems, simultaneous deployment in clinical areas and pharmacy, is necessary to ensure that drug orders can be completed using the new system [8]. Other practical considerations such as financial and time constraints may also influence the implementation approach (for example, if required human resource is only available for a short duration). The drawback of the big-bang is that it exposes an organisation to a large degree of short-term risk. A successful big-bang must ensure that all IT infrastructure and organisational processes, including staff training and down-time procedures, are in place ahead of roll-out [9]. Phased roll-out limits risks by confining initial deployment to a small area. This allows early validation of the system and also

* Corresponding author at: Yorkshire Centre for Health Informatics, Leeds Institute of Health Sciences, Worsley Building, University of Leeds, United Kingdom.
E-mail addresses: d.c.wong@leeds.ac.uk (D. Wong), Nicolas.wu@bristol.ac.uk (N. Wu), peter.watkinson@ndcn.ox.ac.uk (P. Watkinson).

reduces the initial resource required [9,10]. After the initial validation, the phased approach allows for mid-course corrections that are not possible in a big-bang methodology [11]. Furthermore, a phased roll-out offers opportunities to study the effect of a new system using a stepped-wedge approach [12,13]. This methodology monitors an intervention over time, allowing the effect of temporal confounders to be identified.

Phased roll-outs introduce their own problems, including an extended transition period between the existing and new system. During this transition phase, uncertainty in clinical process may lead to duplication of documentation on both the old and new systems, or worse, omission of data from either system [14,15]. For this reason, current UK guidelines on the implementation of e-Prescribing systems recommend rapid phased rollouts, colloquially described as ‘rolling thunder’ [16].

The order in which clinical areas, or groups of areas, are introduced to the new system is a key design decision for phased roll-out. The order of the roll-out is determined by multiple factors. Technical factors include the system's usability which may be influenced by more widespread IT infrastructure failings such as poor Wi-Fi coverage, as well as system performance and financial cost. Social considerations include how well staff engage with a new system. For example, the reticence of clinical staff to engage with new systems has been well-documented as a key problem [17,18].

Organisational factors include effective change management, provision of clear leadership (clinical champions), and successful evaluation of the system [19,20]. Finally, patient safety must be considered. One possible approach is to minimise the number of patient episodes documented using both old and new systems.

In practice, the order of clinical areas in a phased roll-out is usually chosen in an *ad-hoc* manner. In the best cases, CIS roll-out strategy is informed by qualitative information such as on-site interviews to assess human resources, emotional ability to support an CIS, and office dynamics [16,21], whereas often there is no documented strategy.

We address the issue of roll-out order in phased implementation using a graphical framework. The framework explicitly models patient transit between clinical areas using the old and new systems. In doing so, it directly quantifies factors related to both patient safety and clinical workflow. Whilst consideration of patient transits does not account for Organizational or Technical factors, the proposed framework may be adapted to include such factors. We show a simple example of this framework applied to the rollout of an electronic vital sign observation system. The example shows how different ordering strategies can be compared to identify areas at greater risk of patient information being stored on multiple systems, which may complicate clinical care.

2. Methods

2.1. Model

We model a hospital as a directed graph in which clinical areas are nodes. Each area, w , has a state, s , indicating whether it is on the old ($s = 0$) or new ($s = 1$) system. Clinical factors that may impact the effectiveness of a CIS rollout are modelled in two ways. First, the net number of patients transferring between two areas per unit time are modelled as weighted edges. The set of transfers into area w is denoted by I_w , and the set of transfers out are denoted O_w . Other clinical factors associated with area w are represented by a feature vector, V_w . In practice, elements of V_w might include ward acuity (on a scale of 0–3) [22], staff to patient ratio. The general model is depicted in Fig. 1.

The impact of an area changing state from 0 to 1 is evaluated through a cost function, $\delta(w) = \delta(I_w, O_w, V_w)$. The form of the function is set on a case-by-case basis and determined by the relative importance of each factor. The need to explicitly choose a function, a priori, is comparable to other modelling techniques such as Gaussian Process regression [23].

