University of Southampton

Faculty of Social Sciences

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Improving Access to Healthcare among Low-income Populations: Operational Research Modelling Approaches to Support the Outpatient Service Delivery Process

by

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Abstract

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This thesis studies no-show behaviour for medical appointments. It comprises four research papers, each of which addresses a different aspect of the problem. The case study is an outreach program designed to overcome access barriers affecting low-income patients in Bogotá, Colombia. The research uses a range of approaches, both qualitative and quantitative, and represents a scientific contribution in terms of the novel methodology developed to tackle some of these problems. However its key feature is its relevance to real world decision making through a longstanding collaboration with the Secretaria Distrital de Salud in Bogotá, who have supported the research throughout.

First, in Chapter 2, we assess the effectiveness of three machine learning models to predict individual attendance probabilities using routinely collected administrative data. Although all three models allow us to identify those patients at higher risk of no-show, due to the limitations of the data it is not possible to understand the reasons behind patients' health-seeking behaviour. Therefore, in Chapter 3 we show the benefits of combining these machine learning models with an in-depth qualitative methodology. Particularly, we aim at understanding patients' experience with the cervical cancer screening program in Bogotá. This paper uses a mixed methods approach, in which qualitative data are used to explain quantitative results. Sixty semi-structured interviews were conducted, and the Health Belief Model (HBM) used as a conceptual framework to build

second order categories. The Framework method was used to analyse the qualitative data. Then, in Chapter 4, we validate the use of the HBM to explain and predict no-show behaviour for cervical cancer screening appointments among low-income hard-to-reach women in Bogotá. A randomly selected sample of 1699 women was surveyed using a 37-item instrument. We quantify the relationship between each construct of the HBM and the attendance probabilities for cervical cancer screening. Additionally, we propose a sequential approach to improve the accuracy of the no-show prediction, using the survey results. Finally, in Chapter 5 we develop a model to select which patients will receive a given behavioural intervention to increase attendance, in situations where funding is limited. Our aim is to classify patients into three groups, based on their attendance probabilities: one group at high risk of no-show who will receive a more costly personalized intervention; a medium-risk group who will receive a cheaper mass intervention; and a low-risk group who will not receive any intervention at all. To do this in a fair way, i.e. one that does not disadvantage specific subgroups, we develop a novel optimization-based post-processing approach aimed at addressing machine learning bias in the algorithmic classification problem.

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Research Thesis: Declaration of Authorship

Print name: Oscar David Barrera Ferro

Title of thesis: Improving Access to Healthcare among Low-income Populations: Operational Research Modelling Approaches to Support the Outpatient Service Delivery Process

I declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research.

I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;
2. Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
3. Where I have consulted the published work of others, this is always clearly attributed;
4. Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
5. I have acknowledged all main sources of help;
6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
7. Parts of this work have been published as:
    - Barrera Ferro, D., Brailsford, S., Bravo, C., & Smith, H. (2020). Improving healthcare access management by predicting patient no-show behaviour. Decision Support Systems, 113398. https://doi.org/https://doi.org/10.1016/j.dss.2020.113398.
    - Barrera Ferro, D., Bayer, S., Brailsford, S., & Smith, H. (2022). Improving intervention design to promote cervical cancer screening among hard-to-reach women: assessing beliefs and predicting individual attendance probabilities in Bogotá, Colombia. BMC Women's Health, *22*(1), 212. https://doi.org/10.1186/s12905-022-01800-3.
    - Barrera, D., Bayer, S. Bocanegra, L., Brailsford, S., Diaz, A., Gutiérrez, E., and Smith, H. Understanding no-show behaviour for cervical cancer screening appointments among low-income women in Bogotá, Colombia: a mixed-methods approach. PLOS ONE, 17(7): e0271874. https://doi.org/10.1371/journal.pone.0271874.

Parts of this work have been submitted as:

- Barrera, D., Brailsford, S., and Chapman, A. Improving fairness in machine learning-enabled affirmative actions: a case study in preventive healthcare. Under review.

Part of this work has been presented as:

- Barrera, D., Brailsford, S., Smith, H., and Bravo, C. *Predicting no-show probabilities for medical appointments among low-income population in Bogotá, Colombia*. EURO Working Group on Operational Research Applied to Health Services Conference: ORAHS 2019. Karlsruhe, Germany.
- Barrera, D., Brailsford, S., Smith, H., and Bayer, S. Should I stay or should I go? Understanding no-show behaviour among low-income patients in Bogotá, Colombia. EURO Working Group on Operational Research Applied to Health Services Conference: e ORAHS 2020.
- Barrera, D., Bayer, S., Bocanegra, L., Brailsford, S., Diaz, A., Gutiérrez, V. and Smith, H. Cervical cancer screening among low-income women in Bogotá, Colombia: prediction and interpretation of no-show behaviour. EURO Working Group on Operations Research for Development Workshop: EWG-ORD 2020.
- Barrera, D., Bayer, S. and Chapman, A. Prioritizing patients for behavioural interventions in cancer screening uptake: a machine learning approach. EURO Working Group on Operational Research Applied to Health Services Conference: ORAHS 2022. Bergamo, Italy.

Signature: ....Date:............................

A mi mamá:

Siempre he aspirado a ser un testimonio de tu amor y arduo trabajo. Gracias por tanto.

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I am deeply thankful to the Pontificia Universidad Javeriana. Not only for its role during my PhD but for all the support I have received since I joined the University, in 2013. I am a proud member of an institution that believes in the value of research in solving the problems we face as society.

I would also like to thank Colfuturo and Colombia Cientifica for believing in me and in this project. I hope to be able to contribute to build a better country for the generations to come.

Having gone through this process during a global pandemic has been challenging in more aspects I could ever imagine. However, amazing people have stood by my side from before I began planning my PhD, to the very moment I write these words. I will be always grateful for their support and for reminding me how lucky I am to have such a loyal and unconditional support system. I will continue to do my best to live up to their example.

