INTERVENTION EVOLUTION ENGINE - AN INTELLIGENT EHEALTH SERVICE DELIVERY PLATFORM

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Abstract

The rising global population and longevity of individuals place ever-greater demands on healthcare. Increasing choice and complexity of modern treatments make it difficult for clinicians to know and offer the best choices to patients and monitor outcomes to optimise and individualise care. Patients in turn, struggle to adhere to complex treatments offering better outcomes. Information Communication Technologies could improve decision-making by automating aspects of delivery as well as collecting and analysing outcome data that can drive optimisation. We propose an intelligent eHealth-based platform for primary care. The core technology is an Intervention Evolution Engine (IEE) that continuously optimises discreet interventions by comparing two or more versions and replacing the least effective intervention with a new alternative, based on patient feedback. The ultimate aim of this work is to offer a sustainable and exploitable solution for improving and preserving the health and well-being of individuals.

Keywords: Decision Support System, eHealth, Expert System, Information Communication Technology, Machine Learning, Service Delivery

1.0 Introduction

Globally people are living longer and increasing the cost and demand of healthcare. Meeting the demand to maintain the health and life quality of senior citizens will require increasingly effective and efficient treatments (WHO, 2013). Hence, the growing interest in the field of eHealth, defined by the WHO (2016) as the *"use of information and communication technologies in support of health services"*. Interest in eHealth has mainly focussed on the progressive integration of ICT into "paperless" health systems/services, where most growth has been seen since the millennium (WHO, 2016). Improving healthcare is complicated by considerable variability in clinical decision-making, treatment delivery and outcome monitoring (PHE, 2016). On the one hand, this is driven by increasing medical knowledge and complexity in the healthcare environment, and on the other, the limitations of prevailing clinical decision-making that depends heavily on clinician experience rather than data analytics (NIB, 2014).

As a result, the typical Healthcare Service Delivery (HSD) model wastes valuable opportunities to benefit from continuously collecting feedback data from both patients and clinicians to rapidly improve the efficiency and effectiveness of interventions (Picker Institute Europe, 2009). Integrating eHealth into the HSD process therefore remains promising but elusive. In approaching this goal, the question guiding our approach is, *"What is the single most effective implementation of eHealth that will perpetually maximise the benefits to patients and healthcare services as well as facilitate ubiquitous adoption?"* The proposed solution is the Intervention Evolution Engine (IEE), an ICT based HSD system deploying Machine Learning algorithms that utilise the health status and behavioural data of patients to optimise individual treatment and rapidly evolve interventions via a continuous feedback mechanism. To maximise the impact of the system on population health the IEE will prioritise interventions when considering the decision-making algorithms.

2.0 Problem Statement

Despite widespread availability of eHealth technologies and worldwide practice of HSD, a large integration gap remains that makes it difficult to automate more advanced ICT to optimise the HSD process (NHS Digital, 2017). This provides an opportunity to closely integrate an eHealth-based solution to meet healthcare demands. ICT has advanced to a point where it is now possible to build systems that:

- Facilitate the collection and utilisation of data to,
- inform and individualise clinical decision making about interventions via
- an Expert Decision Support System that combines clinician experience (expert aspect) with Machine Learning (decision support aspect).

ICT can also facilitate better standardisation of intervention delivery through clinical workflow management that improves reliability, repeatability, and patient adherence. This can in turn, improve data collection via a continuous feedback mechanism that proceeds from baseline data collection to intervention delivery and outcome measurement to the selection of the most effective interventions.

By bridging the gap between ICT and HSD, the anticipated result is to create a platform where clinicians can select and deliver the most effective and efficient individualised prevention and treatment interventions to patients. The key innovation of the IEE will see interventions automatically evolve in subsequent iterations to facilitate maximum clinical benefit. The system will implement the Stepped Care model, where patients are first allocated to the most efficient and likely effective form of treatment, before proceeding with the next most effective form of treatment if the previous step is deemed unsuccessful (Franx et al., 2012). Intervention selection will be personalised based on health status, personal preferences, and individual requirements. We also plan a comprehensive benchmark and trend analysis of existing eHealth systems and services to form the foundation of developing the IEE as well as address any identified gaps therein.

3.0 Purpose Statement

The purpose is to design and implement the IEE (Figure 1) into routine clinical practice in primary care settings. The core architecture of the IEE will drive the Stepped Care model via Machine Learning algorithms (providing predictive analyses) with ongoing outcome measurement i.e. a continuous feedback mechanism. A core principle of the system is that patients will be randomly allocated to one of two or more available interventions, as in a Randomised Controlled Trial (RCT), where one option will be the current "gold standard" and the alternatives are either variations or novel interventions. Alternative interventions will contain a new attribute that will be compared against the current version and at the end of each iteration; the best performing intervention will proceed on to the next iteration where it will be tested against a new alternative. This will form the basis of the A/B Testing procedure (Kohavi and Longbotham, 2016).