Having developed a model and cost function, a greedy algorithm

(Algorithm 1) can be used to determine a roll-out order [24]. In a greedy algorithm, the ordering is constructed one area at a time. Each area is chosen by selecting the one that minimises the cost function given the order that has been constructed so far. The chosen area is then appended to the current order.

Algorithm 1. Clinical area order algorithm

Assuming W is the set of all clinical areas, P is a list of ordered clinical areas, and δ is the cost function

```
while  $W \neq \emptyset$ 
  find  $w \in W$  that minimizes  $\delta(w)$ 
  let  $W := \text{delete}(w, W)$ 
  let  $P := \text{append}(w, P)$ 
```

2.2. Model instance

One instantiation of the model is now described for the problem of phased roll-out between paper and electronic (e-Obs) systems for recording vital signs. Fig. 2 shows a simple model of a hospital containing 6 clinical areas, labelled A to F. Patients arrive at the hospital from the pre-hospital population, σ , and leave to the post-hospital population, τ . The number of patients transferring between wards per unit time are denoted by the edge weights – for example, 3 patients/time transfer between A and C.

To generate a rollout order, the cost function, $\delta(w)$, must first be defined. To define the cost function we consider that, during a phased rollout, patients may transit between the two systems in the following ways:

1. paper \rightarrow paper
2. paper \rightarrow e-Obs
3. e-Obs \rightarrow paper
4. e-Obs \rightarrow e-Obs

Transition 1 represents current practice where a paper based system is ubiquitous and is considered to be of acceptable clinical risk. Transition 4 represents patient movements in which the receiving and sending areas are using e-Obs. We consider this to be of acceptable clinical risk, since this is the desired transition after roll-out. Transitions 2 and 3 pose greater clinical risk, since these only occur during the phased roll-out. In both of these situations, data must be stored on two separate systems. This may result in situations where clinical staff are unable to quickly synthesize the full patient record. However, transition 2, from paper to e-Obs, is unavoidable in a phased roll-out.

Therefore, the simplest usable cost function considers only the number of patients with an electronic \rightarrow paper transition. No other features are included, so V_w is not used in this instance. The number of e-Obs \rightarrow paper transitions is simply the sum of the subset of O for which adjoining areas have a state $s = 0$:

$$\delta(w) = \sum_{i \in W} o_i \times \bar{s}_i$$

In the event that two or more areas have the same value of $\delta(w)$, we may consider the net number of paper \rightarrow e-Obs transition as a tie-breaker.

A rollout order can now be generated by applying Algorithm 1 using this cost function. The result of two steps of the algorithm is presented pictorially in Fig. 2. In the first step, all clinical areas are considered and their cost functions are calculated. The cost and tiebreaker are shown as the pair $(\delta(w), \text{tiebreak}(w))$ in the first column of Table 1. Initially, area E is activated, since $\delta(E) = 0$ and the tie break is smaller than that of area F (for which $\delta(F) = 0$). In the second step, $\delta(E)$ is no longer

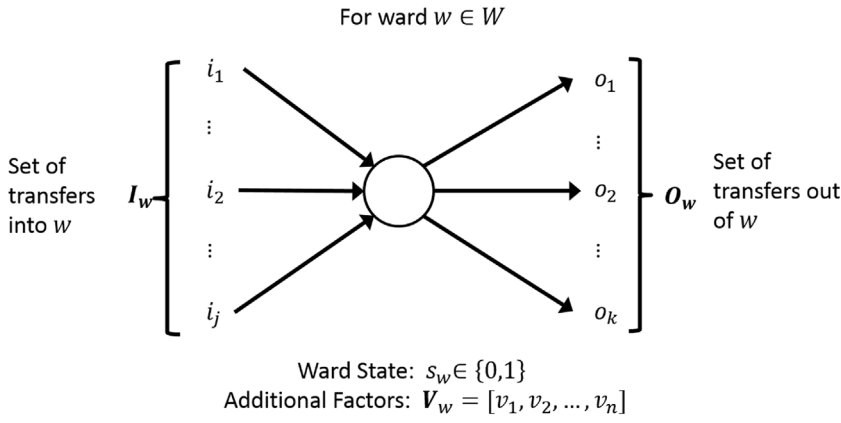


Fig. 1. the proposed graphical model showing all variables pertaining to a clinical area, w .

considered, since E has been deleted from the remaining areas, W . The order selected by the algorithm is: $E \rightarrow F \rightarrow C \rightarrow D \rightarrow B \rightarrow A$. In this simple example, the algorithm produces a roll-out order in which no patients ever switch from e-Obs \rightarrow paper.