Abbreviations

ABS	Agent Based Simulation
ACS	*Acciones Colectivas en Salud*
AUROC	Area Under the Receiver Operating Characteristic Curve
ASIR	Age Standardized Incidence Rate
CHBM	Champion’s revised Health Belief Model
CIN	Cervical intraepithelial neoplasia
DANE	*Departamento Administrativo Nacional de Estadística*
DSR	Design Science Research
DSS	Decision Support System
FNR	False negative rate
FPR	False positive rate
HBM	Health Belief Model
HPV	Human papillomavirus
HTA	Health technology assessment
KMO	Kaiser-Meyer-Olkin test
LASSO	Least Absolute Shrinkage and Selection Operator
LMICs	Low and middle-income countries

LRP	Layer-wise Relevance Propagation
ML	Machine Learning
NN	Neural Networks
OLS	Ordinary least squares
RECORD	The REporting of studies Conducted using Observational Routinely-collected health Data
RF	Random Forest
SDS	*Secretaría Distrital de Salud*
SRQR	Standards for Reporting Qualitative Research
SISBEN	*Sistema de Identificación de Potenciales Beneficiarios de Programas Sociales*
WHO	World Health Organization

Chapter 1 Introduction

This PhD thesis aims at understanding patient no-show behaviour in healthcare systems, with a focus on developing countries. The case study context is an outreach program in the city of Bogotá, Colombia. However, the methods used and the OR models developed are widely applicable. The thesis is structured as a Research Paper PhD in which each paper addresses a different aspect of the problem. The results of the developed models, when linked, can be used to support planning decisions and ultimately, improve health outcomes.

1.1 Research context

My objective is to support the outpatient service delivery process, in high no-show settings, using Operational Research (OR) modelling approaches. No-show behaviour has been identified as a critical issue for health systems, affecting primarily low-income communities (Brewster et al., 2020; Daye et al., 2018). In terms of quality of care, missed appointments might lead to delays in diagnosis and initiation of treatment (Zebina et al., 2019), increased premature mortality rates (McQueenie et al., 2019), increased use of emergency services (Wallace et al. 2018), longer lead times (Mikhaeil et al., 2019), and access problems (Ruggeri et al., 2020), among others. Additionally, economic consequences could include idle time for both physicians and consultancy rooms (Finn et al., 2019), increased cost of care (Weaver et al., 2019), and financial burden for service providers (Kheirkhah et al., 2016). Therefore, there is a growing interest in understanding no-show determinants (Dantas et al., 2018) and minimizing its impact (Millhiser & Veral, 2019).

The case study is of an outreach program called *Acciones Colectivas en Salud* (ACS). ACS was instituted by The District Secretariat of Health (SDS) to overcome access barriers affecting low-income patients in Bogotá, Colombia. Broadly, the program consists of a group of community workers visiting patients, who are sparsely geographically distributed, to assess health risks, quantify needs and define care pathways within the health system. The service process can be summarized in three phases. First, patients are identified using databases of social programs. Second, community workers make home visits to assess general health conditions and classify patients according to their health risk level. Lastly, in the third phase, a medical appointment is scheduled for each assessed patient in one or more services. Table 1.1 presents the objective of the first appointment, in each service, as defined by the National Health Authority (*Resolution 603280*, 2018). Since the General Health Security System in Colombia reached universal coverage in 2014 (OECD, 2016), at the end of this third phase the barrier to access healthcare is considered overcome and the patient is expected to start treatment using the services of their insurance company. The city is divided into four clusters providing health services and, for each cluster, a team is in charge of the operational decisions of the program.

Table 1.1 Services and objectives of the ACS program

Service	Objective
Oral Health (OH)	To assess oral health status and promote self-care.
Growth and Development (G&D)	To assess and follow up growth and development status among children.
Young Adult Program (YAP)	To assess health status and development risks.
Senior Program (SP)	To assess health status and identity major changes.
CCU Program	To increase cervical cancer screening uptake rate.
Breast Cancer Screening	To increase early diagnosis of breast cancer.
Family Planning	To provide relevant information and counselling.
Antenatal Care	To ensure timely access and improve health outcomes.
Emergencies	To control health risks that might endanger quality of life.
Visual Care	To assess health status.

1.2 Research motivation

Over the last three years, the ACS coverage has grown considerably. Therefore, there is a pressure to improve planning processes and resource allocation. The local health authority (*Secretaría Distrital de Salud*, SDS) has defined three performance indicators to assess the operation: (i) the percentage of visits in which risk assessment is performed. (ii) the percentage of appointments given within a target lead time (i.e. the elapsed time between the date of the home visit and the appointment date). (iii) the percentage of attended appointments. After a series of initial meetings with ACS managers and two workshops with the community workers in charge of the operation, it became clear that high no-show rates are a concern. All the efforts to plan the operation and to overcome healthcare access barriers have been hampered by what is perceived as low patient engagement. Consequently, we aim at understanding how OR modelling approaches can be used to support local authorities aiming to improve service delivery processes.

The first step was to model patient no-show behaviour. Individual attendance probabilities were predicted by leveraging administrative health data. We implemented three machine learning techniques and found satisfactory levels of accuracy. Consequently, it was possible to identify the characteristics of the patients with high no-show risk. Then, to understand the reasons behind the low attendance levels, we conducted 60 semi-structured interviews. The sample included patients with high no-show risk who had failed to keep their appointments for cervical cancer screening. Analysing the qualitative data, we found that the Health Believe Model (HBM) was a suitable conceptual framework to build second-order categories. However, it was not possible to draw conclusions about the relationship between the HBM constructs and the no-show behaviour. Therefore, we decided to conduct a survey among 1699 women and validate the use of the HBM to predict no-show for cervical cancer screening, among the targeted population.

Then we used the knowledge about the patient behaviour to support the planning process. SDS decided to design two behavioural interventions to increase cervical screening uptake, among hard-to-reach women. Therefore, patients needed to be classified into three groups: a group who would receive a personalized intervention (Group A), a group who would receive a mass intervention (Group B) and a group that would not receive any intervention at all (Group C). We used a bi-objective optimisation approach to improve the group fairness of a ML-based classification, following a post-processing approach.

