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WORKLOAD PREDICTION MODEL OF A PRIMARY HEALTH CENTRE

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Research paper

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Abstract

Managing the growing demand for care due to long-term conditions (LTCs) is a big challenge for primary care providers across the globe. We argue that population-level care for LTC patients registered at a primary health centre (PHC) is possible through workload prediction using care plans. In this paper, we try to answer two research questions: i) How can the future demand for care of the patients with LTCs be predicted? and ii) How is the future demand for care affected by changes? We present a rule-based simulation model that, given the patient details, will predict the number of LTC patients who will be visiting the primary health centre for the next year. Knowing this workload would help the medical practice to meet the upcoming demand for care effectively. Our approach also allows simulation of the effects of changes to practice and resourcing to foresee how these changes may impact the practice. Following the design science research approach, our prediction results have been shared with an expert and the feedback guides us to refine our model.

Keywords: Simulation, Workload Prediction, Primary Health Care.

1 Introduction

A dramatic increase in the number of patients with long-term conditions (LTCs) challenges healthcare providers to manage the growing demand for care (RNZCGP, 1999; Tattersall, R., 2002; Ministry of Health, 2009; Mays, 2013; Ferrer L & Goodwin N, 2014; Doolan-Noble, Gauld, & Waters, 2015). In New Zealand, the Ministry of Health is trying to meet the growing demand for care through various strategies (Hefford, 2006; Mays, 2013; Dale, 2014). These strategies aim to improve access to care, help patients to self-manage their conditions, refine financial policies to meet the requirements, and, above all, try to find ways to fill the gap between the demand for care and the supply of care providers (RNZCGP, 2012; Townsville–Mackay Medicare Local, 2012; Dale, 2014; Montague, 2014). A key challenge to allow this gap to be managed is to provide support for health care providers to manage a *population* of patients, rather than managing each patient individually (Smith, Soubhi, Fortin, Hudon, & O’Dowd, 2012; Mays, 2013; Burt et al., 2014; Doolan-Noble et al., 2015).

LTC patients require structured planning of care involving access to multidisciplinary services which includes clinical reviews and laboratory tests (Oldroyd et al., 2003; Burt et al., 2014). These patients’ care is formulated as *care pathways* to meet specific LTC management needs (Burt et al., 2014; Reeves et al., 2014) and implemented through *care plans* for each individual (Amir, Grosz, Gajos, Swenson, & Sanders, 2015; Sox & Stewart, 2015). In other words, *care pathways* represent a standardised way to manage a specific LTC covering all cases, whereas a *care plan* captures the required process of treatment and monitoring for an *individual* patient.

We argue that these individual care plans can be used to predict the future workload associated with a *population* of patients.

In this work[1], we focus on the problem of managing the LTC-related workload of a primary health care provider, by investigating ways of doing population-level reasoning based on care plans to anticipate the future workload associated with their LTC patients. Doing this will allow the health provider to plan their staff requirements to meet their patient management needs.

We therefore address the following research questions:

1. *How can the future demand for care of the patients with LTCs be predicted?* We develop a model to predict the workload that is expected to arise from the demand of care of patients with LTCs in the near future; knowing this workload would help the medical practice organise staffing and other resources.
2. *How is the future demand for care affected by changes?* The model allows a range of variations to organisational practices to be modelled to assess their impact. For example, what if a nurse does a diabetic foot check instead of a GP? This would, obviously, make the GP more available for those at high risk. This analysis would help the practice understand the implications of such a change.

The following section discusses related work, followed (Section 3) by a brief description of the design science research methodology that we followed. Section 4 introduces our workload prediction model and describes its implementation. Section 5 describes the evaluation and our observations, and Section 6 summarises and presents directions for future work.

2 Related Work

Our work makes an attempt to predict the upcoming workload at a medical practice. In order to have an informed view, we looked at how long-term conditions are managed medically, and how these management techniques can be integrated into an information systems context. We learned that long-term conditions are managed through timely intervention, and has a process to develop the plan of care to determine this timely intervention (Harris & Zwar, 2007). It is a major challenge is to formalise the care process and resourcing at a medical practice to meet the LTC management needs (Christov et al., 2008). Electronic health records or Personal health record (Mathers et al., 2011) capture the individual patient requisites to share the goals and activities set for the patient across various care providers without the loss of confidentiality (Burt et al., 2014b). However, these Electronic health records do not give an insight as to how to use that captured “digitized patient information” (Kohli et al., 2016) for apopulation based reasoning.