2.3. Extended model instance

A more realistic cost function should consider the effect of other external influences such as clinical area specialty. In practice, areas with similar specialties are grouped into directorates that often share common staff. Migrating areas within a directorate in close succession may simplify staff training and minimise the amount of time that staff have to retain knowledge of both systems.

With this in consideration, transitions between areas in the same directorate might be weighted differently to those outside the directorate. The cost function can then be modified:

$$\delta(w) = d(v_i) \sum_{i \in W} o_i \bar{s}_i$$

$$d(v_i) = \begin{cases} \kappa & v_i = v_w \\ 1 & \text{otherwise} \end{cases}$$

The constant κ is a parameter that weights the importance of intra-directorate transitions. The Matlab code for both of the basic and

Table 1

At each step, the table shows (cost, tiebreak). The bold number shows the chosen area at each step.

Clinical area	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6
A	(10,10)	(10,10)	(10,10)	(7,10)	(4,10)	(0,10)
B	(14,14)	(7,14)	(7,14)	(7,14)	(0,14)	–
C	(3,3)	(3,3)	(0,3)	–	–	–
D	(10,10)	(10,10)	(0,10)	(0,10)	–	–
E	(0,7)	–	–	–	–	–
F	(0,13)	(0,13)	–	–	–	–

extended model instances is available from www.robots.ox.ac.uk/~wong.

2.4. Data

Data were acquired from the Churchill Hospital, Oxford, UK (Oxford University Hospitals Foundation NHS Trust), which had been chosen as the initial roll-out site for a new e-Obs system [25]. The hospital had 37,080 direct admissions between April 2013 and April 2014. For each admission, the Trust informatics department queried the Electronic Patient Record to obtain the clinical areas in which patients were admitted during their stay, in chronological order.

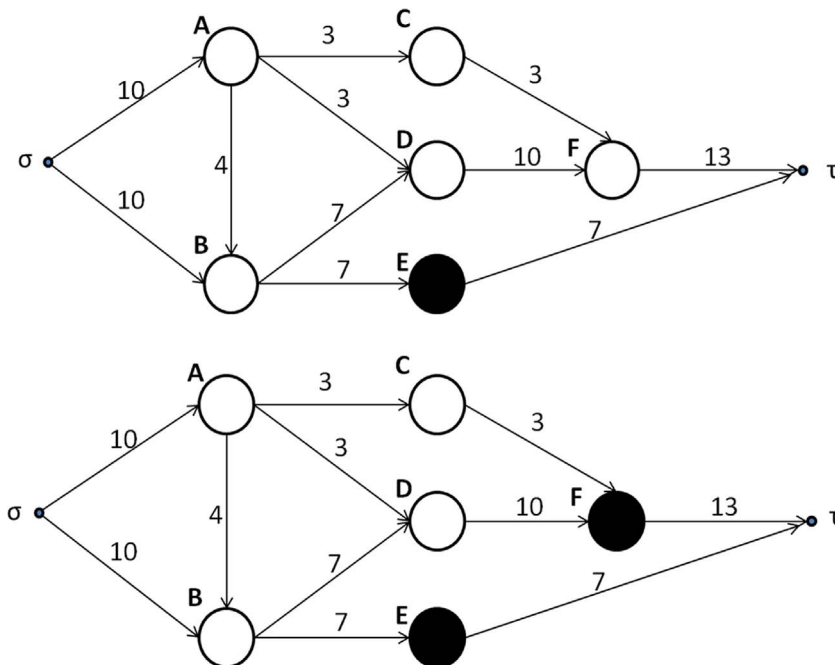


Fig. 2. Steps 1 and 2 of the algorithm. Step 1: Each clinical area is considered in turn. Both clinical area E and clinical area F have zero patients going from e-Obs \rightarrow paper (as all patients leave the hospital). Clinical area E has fewer patients moving from paper \rightarrow e-Obs recording, so it wins the tiebreaker and is activated. Step 2: clinical area F has zero patients going from e-Obs \rightarrow paper. No other clinical area has an equal or lower disruption cost, so F is activated.