1.3 Research aims and contributions

Figure 1.1 is a graphical representation of four research approaches dealing with no-show rates in medical appointments. As can be seen, we propose a classification into two categories considering the main research output: i) new information or ii) recommendations to change the way the system operates. Utilising these categories, on one hand, prediction models can be designed to identify patients with higher no-show risk (research approach 1) or interpretative models can be used to understand perceived barriers of access (research approach 2). On the other hand, it is possible to minimize the impact of no-show rates by supporting the planning process using resource allocation or scheduling models (research approach 3) or to reduce no-show rates by designing and implementing interventions to change patient behaviour (research approach 4).

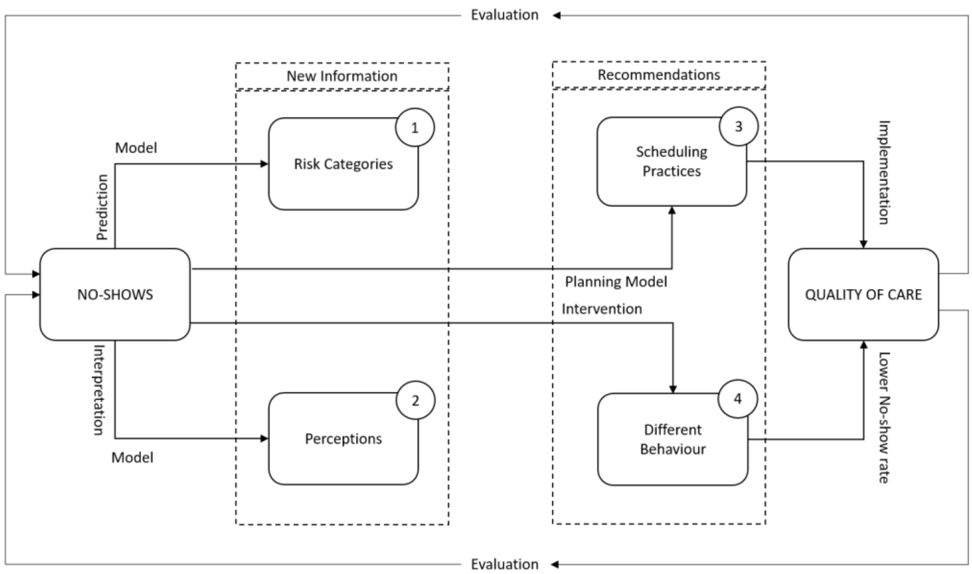

Figure 1.1 Previous research approaches in no-shows for medical appointments

Although different research communities have traditionally conducted research in both categories, generating new information or redesigning service delivery process, we argue that planning models can be improved using information regarding no-show probabilities and perceived access barriers. Therefore, human behaviour is modelled in order to improve system representation and increase potential for implementation of the results (Brailsford, Harper, and Sykes 2012; Alwasel, Fakhimi, and Stergioulas 2019). We pursue the following objectives:

1. To develop machine learning (ML) models to predict individual no-show probabilities.
2. To model the patient decision-making process in healthcare-seeking behaviour.
3. To support intervention operational planning incorporating patient behaviour.

This work has been developed in close collaboration with SDS. Therefore, our results will be used to inform policy decisions and service design. We have made the following three particular contributions:

1. The novel application of an explainable machine learning approach using routine patient data to improve accuracy in no-show prediction.
2. Understanding the reasons for no-show behaviour in our study context and modelling it.
3. Proposing a novel optimisation-based post-processing approach to deal with ML bias and include patient behaviour in planning models.

1.4 Overview of problems and methods

Table 1.2 presents an overview of the studied problems, methods, and data. Four papers were written. In the first paper, we used electronic records from SDS in order to predict individual no-show probabilities. We contributed to research in this field in three ways. First, the effectiveness of machine learning to improve accuracy of the regression models, for no-show prediction, was assessed. We used Random Forest (RF) in order to model non-linear relationships, and Neural Networks (NN) to include possible variable interactions. Second, variables affecting no-show probabilities in a developing context were identified. In order to do this, we used a Least Absolute Shrinkage and Selection Operator (LASSO) regression model. Lastly, we used Layer-wise Relevance

Propagation (LRP) in a novel context to generate insights from the NN prediction. This is particularly relevant considering that lack of explanation, in healthcare decision support systems, can lead to both practical and ethical issues (Guidotti et al., 2018). For example, decision makers need to understand the reasons underpinning a prediction in order to trust the results (Fong & Vedaldi, 2019; Shawi et al., 2019). Additionally, if the outcome of a Decision Support System could potentially have impact in the quality of the provided health service, there is a need to ensure impartiality in decision-making by using interpretable models that enable bias in the data set to be detected and corrected (Barredo Arrieta et al., 2020).

However, several limitations arise from quantitative modelling for no-show behaviour. It has been argued that, due to its retrospective methods, it is not possible to identify the reasons that could lead to a missed appointment (McComb et al. 2017; Lee, Kim, and Kim 2018). Thus, in the second paper, we used a mixed methods approach to understand the reasons for no-show behaviour for cervical cancer screening appointments among low-income women in Bogotá, Colombia. Out of the eleven services included in ACS, we decided to focus on Cervical Cancer Screening as incidence and mortality rates of this disease were a major concern for public health professionals in SDS. In the quantitative phase, individual no-show probabilities were predicted using administrative records from the ACS program using both LASSO regression and Random Forest methods. In the qualitative phase, semi-structured interviews were analysed to understand patient perspectives. Both inductive and deductive coding were used to identify first order categories and content analysis was facilitated using the Framework method (Spencer et al., 2014). In this research, integration occurred at two points: i) a patient was invited to take part in the interviews only if her no-show risk, according to the prediction models, was medium or high and ii) the results of the interviews were used to enhance the analysis of the prediction models. Therefore, we were able to generate some insights regarding the no-show behaviour beyond the identification of risk categories.