The aims of this solution are to:

- Provide end-users with successful User Experience (UX) by following best practices on gathering and organising major business, user, and system requirements at the beginning of each prototype development iteration, emphasising both functional and non-functional system requirements.
- Design a user-friendly and user-centric User Interface (UI) that will collect baseline and outcome data from patients (i.e. patient feedback) at set intervals, which will allow the system to learn and adapt in an iterative manner.
- Develop Machine Learning algorithms with the high predictive ability to calculate the best point of entry into the Stepped Care model as well as a selection of optimal interventions for specific conditions to save time and maximise cost-effectiveness.
- Operationalise randomised A/B Testing of specified attributes in each care module of each step of the Stepped Care model, to speed up the evolution of interventions.

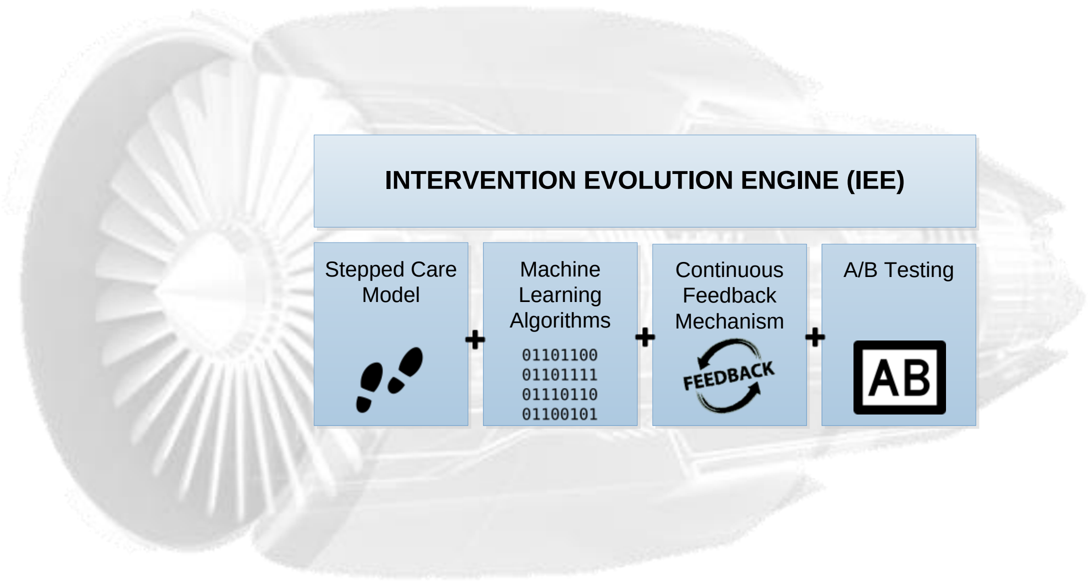

Figure 1. Intervention Evolution Engine (IEE).

4.0 Research Question(s)

The question to answer here is, if eHealth can revolutionise the HSD process, *what is the single most effective implementation of eHealth that will perpetually maximise the benefits to patients and healthcare services as well as facilitate ubiquitous adoption?* In answering this question, it is essential to propose several sub-questions that will ultimately lead to answering this main research question. These sub-questions will also help to guide the study through the Research and Development (R&D) process by breaking down the study and providing us with key objectives to work towards. These additional questions will centre on the Systems Development Life Cycle (SDLC) of the IEE system with emphasis on the design and implementation phases where the study places more focus. Regarding the System Development Methodology (SDM), we propose a novel approach further expanded on in the Conceptual Framework section of this report.

The sub-questions of this study are:

- How can we use eHealth to help automate and manage the healthcare service delivery process applied routinely by healthcare professionals, to eliminate or at least reduce the risk and consequences of conditions such as Type 2 Diabetes Mellitus?
- How can we design and study an eHealth-based system that can effectively deliver diabetes risk detection and reduce these risks by data-driven suggestions as well as optimisation of personalised lifestyle and medical interventions?
- How can we embed eHealth in routine clinical practice to automate use and outcome data collection to regularly assess and enhance the effectiveness of the treatments and therapies administered to patients?