Table 2
Clinical directorates and their constituent clinical areas.

Directorate 1	Directorate 2	Directorate 3	Directorate 4	Directorate 5
Resp X-ray Endocrinology Respiratory Resp Day Case Infectious Disease	Head and Neck Palliative Care Haematology Haem Day Case Oncology Oncology SS Colorectal	Recovery ICU Day Surgery	Renal Urology Transplant	Upper GI Lower GI

The data were processed as an adjacency matrix that fully defines the graph model outlined previously. The organisational structure of the hospital, containing information about each of the clinical directorates, was ascertained through publicly-available documentation, and is shown in Table 2.

This research was approved as a service evaluation for Oxford University Hospitals Foundation Trust (Datix: 2920). As no patient identifiable data was analysed, the study did not require review by the National Research Ethic Service.

3. Results

Admissions data were used to generate the graphical model, showing the clinical areas and annual patient transitions between April 2013 and April 2014 (Fig. 3). For clarity, only edges with weights of 30 or greater are shown and nodes that represent day case units have been removed.

The visualisation highlights clinically significant features unique to this data set. By inspection, we note that the graph has three primary

clusters of inter-connected clinical areas highlighted in red, blue and green. These clusters relate to clinical areas with similar specialties. Nodes coloured in red relate to areas that specialise in respiratory problems, nodes in blue relate to cancer clinical areas, and green nodes denote surgical clinical areas. The remaining area, *Endocrinology*, was coded as a standard clinical area, but acts as a day unit that works independently from the rest of the hospital.

Applying the ordering algorithm to the admission data produces the order shown in Table 3. The algorithm was applied a second time to include information about clinical directorates. In the absence of any prior information, a value of $\kappa = 0$ was chosen. This asserts that transfers within the same directorate are not penalised. The new order is also shown in Table 3. In each case, the algorithm total run-time was less than one second on a standard desktop PC.

Fig. 3 shows that there are relatively few complex patient pathways. Of the hospital clinical areas, *Day Surgery Unit* and *ICU* have the most outgoing edges, and thus the most transitions, to other clinical areas. One would therefore intuitively expect both clinical areas to be ordered last by the greedy algorithm; Table 3 confirms this to be true. One