Table 1.2 Problems and methods.

Paper	Objective	Models/Methods	Data
1	To predict individual no-show probabilities.	LASSO Regression Random Forest Neural Networks	Administrative electronic records (n= 53311) retrieved from SDS information system. Observation time window 2017-2019. This data base includes four (out of eleven services) and one (out of four) city clusters.
2	To understand no-show behaviour for cervical-cancer screening among hard-to-reach low-income women in Bogotá, Colombia	LASSO Regression Random Forest	Administrative electronic records (n=23384) retrieved from SDS information system. Observation time window 2017-2019. This data base includes the four city clusters for the Cervical Cancer Screening Uptake service.
		Framework method for qualitative data	Semi structured interviews (n=60).
3	To assess women's beliefs about cervical screening.	LASSO Regression	Administrative electronic records (n=23384) retrieved from SDS information system. Observation time window 2017-2019. This data base includes the four city clusters.
		Random Forest	Poverty level for each patient, retrieved from the insurance company information system (n=23384).
		Principal Component Analysis	A 37-item questionnaire to measure the constructs of the Champion's revised Health Beliefs Model (CHBM) towards cervical cancer screening. Data were collected through a face-to-face survey (n = 1699)
4	To improve fairness in ML-enabled affirmative actions, following an optimization-based post-processing approach	Optimisation	Administrative electronic records (n=23384) retrieved from SDS information system. Observation time window 2017-2019. This data base includes the four city clusters.
			Poverty level for each patient, retrieved from the insurance company information system.

In the third paper, we aimed at assessing beliefs about cervical cancer screening and quantifying their relationship with the individual no-show probabilities among hard-to-reach women in Bogotá. We used a 37-item questionnaire to measure the constructs of the Champion's revised Health Beliefs Model (CHBM) towards cervical cancer screening. Data were collected through a face-to-face survey (N = 1699). We examined instrument reliability using Cronbach's coefficient and performed a principal component analysis to assess construct validity. Then, Kruskal-Wallis and Dunn tests were conducted to analyse differences on the HBM scores, among patients with different poverty levels. Lastly, to predict individual no-show probabilities we followed a sequential approach. First, we trained a LASSO regression with data retrieved from administrative health records. We hypothesized that by using historical data the model would be better able to identify patterns of attendance. With this model, we predicted the no-show probability for each patient in the survey data set. Then, a second model was fitted using the first model prediction and the 37 items in the survey. The performance of this model was assessed using the average AUROC score of 100 experiments.

In the fourth paper, we proposed an optimization approach to improve group fairness in ML-enabled affirmative actions. As part of ACS, SDS is interested in designing two interventions to increase cervical cancer screening uptake. While the first intervention is personalized and highly resource intensive, the second one is a mass strategy aimed at improving coverage. To ensure cost-effectiveness and financial sustainability of the system, there is a capacity constraint for each strategy. From the operational perspective, the decision of who will take part of each intervention is made based on the predicted individual probabilities of achieving the outcome without intervention. In this context, the population should be divided into three groups: a group for the personalized intervention (Group A), a group for the mass intervention (Group B) and group that will not participate in any intervention at all (Group C). Our bi-objective model maximizes accuracy and minimizes inequality of the classification.

1.5 Collaboration with other researchers

Table 1.3 presents information on the role other researchers have had in this thesis, using the Contributor Roles Taxonomy (CRediT)[1]. Columns two, three and four refer to the members of the supervisory team: Professor Sally Brailsford (SCB), Dr. Steffen Bayer (SB), and Dr. Honora Smith (HS).

Paper 1 was developed with the collaboration of Dr. Cristián Bravo (CB) who was part of the supervisory team until November 2020. Since August 2020, Dr. Bravo holds a Canada Research Chair at Western University, Ontario Canada.

Paper 2 was developed with the collaboration of three researchers from Colombia. Laura Bocanegra (LB) was ACS coordinator between 2018 and 2020 at SDS. She supervised qualitative data collection. Qualitative data analysis was conducted in Spanish. For each interview, two researchers were assigned to code independently. Dr. Valentina Gutiérrez (VG) and Dr. Adriana Díaz (AD) were part of the coding team. They both hold assistant-professor positions at Universidad del Valle and Pontificia Universidad Javeriana, respectively.

Paper 4 was developed with the collaboration of Dr. Adrianne Chapman (AC), Associate professor of the Electronics and Computer Science Department, at University of Southampton. The work of this chapter was partially funded by Institute for Life Sciences, under the project "*Fair access to healthcare: equitable use of routine patient data to prevent no-shows for hospital appointments*."

[1] https://casrai.org/credit/

Table 1.3 Contributor roles for each chapter.

Chapter	SCB	SB	HS	CB	LB	AD	VG	AC
Chapter 2: Predicting no-shows								
Supervision	X		X	X				
Writing - Review & Editing	X		X	X				
Chapter 3: Understanding no-shows								
Data curation					X			
Formal Analysis qualitative					X	X	X	
Supervision	X	X	X					
Writing - Review & Editing	X	X	X					
Chapter 4: Assessing beliefs								
Supervision	X	X	X					
Writing - Review & Editing	X	X	X					
Chapter 5: Improving fairness								
Supervision	X							X
Writing - Review & Editing	X							X

1.6 The structure of this thesis

This thesis is organised as follows:

Chapter 1 presents the introduction. We discuss the research context, motivation and aims. Additionally, we provide an overview of the problems addressed and the data used in each paper.

Chapter 2 contains the paper "Improving healthcare access management by predicting patient no-show behaviour". This paper has been published in the journal *Decision Support Systems.*

Chapter 3 contains the paper "Understanding no-show behaviour for cervical cancer screening appointments among low-income women in Bogotá, Colombia: a mixed-methods approach". This paper has been published in *PLOS One*.