Many studies (Bodenheimer, Wagner, & Grumbach, 2002; Bodenheimer, MacGregor, & Sharifi, 2005; Dennis et al., 2008) refer to the Chronic Care Model (CCM) to address the challenge to meet LTC management needs; using electronic health records and care planning. The CCM also integrates various roles, such as general practitioners, practice nurses and community service providers, in a health system to improve outcomes of patients with LTCs (DHS Primary Health Branch Victoria., 2008). Amir et al. (2015) refer to the CCM to argue that care planning should be focused on whole-patient goals and not specific condition-management needs, while Reeves et al. (2014) use the context of CCM to emphasise the importance of individual goals, clinical goals and integrated care for long

[1] This work is done in collaboration with non-profit organisations, Best Practice Advocacy Centre, New Zealand (BPAC NZ) and BPAC Clinical Solutions, which aim to promote best practice among health practitioners in New Zealand, hereafter, referred to as BPAC throughout this paper.

term management needs. Listing the key features, Amir et al. (2015) show that care planning leads to better coordination and thus better health at a lower cost. In both of these studies, the focus is on individual patient outcomes.

A good care plan should meet all the LTC management needs (Mathers et al., 2011). Burt et al. (2014) distinguish care plans and care planning as two different concepts in the context of long term condition management. They define care planning as a process and a care plan as an outcome of that planning process. Some clinical decision support systems (CDSS) are built on UK National Institute for Health and Clinical Excellence (NICE) guidelines for care planning (Mabotuwana & Warren, 2010; Mathers, Roberts, Hodkinson, & Karet, 2011; O'Leary, Noll, & Richardson, 2013). NICE clinical guidelines ensure that clinical decisions are made on best evidence and target optimal use of resources through published care pathways (Fox, Patkar, Chronakis, & Begent, 2009).

Most health systems use care pathways to standardise care processes (Cavlon et al., 2011; Smith et al., 2012; Burt et al., 2014). Care pathways *"map out a pre-defined set of activities for a single health issue or problem and records the care delivered in such a way that variance between proposed and actual care can be audited.*" (Fox, Alabassi, Patkar, Rose, & Black, 2006). Care pathways have been defined as recommendations of standard best practice to manage the same condition in a group of patients, which can be integrated into an information system (Best Practice Advisory Centre New Zealand, 2012). Thus, care pathways, though defined differently in different contexts, focus on standardising the process of care for individual patients. *Care plans* are care pathways instantiated for an individual patient. These are plans of what activities should take place to meet individual management needs (Fox et al., 2006), and these typically refer to various care providers.

Although, health informatics has developed from computer interpretable languages for clinical guidelines (Isern et al., 2008), such as Asbru (Zhou & Hripcsak, 2007) and PROforma (Fox et al.,1997) to defining medical processes formally (Christov et al., 2008), none address population based reasoning for LTC management needs from the perspective of workload prediction of a medical practice. Considering long-term conditions in particular, there is a gap between the demand for care and the capacity of care providers to handle the challenges due to LTCs (Ministry of Health, 2000; Hefford, 2006; Kolker, 2012; Townsville–Mackay Medicare Local, 2012). The challenge of providing care to patients with LTCs is expected to grow in the next 20–30 years (Mabotuwana & Warren, 2010; Mays, 2013). This paper tries to address this challenge to predict the future workload that may arise from LTC patients at a primary health centre. Studies (Woolf et al., 1999; Chaudhry et al., 2006) show that adherence to clinical guidelines improves the quality of care and patients manage their LTC better. Our study, thus investigates the changes that would be required if the medical practice adopts best practice guidelines at an organisational level.

There are several other studies that emphasize the requirement of creating care teams to work closely with general practitioners (GPs) to offer LTC management support, including self-management advice to patients with LTCs (Ministry of Health, 2000; Bodenheimer et al., 2005; Mays, 2013; Dale, 2014). The partnership between physicians and other non-physician care providers or communities makes LTC management better with intervention of multidisciplinary roles (Stellefson, Dipnarine, & Stopka, 2013). A few developed countries, such as the UK, currently take measures, such as adopting the Medical Home[2] model, to manage patients with long-term or chronic diseases and reduce the burden due to these LTCs on their health care systems (DHS Primary Health Branch Victoria, 2008; Reid et al., 2009; Mays, 2013).

[2] The medical home is a team-based health care delivery model led by a health care provider that is intended to provide comprehensive and continuous medical care to patients with the goal of obtaining maximized health outcomes (Reid et al., 2009).

In this paper, the workload prediction model considers what “activities” should happen “when” following the care pathway for an LTC; we have considered chronic kidney disease (CKD) and diabetes (DM_COD[3]) care pathways and “when” the *recall* should happen. Given the predicted workload, a medical practice will be able manage their resourcing accordingly, and thus would improve the care delivery too.

3 Research Methodology

Design Science Research Methodology (DSRM) is a “learn through building” approach that involves identifying (and motivating) a problem, defining the desired properties of a solution, and then designing and developing an artefact (software in our case) and evaluating the developed prototype through various iterations of system development (Vaishnavi & Kuechler, 2004; Baskerville, Pries-Heje, & Venable, 2009). Finally, an important step, which distinguishes DSRM from solution development, is identifying the (more general) lessons learned, and communicating them to the broader community. The whole process is iterative and informed by relevant literature as stated by Peffers et al. (2008, p. 48) “*development of the artifact should be a search process that draws from existing theories and knowledge to come up with a solution to a defined problem*”.