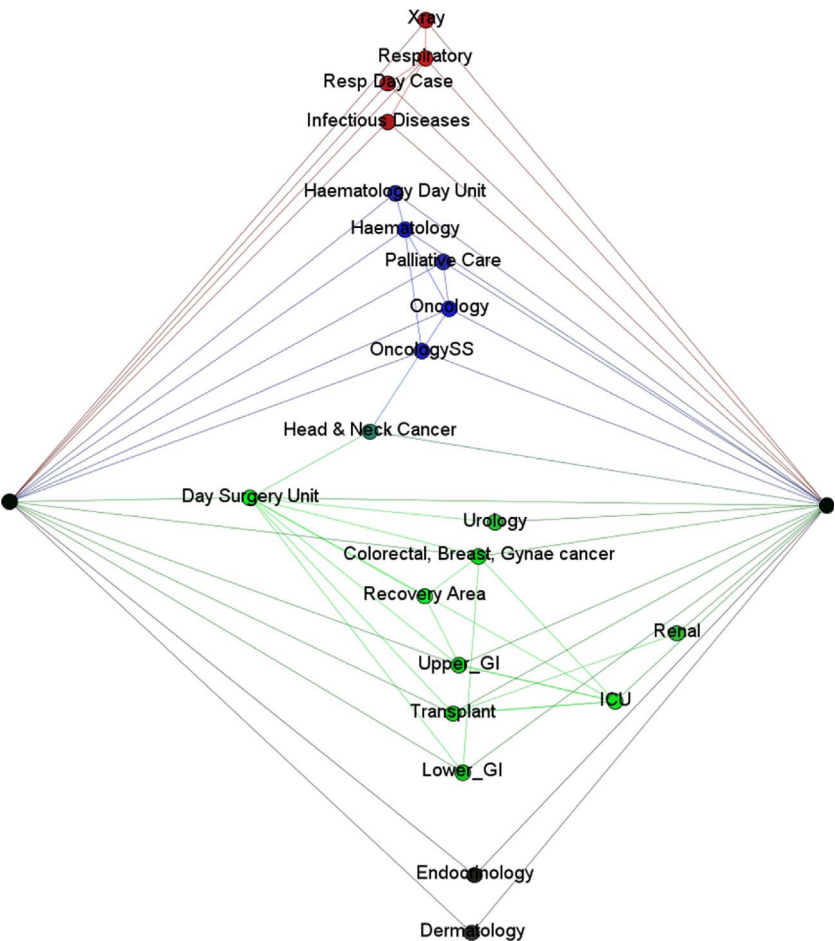


Fig. 3. Graph showing patient transfers between clinical areas at the Churchill Hospital, Oxford. For clarity, only inter-clinical area transfers of more than 30/year are shown, and day-case units for which there were very few inter-clinical area transfers have also been excluded.

Table 3
Recommended clinical area orders derived from the Model Instance and Extended Model Instance.

Order	Without Directorate	With Directorate
1	Head and Neck	Head and Neck
2	Palliative Care	Resp X-ray
3	Renal	Endocrinology
4	Resp X-ray	Palliative Care
5	Endocrinology	Haem Day Case
6	Recovery	Renal
7	Urology	Oncology
8	Lower GI	Resp Day Case
9	Respiratory	Respiratory
10	Resp Day Case	Urology
11	Infectious Disease	Haematology
12	Haematology	Infectious Disease
13	Haem Day Case	Recovery
14	Oncology	Lower GI
15	Colorectal	Oncology SS
16	Oncology SS	Colorectal
17	Upper GI	Upper GI
18	Transplant	Transplant
19	ICU	ICU
20	Day Surgery	Day Surgery

would also expect clinical areas from which patients are commonly discharged from the hospital to be ordered near the start. These include *Endocrinology*, *Palliative Care*, and *Head and Neck*, which each have only one outgoing edge. Given the typical type of patient in the clinical areas, one may have expected *Palliative Care* at the start of the ordering (in practice, of course, vital signs would not be required). However, the algorithm lists *Head and Neck* to be rolled out initially. This is likely due to incomplete data, as the *Head and Neck* area became clinically active part way through the data collection period.

To compare the effectiveness of two competing roll-out strategies, we use the number of e-Obs \rightarrow paper transitions as a cost function. The total cost of the roll-out is then the cumulative number of transitions after rollout. By calculating the cost after the activation of each clinical area, we can also highlight areas that are likely to be more problematic. Fig. 4 shows the estimated cost (cumulative number of electronic to paper transitions) under two roll-out strategies: the standard and directorate-adjusted algorithms.

4. Discussion

The results presented here show how a model of patient flow between clinical areas can be used to guide decision making during CIS

phased roll-out. We presented a cost function that quantitatively evaluates the clinical impact of switching between CIS systems. The cost function, coupled with a greedy algorithm, allowed us to generate a sensible clinical area order using real data.

The greedy algorithm was chosen to demonstrate how the model could be simply interpreted in a useful manner. A significant benefit of the greedy algorithm approach is that it is able to cope with practical numbers of clinical areas. Given N clinical areas, the time for the algorithm to complete is proportional to N^3 (i.e. $O(N^3)$) if each area is connected to every other area. In reality, most clinical areas are more sparsely connected, which means that the order is $O(N^2)$ in practice. If a naive approach to calculating a clinical area order were used instead, one would consider all permutations of orderings leading to an intractable solution requiring $O(N!)$ calculations.