Chapter 4 contains the paper "Improving intervention design to promote cervical cancer screening among hard-to-reach women: assessing beliefs and predicting individual attendance probabilities in Bogotá, Colombia". This paper has been published in the journal *BMC Women's Health.*

Chapter 5 contains the paper “Improving fairness in machine learning-enabled affirmative actions: a case study in preventive healthcare”. This paper has been submitted to the *Journal of the Operational Research Society (JORS)*, and is currently under review.

Chapter 6 presents work in progress on impact evaluation of ACS using Agent Based Simulation (ABS). A conceptual model has been developed and validated with managers and clinicians, but COVID-related issues with data collection have delayed the development of a computer model.

Chapter 2 Predicting No-show behaviour

Abstract

Low attendance levels in medical appointments have been associated with poor health outcomes and efficiency problems for service providers. To address this problem, healthcare managers could aim at improving attendance levels or minimizing the operational impact of no-shows by adapting resource allocation policies. However, given the uncertainty of patient behaviour, generating relevant information regarding no-show probabilities could support the decision-making process for both approaches. In this context many researchers have used multiple regression models to identify patient and appointment characteristics than can be used as good predictors for no-show probabilities. This work develops a Decision Support System (DSS) to support the implementation of strategies to encourage attendance, for a preventive care program targeted at underserved communities in Bogotá, Colombia. Our contribution to literature is threefold. Firstly, we assess the effectiveness of different machine learning approaches to improve the accuracy of regression models. In particular, Random Forest and Neural Networks are used to model the problem accounting for non-linearity and variable interactions. Secondly, we propose a novel use of Layer-wise Relevance Propagation in order to improve the explainability of neural network predictions and obtain insights from the modelling step. Thirdly, we identify variables explaining no-show probabilities in a developing context and study its policy implications and potential for improving healthcare access. In addition to quantifying relationships reported in previous studies, we find that income and neighbourhood crime statistics correlate with no-show probabilities. Our results will support patient prioritization in a pilot behavioural intervention and will inform appointment planning decisions.

2.1 Introduction

High no-show rates are a major issue for health systems. On the one hand, there is a link between low attendance levels and poor health outcomes: consequences include delays in diagnosis and initiation of treatment (Zebina et al., 2019), increased premature mortality rates (McQueenie et al., 2019) and increased use of emergency services (D. J. Wallace et al., 2018), among others. On the other hand, high no-show rates reduce efficiency for service providers. When a patient fails to keep an appointment, it usually results in a vacant slot that might have been used by another patient (Mikhaeil et al., 2019), increases cost of care (Weaver et al., 2019) and generates idle time for both physicians and consultancy rooms (Finn et al., 2019). Consequently, there is a growing interest from the healthcare community in understanding the determinants of no-show behaviour (Dantas et al., 2018) and minimizing its impact (Millhiser & Veral, 2019).

Two main approaches can be used to deal with no-shows in healthcare settings: to improve attendance levels or to minimize impact. The first approach is premised on the idea that it is possible to change patient behaviour. Strategies such as phone reminders (Wu et al., 2019) and education programs (Weaver et al., 2019) have been successfully implemented in different contexts. According to Zebina et al. (2019) a key element in this approach is to be able to correctly identify the patients that should be targeted with each strategy. In contrast, the underlying assumption of the second approach is that such changes in behaviour are unlikely to be achieved, and thus the objective is to minimize the impact of no-shows, e.g. by improving the decision-making process regarding resource allocation and scheduling (Millhiser & Veral, 2019). Given the uncertainty of patient behaviour, generating relevant information concerning no-show probabilities could improve the results of both approaches (Ahmadi-Javid et al., 2017; Schwebel & Larimer, 2018).

Good estimates of attendance levels have the potential to improve policy evaluation (Brailsford, Harper, and Sykes 2012), to minimize undesired effects of resource allocation practices (such as overbooking) (Daggy et al., 2010) and to inform identification of influential stakeholders.

This is particularly important considering that one of the main objectives is to generate information that can be used to improve management practices (Shuja et al., 2019). However, there has been very little discussion in the literature on the trade-offs between using ‘black box’ approaches (sophisticated analytical methods that would be incomprehensible to most healthcare managers) and more easily interpretable but less accurate approaches such as regression models (Topuz et al., 2018).

The context of the study described in this paper is a primary healthcare program targeted at underserved communities in Bogotá, Colombia. Under this program, community workers make home visits to assess health-risk levels and then, if required, schedule medical appointments. Over the two years 2017-2018 the program coverage grew considerably but unfortunately no-show rates for the scheduled medical appointments also grew, reaching levels of 35% and above. Consequently, there was pressure to improve planning processes and use resources more efficiently. In this context, SDS decided to implement two types of behavioural interventions to increase attendance levels. However, some patients are expected to attend their appointments without any intervention. Then, a decision on who will be invited to each intervention needs to be made.

In this work, we develop a Decision Support System (DSS) to support the implementation of strategies to reduce no-show rates in this program. It has been argued that in complex problems with multiple variables and fragmented data, information systems have potential to improve resource allocation practices (Chaudhuri & Bose, 2020) and increase system performance (Fredrickson et al., 2019). Hence, the DSS will use routinely collected data and Machine Learning (ML) methods to classify patients in three risk categories (low, medium and high) in terms of their individual no-show probability. Any intervention to encourage attendance will incur a cost, and hence it is expected to be more cost-effective to target such interventions at medium and high risk patients.

We describe the development of a DSS to support patient classification. When designing socio-technical artefacts such as models and DSSs, Design Science Research (DSR) offers a framework to include human actors in the process, increasing the potential of implementation (Gregor & Hevner, 2013). Therefore we adopt the DSR approach of Peffers et al. (2007) and address three research questions:

- How reliably can routinely collected data on patient and appointment characteristics be used to predict no-show probabilities?
- What is the added value, in terms of AUROC (Area Under the Receiver Operating Characteristic curve), of using different ML approaches to predict no-show probabilities?
- How might insights obtained from these classification models be used in practice to reduce no-shows?