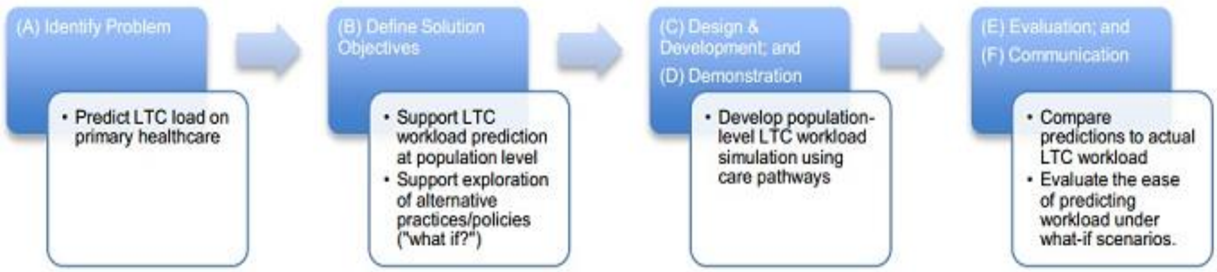

Figure 1. Design Science Research Methodology applied in our work.

Figure 1 shows the DSRM (the arrows showing the iterative aspects of the methodology are not shown) and how the different aspects of the methodology are present in our work. We began our work by (A) identifying the problem that the increasing prevalence of long-term conditions (LTCs) poses to healthcare systems, and in particular, we have chosen to focus on primary healthcare. In identifying this problem, we were guided by both the literature and by discussions with our partner BPAC. We then, with BPAC, continued to (B) define the desired characteristics of a solution: firstly, that it allows a primary healthcare provider to anticipate the workload demands associated with LTCs, to support planning; and secondly, that it allows the provider to explore the impact of potential changes to practices, processes, and policies on the workload associated with LTC care. This then led to (C) the design and development of the prediction model using care pathways, and its implementation as a rule-based system using Drools (Salatino et al.,2016) (see Section 4). The resulting system was then (D) demonstrated and (E) evaluated. The evaluation (see Section 5) involved comparing the workload predictions based on year *N* with the actual workload that occurred in year *N+1*. It is worth emphasising that while our description of the process in this paper is sequential, the actual process was iterative, with regular consultation with BPAC to guide our work. We will have future iterations to experiment with what-if scenarios involving changes in care pathways, resourcing, etc.

[3] DM_COD is used to refer diabetes mellitus condition.

4 Our Workload Prediction Model

As mentioned beforehand, we aim to predict the workload that may arise from LTCs at a medical practice. Guided by both the literature and BPAC, we analysed care pathways and use these as a tool to predict the future workload, specifically to predict the number of patients that would visit the practice in near future.

Read codes are the standard clinical terminology system used in general practice in the United Kingdom and in New Zealand to represent patient details including symptoms and diagnoses (Mabotuwana & Warren, 2010). There are multiple Read codes associated with each LTC, e.g., any Read code starting with G2, such as G20 and G27, is associated with Hypertension. Since the Read codes capture more details about the patient condition than we need, and, because we assume that the care plan for a patient does not change during the simulation period, we map these Read codes to *problem codes*. Problem codes are a more generic name for the LTCs; e.g., CKD is the problem code for chronic kidney disease, and multiple Read codes are mapped to it.

Every LTC follows a care pathway to meet its management needs (Bodenheimer et al., 2002). We analysed these care pathways to find the key events such as recall in 3 months, blood test in 6 months and so on, that should happen for better management of that specific condition in individual patients. These key events are depicted as factors that contribute towards the workload at the primary health centre (PHC). An individual care plan captures these key events associated with various LTCs in a patient.

Table 1 gives an example of a care pathway for diabetes in a tabular form. Based on the risk of diabetes in the patients, clinical decisions are made, such as when the patient should be recalled, the frequency of various lab tests, and the frequency of foot checks. This care pathway reads (first column of Table 1) as follows: Any diabetic patient with “Low Risk” should be recalled in 6 months, with HBA1C and blood pressure checks performed every 6 months, and Lipids, ACR, and eGFR tests and foot checks done annually.