In an ideal situation, the combination of optimal sub-solutions would lead to an optimal solution. When this is the case, alternative approaches such as dynamic programming may be employed which leads to a correct and efficient implementation. However, we have no assurance that the cost functions considered here lead to this principle of optimality, and so we must resort to a greedy approach. Our approach is therefore heuristic and cannot guarantee that the optimal result ensues.

We further demonstrated, using clinical directorates as an example, how the cost function can incorporate additional factors. Table 3 showed that the inclusion of clinical directorates had a limited effect on the proposed order. Highly connected clinical areas, such as *Day Surgery Unit* and *Intensive Care Unit*, which were ordered last in the standard algorithm remained last in the directorate-adjusted algorithm. Similarly, many of the initial clinical areas had a similar order. The reason for the similarity between the two clinical area orders is that the number of intra-directorate patient transfers was small in comparison to the inter-directorate transfers.

When there were differences in order, the cumulative number of e-Obs \rightarrow paper transitions (Fig. 4) indicated whether the differences were important. There were more transitions in the directorate model than in the basic model, as the directorate model attempts to optimise competing goals (transitions and ward grouping). Visual inspection of the directorate-adjusted clinical area order showed large increases in cost for areas 5, 8 and 15. These indicate clinical areas for which there are a high numbers of e-Obs \rightarrow paper transitions and may have greater practical difficulties during roll-out.

The comparison of cumulative cost in Fig. 4 allowed us to identify, prior to roll-out, individual clinical areas in the roll-out order that may cause extra difficulties due to high numbers of e-Obs \rightarrow paper transitions. This analysis shows how a CIS implementation strategy may be

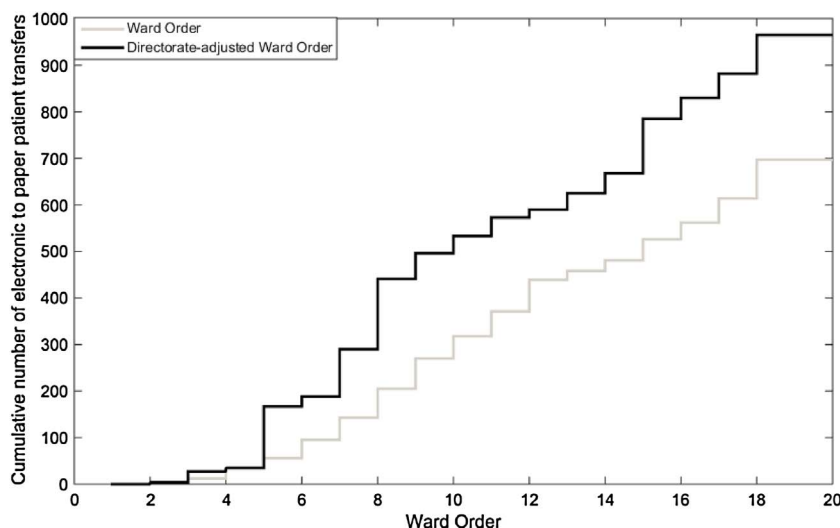


Fig. 4. The cumulative number of patients (annually) with e-Obs \rightarrow paper transitions (cost) by roll-out step for the without (grey) and with (black) directorate clinical area orderings.

analysed and refined prior to live roll-out. The method may also be applied on real-time data to monitor progress of deployment. In the event of an unexpectedly high number of transitions, the approach here would allow a change of strategy mid-deployment as espoused by Catwell [26].

Whilst we have only considered the phased roll-out of individual clinical areas, the proposed approach may be extended for a ‘rolling-thunder’ roll-out. Under this scenario, groups of clinical areas to be rolled-out simultaneously would be modelled as a single node. Alternative groupings may be tested, and evaluated using the cumulative cost.

The approach of modelling flows between wards may also be used for other clinical information systems. For instance, modelling patient flows would be appropriate for blood/patient tagging, whereas one may wish to model clinician location for a change in hospital communication system (e.g. bleep to phone). For a general CIS, it may be that other clinical factors, such as the level of staff training, the ward acuity or type (medical or surgical), or staff-to-patient ratio may be more important than patient transfers. In such scenarios, the additional factors may be included in the variable, V_w . A corresponding cost function would then be required to weight each factor. The choice of cost function would rely on clinical judgment. However, unlike current approaches, any clinical assumptions would be modelled explicitly.