The paper is structured as follows. Section 2 presents recent work in no-show prediction, both in terms of the variables used and the modelling approach. Section 3 presents our DSR approach, describing the problem definition, the proposed solution, the design, and the demonstration and evaluation phases. Section 4 presents a descriptive analysis of the available data. Section 5 discusses the results and how these no-show risk classifications could be used in practice. Finally, Section 6 presents some general reflections.

2.2 Related work

Dantas et al. (2018) reviewed studies about no-show prediction in health care, published between 1980 and 2016, and classified each reference considering the prediction variables, the modelling approach and the context of the application. The authors found that, over the last ten years, most studies use Multiple Logistic Regression models to quantify relationship between patient characteristics and no-show behaviour. Additionally, despite the highest no-show rates in the world being in Africa (43%), South America (28%) and Asia (25%), this problem was found to have been mainly studied in developed countries.

No-show behaviour in primary care appointments has been widely studied (Dantas et al., 2018). At least two features can been argued to explain the scientific interest: firstly, since primary care services are designed to serve large populations, the economic impact of inefficiencies may be greater than in specialized low-coverage services (Norris et al., 2014). Secondly, primary care patients are highly heterogeneous; thus, there is evidence that supports contradictory results regarding the impact that patient characteristics might have on no-show rates (Ellis et al., 2017). In this section, we discuss no-show studies that are related to primary care settings and were published after the review conducted by Dantas et al. (2018). Table 2.1 presents the modelling approach, sample size and main predictive variables in each of the relevant studies.

To understand the impact of a particular feature on no-show rates, several studies have been conducted using large datasets. McComb et al. (2017) find that the impact of lead time on no-show rates is greater among patients who cancel and were rescheduled. Ellis, Luther, and Jenkins (2018) conclude that reduced sleep consequence of the spring daylight savings change, increased no-show rates, suggesting seasonality on the patterns. Both studies present ways in which the results could be used to improve scheduling practices. More recently, Wallace et al. (2018) conclude that patients with lower income and longer travel times to the medical facility are more likely to miss their appointments.

A second approach is to identify patient- and practice-related factors that predict no-show probabilities, using regression models. Ellis et al. (2017) find that age, socioeconomic status and lead times are good predictors for repeated non-attendance in Scotland. Analysing data from hospitals in south-west England, French et al. (2017) conclude that children from higher deprivation areas are more likely to miss their appointments. Goffman et al. (2017) report that no-show history, age and having multiple appointments scheduled on the same day are good predictors for no-show rates among veterans in the United States. Ding et al. (2018) discuss the need for designing different risk models for each medical service and facility in order to improve accuracy. Lastly, Tsai et al. (2019) find that patient gender, age and no-show history are good predictors in Taiwan.

Table 2.1 No-show studies in primary care settings published since 2017

Reference	Country	Sample size	Method	Appointment variables					Patient variables				
				Lead time	Day	Distance	Weather	Season	Gender	No-show history	Age	Race	Marital Status
(Ellis et al., 2017)	United Kingdom	9,177,054	LR	X					X				
(French et al., 2017)	United Kingdom	2,488	LR						X				
(Goffman et al., 2017)	United States	18,000,000	LR						X				X
(McComb et al., 2017)	United States	46,710	Chi-squared	X						X			
(Ding et al., 2018)	United States	2,231,000	LR	X						X	X		
(Ellis et al., 2018)	United Kingdom	7,351,597	Chi-squared					X					
(Mohammadi et al., 2018)	United States	73,811	LR/BC/NN	X	X				X	X		X	X
(Topuz et al., 2018)	United States	105,344	BBN	X	X	X				X	X		
(D. J. Wallace et al., 2018)	United States	51,580	LR			X		X			X	X	
(Parker et al., 2019)	United States	509	LR									X	X
(Tsai et al., 2019)	Taiwan	2,132,577	LR	X	X		X		X	X	X		

LR: Logistic regression, BC: Bayes Classifier, NN: Neural Networks, BBN: Bayes Behaviour Network

In Design Science Research (DSR), knowledge can be descriptive (about the phenomena) or prescriptive (about the human-built artefacts) (Gregor & Hevner, 2013). This paper adds to the existing body of research on no-show behaviour not only by its use of ML methods on routine health data (the artefact) but also through its focus on developing countries (the phenomena). According to Dantas et al. (2018), between 2005 and 2016, most of the research uses regression models in order to predict no-show probabilities. However, recent studies explore the use of other machine learning techniques. Mohammadi et al. (2018) analyse data from electronic health records, over a 3-year period, from Community Health Centres in Indianapolis. The authors implement logistic regression, neural networks and a Bayes classifier to predict no-show probabilities on a dataset containing 73,811 appointments. Unusually, the regression models and Bayes classifier perform better than neural networks, with AUROC values of 0.81, 0.86 and 0.66, respectively. Similarly, Topuz et al. (2018) assess the effectiveness of Bayesian Belief Networks and propose an elastic net variable selection methodology. The authors conclude that there is a potential for machine learning methods to support improvements in management practices by providing accurate prediction of no-show probabilities. These studies make no mention of interpretability of these black-box models, a topic we tackle in this paper.

Lastly, while the same modelling methodology can be generalized to different countries, and the same independent variables have been used across different contexts and service settings, there is considerable variation between service delivery processes and the demographic and epidemiological population profiles in different countries. Each setting must be independently modelled to generate relevant information. Furthermore, previous studies in developing countries report specific features unique to that setting. Challenges such as low use of technology to centralize patient information (Ade et al., 2016; Giunta et al., 2013), income inequality and job instability (Barjis et al., 2013; Machado et al., 2011), long travel distances and poverty (Mbada et al., 2013), access barriers to specialized care (Tseng, 2010) and even low quality expectations (Machado et al., 2011) lead to different interactions between patients and service providers.

Consequently, a systematic effort to develop prediction models and customize strategies for developing countries is required, and we do so in this work.