Review Name	**Low Risk**	**Medium Risk**	**High Risk**	**Very High Risk**
Clinical Review	6	3	3	3
HBA1C	6	3	3	3
Blood Pressure	6	3	3	3
Lipids	12	12	12	12
ACR	12	6	6	6
eGFR	12	3	3	3
Foot Check	12	12	6	3

Table 1. Care Pathway for diabetes patients in a tabular form (This is a re-created version of the one shared by BPAC)

Figure 2 gives an overview of our prediction process. As depicted in the figure, medical practice follows care pathways to meet LTC management needs. We associate problem codes with these care pathways. The patients with LTCs suffer from more than one condition and hence most of the patients are associated with multiple problem codes. The care pathways are implemented as rules, which are instantiated as care plans for each patient. Minutolo (2017) highlights the benefits of using a rule based system in medical settings. Rule based systems are built on fixed “When-If-Then” formulae, and draw conclusions based on all the facts in its working memory. The advantages of using rule based systems are: (i) flexibility for different rules being chosen based on facts expressing the current context, and (ii) dynamic handling of changes through rules being re-activated based on changes to facts during the execution of rules. Hence, rule-based systems facilitate modelling the subtleties of clinical guidelines and changing nature of patient conditions.

De-identified data[4] from a single medical practice was used to form the model. This data includes patient details, such as patient id, age, ethnicity, and funding code, classification details, such as patient id, read code and date of classification and so on. The details such as last lab results, age and ethnicity of the patient including historic events (depicted as patient records up to the simulation start date) are seeded into our pre-processing step (see below) to determine the cohort patients and their individual recall details (patient specific care plans). Given these details, our model predicts the future recalls for these patients. Aggregating these recalls, gives an anticipated workload in future.

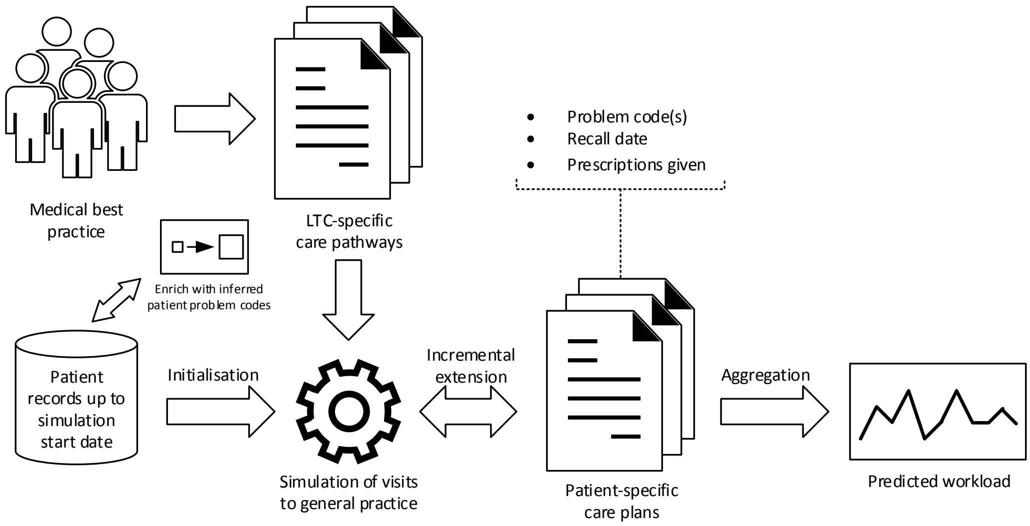

Figure 2 Our prediction process

We follow an iterative process to develop our prediction model. We developed our model through three steps:

- **Pre-processing**: Here, we map Read codes to *problem codes*. Every problem code is associated with its care pathway. Each care pathway is implemented as a Drools decision table (Salatino et al. (2016), p.167-176). Based on the severity of LTC in the patient, depicted from the lab results, these rules infer the individual recall periods (how frequently the patient should be recalled in weeks).

  Table 2 shows an example of individual recall details.

Patient id	Problem code	Recall in Weeks
A	DM_COD	48
B	DM_COD	48
A	CKD	12

Table 2. Individual recall table.

[4] Approval for this research using the anonymised patient data provided by BPAC has been given by the University of Otago Human Ethics Committee (Health)

Suppose we are interested in predicting workload for the year *N*. We look historically into the appointments by these patients in the year *N-1*. For each patient, from their previous appointments, we get the most recent appointment related to an LTC. To determine appointments related to an LTC, we consider those LTC appointments that involve a consultation with a GP or nurse, and where the patient's long-term medication was prescribed within a two week window (one week before or one week after) the LTC appointment. A patient's LTC medication is deemed to be prescribed on a given date if the patient is:

- not on any LTC medicine but an LTC medication is prescribed; or
- on one LTC medicine and there is one LTC medication prescribed; or
- on two LTC medicines and at least one LTC medicine is prescribed; or
- on three LTC medicines and at least two LTC medicines are prescribed; or
- on more than three medicines and at least three medicines are prescribed; on the date of prescription.

We consider only LTC appointments for the previous year and prescriptions of long-term medication without appointments that were within the last 6 months. This is because medication prescriptions last three to six months. As shown in Table 2, an individual patient may be associated with more than one recall period. It is known that more severe the condition is shorter the recall period. Adding the least recall period for the patient (from the individual recall details) to the date of most recent LTC appointment by that patient, gives the first recall date for that patient in the year *N*.