5. Conclusion

In this paper, we developed a framework for quantitatively assessing the phased rollout of CISs. The approach considered here differs from previous work by explicitly identifying factors and quantitatively assessing their relative importance via a cost function. The cost function was used within a greedy algorithm to derive a clinical area order.

By applying the greedy algorithm on one year of clinical area transition data acquired at the Churchill Hospital, Oxford, we generated a clinically sensible roll-out order that minimises the number of “high-cost” transitions (from electronic to paper recording). Furthermore, we showed how the cost function could be extended to account for additional factors. We considered the impact of similar clinical specialties (directorates) by incorporating an additional element to the tuple that allowed us to model clinical areas with known similar clinical specialties. The inclusion of directorate had a limited effect of the proposed order, but greatly increased the number of problematic transfers. Finally, we demonstrated how, given a proposed roll-out order, the cost function may be used to evaluate the effectiveness of the clinical area ordering and highlight areas that are likely to cause greater difficulty. Whilst the roll-out of CISs and other clinical interventions remains a complex problem, the graphical model introduced here may help in implementing and evaluating roll-out strategies objectively. The approach taken here is simple to understand, computationally light, and a useful additional tool for understanding potential problems in CIS phased roll-outs.

Contributor statement

PW and DW contributed to the study design. DW and NW developed the methodology, collected analysed the data and drafted the manuscript. All authors were responsible for drafting the manuscript. All authors read and approved the final manuscript.

Acknowledgements

The work described in this paper was funded by the NIHR Oxford Biomedical Research Centre. DW was funded by the NIHR Oxford Biomedical Research Centre (grant: DFRWAO00). PW is employed by

the Oxford University Hospitals NHS Trust. We gratefully acknowledge the contribution of Julia Knight and the Informatics service at the Oxford University Hospitals NHS Trust for their help in accessing the relevant data.