2.3 A Design Science Research Approach

In this section, we present a DSR approach to allow program managers to select patients who will participate in different behavioural interventions, by designing an ML-based DSS. Table 2.2 presents an overview as five of the six steps in the DSR methodology proposed by Peffers et al. (2007).

Table 2.2 Methodology for Design Science Research (Peffers et al., 2007)

Phase	Our Study
Problem definition and motivation	To reduce no-show rates, associated with poor patient outcomes and inefficient use of resources
Objectives for a solution	To allow program managers to select patients who will participate in different behavioural interventions aimed at increasing attendance levels.
Design and development	We compare four ML modelling approaches and address three questions: 1. How reliably can routinely collected data on patient and appointment characteristics be used to predict no-show probabilities? 2. Which ML approach performs best, using the AUROC metric? 3. How might insights obtained from these classification models be used in practice to reduce no-shows?
Demonstration	Performance assessment using the average AUROC score of a 10-by-10 Cross validation.
Evaluation	Impact on the coverage and risk of an intervention when a classification algorithm is used

2.3.1 Problem Definition, Scope and Context.

Broadly speaking, the national healthcare system in Colombia (*Sistema General de Seguridad en Salud*, SGSS) can be understood as a managed competition model with two insurance schemes: one contributory, covering people who are in formal employment, and one subsidized, covering people unable to pay (Vargas et al., 2016). Despite guaranteeing universal coverage, the SGSS faces constant challenges to improve service quality, increase efficiency and eliminate access barriers (OECD, 2016). Recent studies have shown that these challenges primarily affect patients of lower socioeconomic status (Garcia-Subirats et al., 2014; Rivillas & Colonia, 2017; Vargas et al., 2010). Therefore, the District Secretary of Health (*Secretaría Distrital de Salud*, SDS) in Bogotá instituted a program to eliminate access barriers affecting low-income patients in the city. The program consists of a group of community workers visiting patients, who are sparsely geographically distributed, to assess risks, quantify needs and define care routes within the health system.

The service process of the program can be summarized in three phases. First, patients are identified using existing databases from other social programs. Second, community workers make home visits and classify patients as high, medium or low risk. Finally, in the third phase, a primary care pathway is defined for each patient, according to their level of health risk of needing a service. For each high or medium risk patient, a first medical appointment is scheduled in one or more services. Table 2.3 presents the objective of the first appointment, in each service, as defined by the National Health Authority (*Resolution 603280*, 2018). At the end of this phase, the barrier is considered to be overcome, and the patient is expected to start treatment using the services of the relevant insurance scheme. The city is divided into four clusters providing health services and, for each cluster, a team is in charge of the operational decisions of the program.

Table 2.3 Services and objectives of the program

Service	Objective
Oral health (OH)	To assess oral health status and promote self-care.
Grow and Development (G&D)	To assess and follow up growth and development status among children.
Young Adult Program (YAP)	To assess health status and development risks.
Senior Program (SP)	To assess health status and identity major changes.
CCU Program	To increase early diagnosis of cervical cancer.
Breast Cancer Screening	To increase early diagnosis of breast cancer.
Family Planning	To provide relevant information and counselling.
Antenatal Care	To ensure timely access and improve health outcomes.
Emergencies	To control health risks that might endanger quality of life.
Visual Care	To assess health status.

The SDS has defined three performance indicators to assess the operation of the program.

(i) The percentage of *effective* visits, i.e. where the patient was physically present at the registered address at the time of the visit, and the community worker was able to assess them and make a risk classification.

(ii) The percentage of appointments given within a target lead time. The designated health centre may not have the capacity to treat the patient within the required time limit, and in such cases the earliest appointment is given.

(iii) The percentage of attendance at appointments (i.e., the percentage of no-shows). These patients might enter the health system later via emergency departments due to complications of the identified risks.

By the end of 2018, program managers faced challenges with indicators (ii) and (iii). Only 30% of appointments met lead time targets and no-show rates reached levels of 35% in some services.

2.3.2 The proposed solution

In this context, different interventions could be used to modify patient behaviour and improve program performance. Phone reminders (Steiner et al., 2018; Tull et al., 2019), education (Weaver et al., 2019) and engagement programs (Michelson & Day, 2014), among others, have shown positive impact in decreasing no-show rates in different service contexts. However, such interventions are most cost-effective when patients are classified according to their no-show risk (Weaver et al., 2019; Wu et al., 2019). Therefore, SDS has identified the need to divide patients into three groups. Group A will contain 30% of the patients, due to economic and operational constraints, no additional action will be implemented for them. For Group B, 40% of patients, lower-cost technology-based interventions such as SMS reminders will be evaluated. Group C will contain the remaining 30% of patients. For these, personalized interventions such as engagement or education programs will be designed to improve attendance levels.

It has been argued that by introducing decision support tools, organizations can encourage reasoned thinking, reduce bias and improve decision quality (Féris et al., 2017). Therefore, in this paper, we design a DSS to allow program managers to select patients who will participate in different behavioural interventions. Additionally, when adopting a DSR approach, there is a need to explicitly formulate a set of statements describing the goal, and the means to achieve it. These prescriptive statements are called design principles and are a distinctive characteristic of design knowledge (Gregor et al., n.d.). After conducting a series of meetings with program managers at SDS and reviewing research papers dealing with no-show behaviour for healthcare appointments, Table 2.4 presents the resulting components of our design principle using the schema proposed by Gregor, Chandra Kruse, and Seidel. Within this strategy, the success of a set of interventions relies on the quality of the classification. Then, we define two performance indicators that describe the accuracy. The first is the coverage, defined as the percentage of no-show patients that end up classified in Group C, and the second is the risk, defined as the percentage of such patients that end up classified in Group A. A good classification will have high coverage and low risk. In contrast, considering the sizes of groups A and C, a random classification would have both coverage and risk equal to 30%.

