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AI Can Improve the Economics of Blindness Prevention in Canada

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Abstract. Diabetic retinopathy is a leading cause of vision loss in Canada and creates significant economic and social burden on patients. Diabetic retinopathy is largely a preventable complication of diabetes mellitus. Yet, hundreds of thousands of Canadians continue to be at risk and thousands go on to develop vision loss and disability. Blindness has a significant impact on the Canadian economy, on families and the quality of life of affected individuals. This paper provides an economic analysis on two potential interventions for preventing blindness and concludes that use of AI to identify high-risk individuals could significantly decrease the costs of identifying, recalling, and screening patients at risk of vision loss, while achieving similar results as a full-fledged screening and recall program. We propose that minimal data interoperability between optometrists and family physicians combined with artificial intelligence to identify and screen those at highest risk of vision loss can lower the costs and increase the feasibility of screening and treating large numbers of patients at risk of going blind in Canada.

Keywords. Diabetic retinopathy, screening, artificial intelligence, risk prediction, vision loss, blindness

1. Introduction

Diabetic retinopathy (DR) is one of the most common complications of diabetes mellitus (DM) and is the leading cause of vision loss (VL) in Canada [1,2]. It causes blindness in the working age group, making it an important cause of disability, lost earnings, and lost productivity [1,3]. Its clinical costs are high as the symptoms are not evident until significant eye damage has already occurred. For example, glucose control and timely retina screening are key to minimize risk of severe DR and its associated VL. Apart from medical costs, a person with DR has non-medical costs such as loss of quality of life, cost of disability, lost productivity, increased insurance costs and lost earnings due to premature death/retirement, which is a major part of diabetes-related expenditures [3].

Ontario has the highest number of people with VL from DM (465,826 cases), followed by Quebec (283,935 cases) and British Columbia (166,754 cases) [3]. By 2040, DR associated VL is predicted to increase by 55% [3]. This will be a massive

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tragedy unless addressed early by regular screening, which can prevent 95% of the cases.

In Ontario, 440,000 patients with diabetes were not screened between 2016 and 2020 making 30% susceptible to DR in 3-5 years, and 50% may go blind in 5 years [3-5]. A recent study in Ontario revealed a continuing, accelerated decline in DR screening due to the pandemic, to as low as 20% in some populations which was influenced by their age group, ethnicity, and income [6,7]. The most vulnerable are at greatest risk.

There have been multiple attempts to solve the problem of not screening over the last 2 decades, with very little impact at the ground level for all the efforts and money spent on the problem [8]. All previous attempts used a customer relationship management system to reach out to patients at risk; however, scalability was a challenge as it is integrated neither with primary care, nor with optometry.

This paper reports on our economic analysis of two novel informatics scalable and affordable interventions to convert our system from the current reactive state to proactive.

2. Cost Effectiveness Analysis (CEA)

We used a CEA methodology for our study [9]. The population used is the 1.1 million people of Ontario who have DM Type 2, between 2016 and 2020. Forty percent, that is, 440,000 Ontarians did not undergo screening in this period [3].

2.1 Interventions evaluated

The informatics approaches we evaluated were 1) the Data Interoperability (DI) approach –interoperating data between optometrists and family physicians to identify those patients who have not received DR screening in the last year [10]. In this approach, every DM patient identified as not being screened for DR by a family physician, based on data received from optometrists on who has already been screened, is referred to an optometrist for screening. In Ontario for example, 440,000 patients would be referred. 2) The Risk Profiling (RP) approach –a modification of DI where only the 20% at highest risk of developing VL undergo screening by an optometrist. For example, in this model only 108,000 people would have to be recalled and screened instead of the full 440,000.

CEA was performed from the perspective of the Canadian Healthcare system and the perspective of a patient. Cost comparison was conducted in the following areas: a) the cost of inaction (the current costs), b) the cost of action (future clinical costs if implemented), c) the cost of the intervention (IT and management infrastructure to deliver the intervention) and d) patient out-of-pocket costs and loss of income.

The cost of inaction includes cost of treating DR with laser therapy and costs of VL for the unscreened population over a span of 4 years (2016-2020). The ***cost of action*** includes the costs of screening for DR (currently NOT incurred), laser treatment costs and blindness costs.

The cost of intervention is the cost of program implementation, including costs to identify patients at risk, data interoperability costs, the costs of recalling patients and the cost of human resources. For RP, it includes additional costs of designing, testing and validation of artificial intelligence (AI) or machine learning (ML) prediction models.