References

- [1] A. Sheikh, T. Cornford, N. Barber, A. Avery, A. Takian, V. Lichtner, D. Petrakaki, S. Crowe, K. Marsden, A. Robertson, Z. Morrison, Implementation and adoption of nationwide electronic health records in secondary care in England: final qualitative results from prospective national evaluation in early adopter hospitals, *BMJ* 343 (2011) d6054.
- [2] J. Spetz, D. Keane, Information technology implementation in a rural hospital: a cautionary tale, *J. Healthc. Manag.* 54 (5) (2009) 337–349 PMID: 19831118.
- [3] A. Takian, A. Sheikh, N. Barber, We are bitter, but we are better off: case study of the implementation of an electronic health record system into a mental health hospital in England, *BMC Health Serv. Res.* 12 (1) (2012) 1, <http://dx.doi.org/10.1186/1472-6963-12-484>.
- [4] P. Darbyshire, ‘Rage against the machine?’: nurses’ and midwives’ experiences of using Computerized Patient Information Systems for clinical information, *J. Clin. Nurs.* 13 (1) (2004) 17–25.
- [5] T.R. Huerta, M.A. Thompson, E.W. Ford, W.F. Ford, Implementing electronic lab order entry management in hospitals: incremental strategies lead to better productivity outcomes, *Int. J. Inf. Manage.* 33 (February (1)) (2013) 40–47.
- [6] D.C. Bower, D.H. Walker, Planning knowledge for phased rollout projects, *Project Manag. J.* 38 (September (3)) (2007) 45–60.
- [7] M.F. Walji, D. Taylor, J.R. Langabeer, J.A. Valenza, Factors influencing implementation and outcomes of a dental electronic patient record system, *J. Dent. Educ.* 73 (5) (2009) 589–600.
- [8] J.M. Teich, C.D. Spurr, J.L. Schmitz, E.M. O’Connell, D. Thomas, Enhancement of clinician workflow with computer order entry, *Proceedings of the Annual Symposium on Computer Application in Medical Care, American Medical Informatics Association*, 1995 p. 459, PMID: PMC2579135.
- [9] L.K. Anderson, C.J. Stafford, The big bang implementation: not for the faint of heart, *Comput. Nurs.* 20 (1) (2001) 14–20 PMID:11838384.
- [10] H.W. Ryan, Managing development in the era of large complex systems, *IS Manag.* 16 (2) (1999) 89–91.
- [11] E. Pennings, O. Lint, Market entry, phased rollout or abandonment? A real option approach, *Eur. J. Oper. Res.* 124 (1) (2000) 125–138.
- [12] T. Bonnici, S. Gerry, D. Wong, J. Knight, P. Watkinson, Evaluation of the effects of implementing an electronic early warning score system: protocol for a stepped wedge study, *BMC Med. Inform. Decis. Mak.* 16 (1) (2016) 1, <http://dx.doi.org/10.1186/s12911-016-0257-8>.
- [13] K. Hemming, T.P. Haines, P.J. Chilton, A.J. Gilling, R.J. Lilford, The stepped wedge cluster randomised trial: rationale, design, analysis, and reporting, *BMJ* 350 (2015) h391.
- [14] R.R. Shield, R.E. Goldman, D.A. Anthony, N. Wang, R.J. Doyle, J. Borkan, Gradual electronic health record implementation: new insights on physician and patient adaptation, *Ann. Family Med.* 8 (4) (2010) 316–326.
- [15] M. Cifuentes, M. Davis, D. Fernald, R. Gunn, P. Dickinson, D.J. Cohen, Electronic health record challenges, workarounds, and solutions observed in practices integrating behavioral health and primary care, *J. Am. Board Fam. Med.* 28 (Suppl. 1) (2015) S63–S72.
- [16] K. Cresswell, J. Coleman, A. Slee, R. Williams, A. Sheikh, Investigating and learning lessons from early experiences of implementing ePrescribing systems into NHS hospitals: a questionnaire study, *PLoS One* 8 (1) (2013) e53369.
- [17] C. May, L. Gask, T. Atkinson, N. Ellis, F. Mair, A. Esmail, Resisting and promoting new technologies in clinical practice: the case of telepsychiatry, *Soc. Sci. Med.* 52 (12) (2001) 1889–1901.
- [18] L. Mc Quaid, P. Breen, J. Grimson, C. Normand, M. Dunne, N. Delanty, D. Kalra, M. Fitzsimons, Socio-technical considerations in epilepsy electronic patient record implementation, *Int. J. Med. Inf.* 79 (5) (2010) 349–360.
- [19] D.A. Handel, J.L. Hackman, Implementing electronic health records in the emergency department, *J. Emerg. Med.* 38 (2) (2010) 257–263.
- [20] S.D. DeVore, K. Figlioli, Lessons premier hospitals learned about implementing electronic health records, *Health Aff. (Millwood)* 29 (4) (2010) 664–667.
- [21] K. Keshavjee, R. Kyba, P. Naisbitt, A.M. Holbrook, Electronic medical records in family practice: what drives physician interest and how much are they willing to pay, *May Proceedings of Toward an Electronic Patient Record* 98 (1998) p. 30A.
- [22] Levels of Critical Care for Adult Patients, *The Intensive Care Society*, 2009.
- [23] C.E. Rasmussen, Gaussian processes in machine learning, *Advanced Lectures on Machine Learning*, Springer, Berlin Heidelberg, 2004, pp. 63–71.
- [24] Thomas H. Cormen, C.E. Leiserson, R.L. Rivest, C. Stein, *Introduction to Algorithms*, MIT Press, Cambridge, 2001.
- [25] D. Wong, T. Bonnici, J. Knight, L. Morgan, P. Coombes, P. Watkinson, SEND: a system for electronic notification and documentation of vital sign observations, *BMC Med. Inform. Decis. Mak.* 15 (1) (2015) 1, <http://dx.doi.org/10.1186/s12911-015-0186-y>.
- [26] L. Catwell, A. Sheikh, Evaluating eHealth interventions: the need for continuous systemic evaluation, *PLoS Med.* 6 (8) (2009) e1000126.