- **Simulate the recalls**: In this step, we populate the rule engine with facts; i.e., we seed into the working memory patient details, individual recall details and the first recall dates (from the pre-processing step). Patient visits are created on the recall dates. These patient visits are implemented as Drools "events" that insert a next recall date. To decide the next recall date, our rules determine the *least*, i.e. after considering multiple care plans associated with the patient, recall period for the patient, making sure that the most severe condition in the patient is always addressed during the visit. Our simulation walks through time. Each day at the practice is simulated with patient visits. Recall dates are recorded.

  We assume that the LTC in the patient is stable and hence no change of the plan of care is considered over the simulation period. We also assume that patients do turn up for their recalls as per the care plan. Our rules also account for recalls that fall on a holiday or weekend being pushed to the next working day for the practice.

- **Aggregate the predicted workload**: Querying the working memory, the simulated recall dates are stored in the database. The aggregation is done on a weekly basis. This weekly aggregation takes into consideration that patients might not turn up on exactly the day of recall, but sometime during the same week.

In short, with the individual recall details and first recall dates, the rules in our model instantiates a care pathway in an iterative fashion, for each patient, visit-by-visit, resulting in a care plan for the patient. This gives an anticipated frequency of required GP appointments for each patient over a period (a year, for now). Aggregating this, for all the patients, gives the overall workload for the specified time frame, on a weekly basis.

5 Evaluation and Observations

In our prediction model, we had made a few assumptions. In this section, we discuss how realistic our assumptions are and give an evaluation of our model. Patients with at least one LTC often have multiple LTCs (Smith et al., 2012). BPAC shared an anonymised patient database from a general practice.

The dataset included 5048 LTC patients and Table 3 gives the comorbidity i.e. the existence of multiple LTCs in a patient at the same time.

PC	Asthma	Atrial	**CKD**	COPD	**DM_ COD**	H-Disease	H-Failure	***HYP COD***	PAD	Psych-osis	Stroke
Asthma	1148	51	267	45	86	81	20	235	5	7	18
Atrial	51	385	213	43	67	147	71	237	20	2	42
CKD	267	213	**1929**	144	536	423	92	**1157**	62	11	110
COPD	45	43	144	280	48	78	20	141	18	1	18
DM COD	86	67	**536**	48	**582**	152	42	**335**	29	3	42
H-Disease	81	147	423	78	152	749	92	432	41	4	59
H-Failure	20	71	92	20	42	92	156	100	14	2	15
HYP_COD	235	237	1157	141	335	432	100	1933	58	10	114
PAD	5	20	62	18	29	41	14	58	93	0	15
Psychosis	7	2	11	1	3	4	2	10	0	39	1
Stroke	18	42	110	18	42	59	15	114	15	1	187

Table 3 Comorbidity table

As a starting point, BPAC guided us to implement care pathways for chronic kidney disease (CKD) and diabetes (DM_COD). These conditions are more likely to be stable during a year, if the plan of care is followed reliably. Usually, deterioration of health in CKD patients is calculated over five years. Studies show that diabetes patients, if on a well followed care plan, tend to manage their condition well (Stellefson et al., 2013). These considerations support our assumption (for now) that patients do not change their plan of care during the simulation period. We model patients leaving and joining the practice in any year and we assume this results in a “steady state” for the practice.

Out of 5048 LTC patients, 1929 patients had CKD and 582 patients had diabetes (which included 536 patients with both conditions). We predict the number of patient visits that might happen in 2014, if the best practice guidelines for LTC management are followed. Our cohort of patients is defined as:

- those patients who have CKD or DM_COD (Diabetes) problem codes associated with them, and
- either there is an LTC appointment in the year 2013, or if an LTC prescription (see Section 4; Pre-processing step) was issued for that patient since June 2013.

For this cohort of patients, we calculated the first recall date for these patients in 2014 and simulated the future recalls for these patients.

Figure 3 shows a comparison of the number of LTC appointments vs the number of simulated recalls per week for the cohort patients. Our BPAC advisor considers that most patients turn up during the second week of December due to the forthcoming (southern hemisphere) summer holidays. Very few patients turn up in the beginning of the year, as most of them will have their medicines prescribed before the New Year, and so there is a low number of recalls at the start of the year. This pattern of rising number of patient visits is not significantly observed in the historic data. Our BPAC advisor suspects it could be due to one or more of the following possibilities

- Best practice is not always followed
- Patients may not follow their plan of care due to various reasons
- Existence of other LTC conditions makes the patients visit earlier than their expected recall for CKD and/or diabetes.
- A few patients might turn up one or two weeks early for a GP consultation before their medication runs out.

Our BPAC advisor reflected that, for the above reasons, the gap in predicted recalls with the actual visits that happened is as expected. We emphasise the aim of this work is not to make the prediction align with what happened but to give a sense of what would happen when the practice follows best practice guidelines for LTC patients.