Patient costs include out of pocket costs incurred by patients due to vision loss. This includes direct healthcare costs and indirect costs due to the complications of blindness. It also includes financial cost of blindness, hospitalization costs, wellbeing cost, private expenditures on aids, equipment etc., rehabilitation cost, economic efficiency loss, medication cost and long-term disability cost [3].

Data values for each of the aspects of DI and RP approaches was based on costs obtained through literature review of existing studies done in Canada [3]. CEA and cost comparison of annual spending was conducted in each of the above-mentioned key areas.

3. Results

3.1. Cost comparison of DI vs RP

Table 1. Cost breakdown of Data Interoperability vs Risk Profiling Approaches.

	Data Interoperability	Risk Profiling
Percent impact	95%	90%
Cost of Inaction	$230 M	$230 M
Cost of Action (Additional Screening)	$56 M	$13.4 M
Cost of Intervention (IT infrastructure and Call Centre)	$90 M	$19 M
Total Cost of Program	$146 M	$32.4 M
Potential Cost Savings	$84 M	$197.6 M

Table 1 shows that the DI approach would prevent 95% of VL if implemented fully for 440,000 patients in Ontario vs. RP which would prevent approximately 90% of VL while screening only 108,000 patients. Implementation of DI would cost $146 million, while RP would cost only $32.4 million across Ontario. These costs are approximate average costs spent annually. Although RP costs are lower, it should be noted that it requires a new prediction model and research studies to confirm their effectiveness and therefore could take longer to implement. However, it is a significantly simpler solution for similar outcomes in the long run.

4. Option Evaluation

Results of this CEA strongly support the use case for improving DR screening strategies. There are three options available to address DR screening rates. Option one is to continue the current approach and do nothing. The benefits of this approach are that screening costs are not incurred and we avoid spending on IT interoperability, patient outreach infrastructure, clinician training and the costs of training and maintaining AI. However, this option is associated with rising healthcare costs due to rising rates of DR and VL.

The second option is to implement the DI approach to catch unscreened patients early. This approach is easier to implement and scalable. It requires sharing minimum data between optometrists and family physicians, making the transition easier. This approach is costly and would require significant investment in patient outreach and tracking infrastructure. More than 440,000 patients whom are not currently screened would incur additional costs of screening and time-consuming outreach plans.

The third option is to implement RP, the preferred and recommended approach. This approach identifies and screens only those who are at highest risk of VL. It requires fewer resources to maintain and is sustainable. Although it requires a longer time to implement, the total cost of RP will be less than DI and will be more feasible in the long term. Additional time is required to commission the development of prediction models whose accuracy relies on large, mixed data sets with minimal bias and are representative of the patients at risk.

5. Discussion and Recommendation

Recently the Ontario Health Data Council published a report for responsible use of health data to establish a sustainable, learning health data ecosystem that benefits the people of Ontario [11]. This business case fits their vision and high-value system-level recommendations such as an integrated and accountable care approach between providers of different care settings, population health management identifying specific strata of our society, and the unique needs of individuals with DR. Both proposed approaches will focus on primary use of health data, not secondary use, with an objective of stratifying the population for targeted DR screening. This will entail data sharing agreements with essential policy requirements, process, and funding that facilitate sharing among all signatories with an entity commissioned to oversee it. Inputs from a report by Health Data Research Network Canada on *Social License for Uses of Health Data* could be utilized as a guide for next steps [12].

Risk prediction models have been used in clinical care for decades, and AI prediction models can enhance clinical decision making while fostering patient centered care. However, challenges like privacy, security and ethics need to be addressed for effective solutions to be accepted and trusted. Utilizing existing robust frameworks such as MINIMAR, TRIPOD-ML and PROBAST, can help address data transparency, minimal standards for reporting, potential biases and unintended consequences [13-15]. Further validation of the effectiveness of AI should be considered before implementing the policy recommendations.

Canadians witnessed a rapid digital health transformation in recent years with the COVID-19 pandemic. However, the increased digital uptake has only served to deepen the digital divide [16]. Fragmented systems, lack of data sharing and standardization have posed barriers to adoption. This could be overcome by prioritizing a data governance culture with clarity on data ownership, its accountability and IT infrastructure. Digital health interventions such as interoperability tools and risk prediction calculators can offer new possibilities for the early identification and treatment of DR, saving many Canadians from going blind.

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