5.0 Conceptual Framework

Using Type 2 Diabetes as a case study, this research will focus on administering interventions related to two key priority areas of Diabetes management (NICE, 2015):

- Patient Education - Offer structured education to adults with Diabetes at and around the time of diagnosis.
- Lifestyle Advice - Integrate dietary advice with a personalised diabetes management plan, including other aspects of lifestyle modification, such as increasing physical activity.

We will identify current best practices, advised by the National Health Service (NHS) and National Institute for Health and Care Excellence (NICE) guidelines, in biological, psychological, and social data collection by collating data collection measures (surveys and questionnaires) that either contribute to risk calculations or guide interventions. In terms of software and algorithm development, we will benchmark, source, and reuse or adapt existing code where available. However, unique functionalities of the IEE system will be coded from scratch.

The IEE will be developed using a novel System Development Methodology (SDM), conceived by adapting the Cross-Industry Process for Data Mining (CRISP-DM) methodology and combining it with Eric Ries's The Lean Startup approach along with Tim Brown's process of Design Thinking (Figure 2).

- CRISP-DM is considered the leading methodology for data mining and predictive analytics projects, covering the typical phases of an analytical project (IBM, 2011).
- The Lean Startup approach guides fast, efficient solution development and delivery by focussing time and capital into iteratively building solutions to meet the needs of customers, thereby reducing their product development life cycles (Ries, 2011).
- The Design Thinking process allows decisions to be made based on what future customers want instead of relying only on historical data or making risky assumptions based on instinct rather than evidence (Brown, 2009).

This novel methodology was designed to optimise software as a service development.

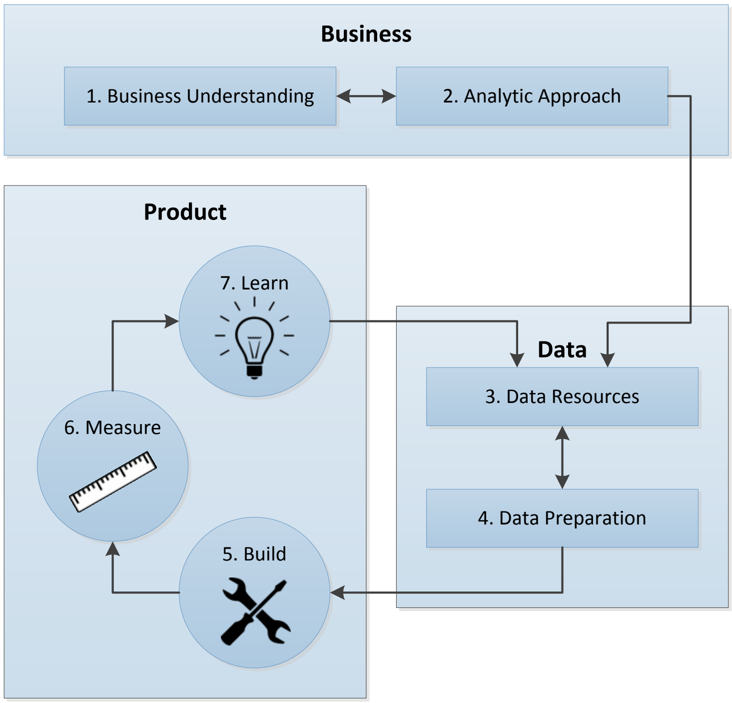

Figure 2. A Lean Design Thinking Methodology for Data Science.

6.0 Rationale and Significance

The IEE in concise will aim to reliably deliver proven prevention interventions in a Stepped Care model approach, possess functionality that routinely measures outcomes to continuously evaluate and improve the effectiveness of interventions as well as facilitate randomised A/B Testing to speed up the evolution of these interventions for subsequent application. Using primary and secondary prevention methods to aid in targeting a few common serious health conditions that carry risk to healthy ageing and have high morbidity (such as those associated with Type 2 Diabetes) can have vast potential benefits for all patients and the public. This project can consequently assist researchers and HCPs by helping them to identify and understand the correlations and dependencies between patient preference and adherence, their health conditions, and its associated treatments. This could at the right time help add to our understanding of the causative and contributory factors of these disorders.

The IEE would prove to be a very valuable tool serving many of its stakeholders. Not only will it help patients to tackle problems early on before the need and involvement of significant and costly interventions it would also help researchers and HCP's collate vital information that would essentially help them to pinpoint the best form of treatment to treat a health condition. This work is aimed at contributing to the realisation of a sustainable and exploitable solution for improving and preserving the well-being of individuals. The significance of our work will be determined by our success in uniting the necessary technologies and managing related HSD processes into a valuable automated eHealth-based platform. Further developments and advances to the platform (beyond this study) can form the core of an Artificially Intelligent (AI) technology used to treat other types of health conditions and disorders.

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