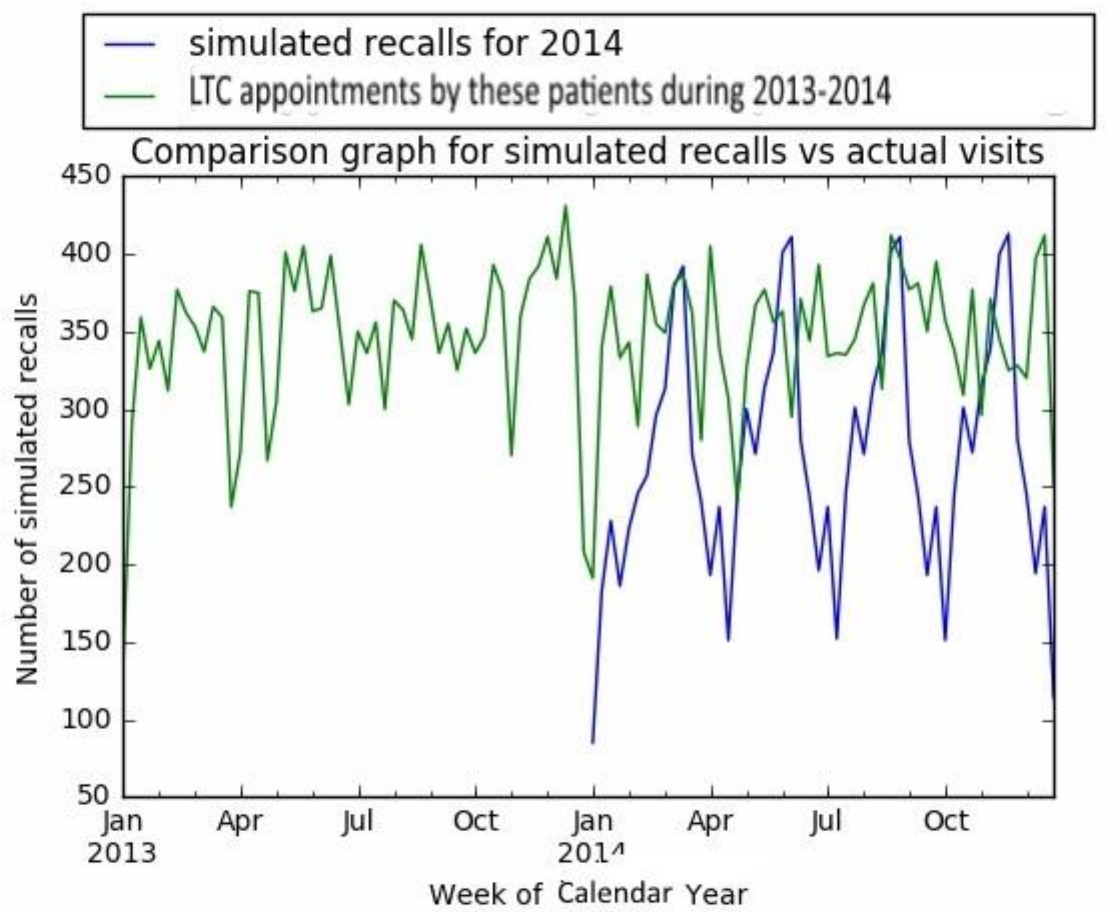

Figure 3 *Comparison of LTC appointments with Simulated Recalls.*

6 Future Work and Conclusion

Following the design science research methodology, we take feedback from BPAC to refine our prediction model. BPAC points out that the mere implementation of CKD and diabetes care pathways is not enough to get a sense of the workload at a primary health centre. The following feedback will be considered in our future work.

1. The comorbidity table shows that much of the cohort patients also suffered from hypertension. Hence implementation of CKD and diabetes care pathways does not account for all LTC visits from the cohort patients. The hypertension care plan would cover a majority of patients and would refine the model in two ways:

    a. It would include most of the LTC visits from the cohort patients, and thus the workload prediction would be more accurate.

    b. The model will be extended to handle a non-fixed recall frequency for patients. Hypertension follows an intensification period of recalls for very high or very low blood pressure readings in patients of a specific age group, based on the lab results.

    The recent feedback from BPAC included the care pathway for hypertension. The most challenging feature of hypertension care pathway is the *intensification of care* for hypertensive patients when their blood pressure is high and medications needs to be stepped up promptly (Lovibond et al., 2011). This intensification of care requires patients to be recalled more frequently (with a weekly or two weekly recall periods). The reduction of blood pressure medication also needs to occur when the blood pressure is low. The reduction in medication also requires more intense review. Hence, implementation of this care pathway will include a majority of the patients (patients with CKD, diabetes or hypertension) visiting the medical practice, how our simulation model relates to a real-world scenario (recall period varies based severity of problem code associated with each patient) and how the workload changes over a year.

2. Given the current capacity of the practice, one of our major next steps is to match the predicted recalls to the resources available. Every medical practice has registered GPs, practice nurses and nurses. Mapping of predicted workload to these care providers would help the medical practice to plan their resources efficiently. This step would also help medical practice to balance the LTC appointments and other appointments.
3. We will also implement various what-if scenarios, such as shifting patients from GPs to nurses, patients visiting the practice early or late depending on the patient characteristics from historic data, and the impact of family and social aspects on LTC management.

With this scope for future work, we conclude this paper, arguing that the demand for care is predictable if a practice follows best practice guidelines to manage its long-term patients. The initial results from this simulation study look promising. In our future work we plan to visualise the workload mapped to the capacity of medical practice and helps to ensure that *Best Practice* guidelines can be achieved within the capacity of current primary care resourcing. This predicted workload would help practices manage their patients and resources more efficiently enabling them to provide better care for patients with LTCs.

References

Amir, O., Grosz, B. J., Gajos, K. Z., Swenson, S. M., & Sanders, L. M. (2015). From Care Plans to Care Coordination: Opportunities for Computer Support of Teamwork in Complex Healthcare. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. ACM.

Baskerville, R., Pries-Heje, J., & Venable, J. (2009). Soft Design Science Methodology. In *Proceedings of the 4th International Conference on Design Science Research in Information Systems and Technology*, article 9. ACM.

Bodenheimer, T., Wagner, E. H., & Grumbach, K. (2002). Improving Primary Care for Patients with Chronic Illness. *Journal of the American Medical Association*, *288*(14), 1775–1779.

Bodenheimer, T., McGregor, K., & Sharifi, C. (2005). Helping Patients Manage Their Chronic Conditions. California Health Care Foundation. http://www.chcf.org/publications/2005/06/helping-patients-manage-their-chronic-conditions.

Best Practice Advocacy Centre New Zealand (2012), Care Pathways for Long-Term Conditions: Using Type 2 Diabetes as an Example. Best Practice Journal, 47, 38–41.

Burt, J., Rick, J., Blakeman, T., Protheroe, J., Roland, M., & Bower, P. (2014). Care Plans and Care Planning in Long-Term Conditions: A Conceptual Model. *Primary Health Care Research & Development*, *15*, 342–354.

Cavlan, O., Dash, P., Drouin, J., Fountaine, T., & Riahi, F. (2011). Using Care Pathways to Improve Health Systems. *Health International*, 11, 6–17.

Chaudhry B1, Wang J, Wu S, Maglione M, Mojica W, Roth E, Morton SC, Shekelle PG (2006) Systematic Review: Impact of Health Information Technology on Quality, Efficiency, and Costs of Medical Care. *Annals of Internal Medicine*, *144(10)*, 742 -752.

Christov, S., Chen, B., Avrunin, G. S., Clarke, L. A., Osterweil, L. J., Brown, D, Cassells, L. and Mertens, W. (2008). Formally Defining Medical Processes. *Methods of Information in Medicine*, *47*(5), 392-398.

Dale, M. C. (2014). *Turning Silver to Gold: Policies for an Ageing Population*. Retirement Policy and Research Centre, Working Paper 2014-2, The University of Auckland.

Dennis, S. M., Zwar, N., Griffiths, R., Roland, M., Hasan, I., Davies, G. P., & Harris, M. (2008). Chronic Disease Management in Primary Care: From Evidence to Policy. *Medical Journal of Australia*, *188*. https://www.mja.com.au/journal/2008/188/8/chronic-disease-management-primary-care-evidence-policy

DHS Primary Health Branch Victoria. (2008). *Revised Chronic Disease Management Program Guidelines for Primary Care Partnerships and Primary Health Care Services.* DHS Primary Health Branch Victoria.

Doolan-Noble, F., Gauld, R., & Waters, D. L. (2015). Are Nurses More Likely to Report Providing Care Plans for Chronic Disease Patients than Doctors? Findings from a New Zealand Study. *Chronic Illness,* 3 (11), 210-217. doi:10.1177/1742395314567479

Ferrer, L., & Goodwin, N. (2014). Developing a Population Health Based Approach to Integrated Care in Local Communities. In *GPNZ Network Symposium: Towards a shared vision for integrated care*.

Fox, J., Alabassi, A., Patkar, V., Rose, T., & Black, E. (2006). An Ontological Approach to Modelling Tasks and Goals. *Computers in Biology and Medicine*, *36*, 837–856.

Fox, J., Fox, J., & Patkar, V. (2009). From Clinical Guidelines to Decision Support Systems: Closing the Loop. *Journal of the Royal Society of Medicine*, 102 (11), 464–473.

Harris, M. F., & Zwar, N. A. (2007). Care of Patients with Chronic Disease: The Challenge for General Practice. *Medical Journal of Australia*, 187 (2).

Hefford, B. (2006). Future Delivery of Community Based Health and Care Services. http://www.achc.org.co/hospital360/tendencias_emergentes/Atencion%20_en_salud_basada_en_la_comunidad.pdf

Kolker, A. (2012). Health Management Engineering. *Analytics*. January, 28–32. Retrieved from www.informs.org

Lovibond, K., Jowett, S., Barton, P., Caulfield, M., Heneghan, C., Hobbs, F. R. (2011). Cost-Effectiveness of Options for the Diagnosis of High Blood Pressure in Primary Care: A Modelling Study. *The Lancet*, 378 (9798), 1219–1230.

Mabotuwana, T., & Warren, J. (2010). ChronoMedIt - A Computational Quality Audit Framework for Better Management of Patients with Chronic Conditions. *Journal of Biomedical Informatics*, 43 (1), 144–158.

Mathers, N., Roberts, S., Hodkinson, I., & Karet, B. (2011). Care Planning: Improving the Lives of People with Long Term Conditions. *London: Royal College of General Practitioners*.

Mays, N. (2013). Reorienting the New Zealand Health Care System to Meet the Challenge of Long-Term Conditions in a Fiscally Constrained Environment. *Wellington: New Zealand Treasury*.

Ministry of Health. (2000). *A Discussion Document: The Future Shape of Primary Health Care*. Wellington: Ministry of Health.

Ministry of Health. (2009). *Report on New Zealand Cost-of-Illness Studies on Long-Term Conditions*. Wellington: Ministry of Health.

Minutolo, A., Esposito, M., & De Pietro, G. (2017). Optimization of Rule-Based Systems in mHealth Applications. *Engineering Applications of Artificial Intelligence*, *59*, 103–121.

Montague, E. (2014). The Promises and Challenges of Health Information Technology in Primary Health Care. *Primary Health Care Research & Development*, 15, 227–30.

O'leary, P., Noll, J., & Richardson, I. (2014). A Resource Flow Approach to Modelling Care Pathways. *Foundations of Health Information Engineering and Systems*, Lecture Notes in Computer Science, vol 8315, Springer, 41–58.

Oldroyd, J., Proudfoot, J., Infante, F. A., Davies, G. P., Harris, M. F., Bubner, T., Beilby, J. J. (2003). Providing Healthcare for People with Chronic Illness: The Views of Australian GPs. *Medical Journal of Australia*, *179*, 30–33.

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2008). A Design Science Research Methodology for Information Systems Research. *Journal of Management Information Systems*, *24*(3), 45–77.

Reeves, D., Hann, M., Rick, J., Rowe, K., Small, N., Burt, J., Bower, P. (2014). Care Plans and Care Planning in the Management of Long-Term Conditions in the UK: A Controlled Prospective Cohort Study. *British Journal of General Practice*, 64 (626), e568–e575.

Reid, R. J., Fishman, P. A., Yu, O., Ross, T. R., Tufano, J. T., Soman, M. P., & Larson, E. B. (2009). Patient-Centered Medical Home Demonstration: A Prospective, Quasi-Experimental, Before and After Evaluation. *The American Journal of Managed Care*, *15*(9), 71–87.

RNZCGP. (1999). General Practice into the Future. *Report of the RNZCGP Primary Care TaskForce, Occasional Paper Number 5*.

RNZCGP. (2012). *A Consultation Document: Developing a Career Pathway for General Practice*.

Salatino, M., De Maio, M., & Aliverti, E. (2016). *Mastering JBoss Drools 6*. Packt Publishing Ltd.

Smith, S. M., Soubhi, H., Fortin, M., & Hudon, C. (2012). Managing Patients with Multimorbidity: Systematic Review of Interventions in Primary Care and Community. *British Medical Journal*, *345*, e5205.

Sox, H. C., & Stewart, W. F. (2015). Algorithms, Clinical Practice Guidelines, and Standardized Clinical Assessment and Management Plans. *Academic Medicine*, *90* (2), 129–132.

Stellefson, M., Dipnarine, K., & Stopka, C. (2013). The Chronic Care Model and Diabetes Management in US Primary Care Settings: A Systematic Review. *Preventing Chronic Disease*. doi: 10.5888/pcd10.120180

Tattersall, R. (2002). *Chronic disease management: A compendium of information*. *Clinical Medicine* (Vol. 2). Royal College of Physicians. doi: 10.4135/9781412952576.n54

Vaishnavi, V., & Kuechler, B. (2004). Design Science Research in Information Systems. http://desrist.org/design-research-in-information-systems.

Woolf, H.S., Grol, R., Hutchinson, A., Eccles, M., Grimshaw,J. (1999) Potential Benefits,Limitations, and Harms of Clinical Guidelines. *British Medical Journal*, 318 (7182), 527-530.

Zhou, L., & Hripcsak, G. (2007). Temporal Reasoning with Medical Data—A Review with Emphasis on Medical Natural Language Processing. *Journal of Biomedical Informatics*, doi: 10.1016/j.jbi.2006.12.009