Table 2.4 Components of the design principle

Design principle	Our DSS
Aim, Implementer and User	To allow program managers to select patients who will participate in different behavioural interventions aimed at increasing attendance levels.
Context	A primary care program, in a developing country, with high no-show rates.
Mechanism	Predict individual no-show probabilities using ML techniques.
Rationale	Behavioural interventions are most cost-effective when patients are classified according to their no-show risk.

2.3.3 Design and development: the tested modelling approaches

The first step in the process is the quantification of linear relationships between variables and no-show probabilities. Ordinary least squares (OLS) estimation is widely used to that end. However, Tibshirani (1996) analyses two major drawbacks of OLS: accuracy and interpretation. Since OLS estimates have large variance, setting some coefficients to zero contributes to overcoming both limitations. Therefore, Tibshirani proposes the LASSO regression model, which minimizes the residual sum of squares and ensures that the sum of the absolute value of the coefficients is less than some chosen value. Recent applications of this model include forecasting (Wang et al., 2018) and classification problems (Z. Zhang & Hong, 2017). We have used Scikit-Learn's logistic regression CV implementation, setting the alpha value to 0 so as not to not use ridge regression, and all other parameters have been left at their default values (Pedregosa et al., 2011). Additionally, we perform a parametric analysis on the penalty constant of the model. For each service, thirty values are tested (10 values for each of the following three intervals: (0-0.1], (0.1-1], (1-10]) selecting the constant under which the AUROC is stable (i.e. its improvement is marginal) and the prediction depends on the minimum number of variables. Then, for each input variable, we interpret the average coefficients of a 10-by-10 CV. These results are used to inform feature selection for both the RF and the NN.

Although logistic regression (LR) models are highly interpretable (i.e. understandable by non-experts), they may not be useful in contexts where the relationships between variables are nonlinear (Auret & Aldrich, 2012). For those cases, tree-based ensemble algorithms have shown good performance and modelling flexibility (Breiman, 2002). Tree classifiers split the data set according to a criterion maximizing separation; the result is a tree-like structure (Dreiseitl & Ohno-Machado, 2002). An ensemble of tree predictors, where each tree depends on the values of a random sample of both cases and variables, is called a Random Forest (Breiman, 2001). For classification problems, RFs help to overcome the risk of overfitting, are less sensitive to outliers, and eliminate the need of pruning (Ali et al., 2012). It is been argued that the use of oversampling techniques could lead to overly optimistic prediction results (Vandewiele et al., 2020). Therefore, in order to deal with an unbalanced data set, we decided to use weight class balancing. Table 2.5 provides detailed information of the parameters optimization process for the RF using Scikit Learn's GridSearchCV function (Pedregosa et al., 2011).

Table 2.5 Parameter optimization for RF

Parameter	Tested values
Number of trees	From 50 to 1000 (step length =50)
Number of variables for each split	2,6,8,10
Minimum number of samples required to be at a leaf node	$1x10^{-2}$, $1x10^{-3}$, $1x10^{-4}$, $1x10^{-5}$, $1x10^{-6}$
Minimum impurity required to split a node	$1x10^{-2}$, $1x10^{-3}$, $1x10^{-4}$, $1x10^{-5}$, $1x10^{-6}$

Lastly, NNs are widely recognized for their capability to model complex statistical interactions between variables (Barrow & Kourentzes, 2018; Tsang et al., 2017). An NN is a system of interconnected neurons, organized by independent layers, inspired by biological nervous functioning (W. Wong et al., 2003). Each neuron accepts a number of weighted inputs and processes them to produce an output (Dancey et al., 2007). The weights of the network connections measure the potential amount of the knowledge of the network (Abiodun et al., 2018). Therefore, a training phase is needed in which the NN adapts the weights through minimization of the error between actual and estimated outputs (W. Wong et al., 2003).

NNs have been shown to be highly accurate for classification problems. However, the major drawback is that they are considered black-box models (Dreiseitl & Ohno-Machado, 2002). Their nested non-linear structure makes it difficult to understand what information in the input data makes them arrive at their decisions (Samek, Wiegand, et al., 2017). Recently, Layer-wise Relevance Propagation (LRP) has been proposed as a general solution to the problem of understanding classification decisions (Bach et al., 2015). The algorithm relies on a conservation principle to propagate the prediction back throughout the network, ensuring the network output is fully redistributed through the layers of the NN back to the input variables (Samek, Binder, et al., 2017). The main idea is to understand which input variables contribute to a positive or negative classification result (Bach et al., 2015). Recent applications of LRP include sentiment analysis (Arras et al., 2017) and image classification (Y. Yang et al., 2018). However, to the best of our knowledge, this explainable approach has not been used in the prediction of no-show probabilities. This is particularly relevant in our case, since lack of explainability in decision support systems can lead to both practical and ethical issues (Guidotti et al., 2018).

According to Guo and Berkhahn (2016), the continuous nature of NNs limits their applicability to categorical variables. Although one-hot encoding is a popular approach to overcome such limitations, it can require an unrealistic amount of computational resource, increase variance and ignore informative relationships between variables. To deal with this problem, Guo and Berkhahn (2016) apply the logic used in natural language processing and design an entity embedding method for categorical variables. The idea is to map discrete values to a multi-dimensional space where values with a similar function output are close to each other. Since the new representation increases the continuity of the data, it speeds up the training process and exploits intrinsic properties of categorical variables. For this work, both one-hot encoding and categorical embeddings are tested. Therefore, we implement an NN with one hidden layer and use heat maps produced by LRP to identify features supporting the classifier's decision for or against a specific class (Arras et al., 2017). Table 2.6 provides basic information regarding parameters optimization using Scikit Learn's GridSearchCV function (Pedregosa et al., 2011). All other parameters have been left at their default values.

Table 2.6 Parameter optimization for NN

Parameter	Tested values
Number of iterations	From 100 to 1600 (step length =100)
Number of neurones	10 values from N/2 to 2N, where N is the number of variables

2.3.4 Demonstration and Evaluation

Models performance was assessed using the AUROC score. From the available database, we randomly generated training (70%) and test (30%) sets. In the demonstration phase, a 10-fold Cross Validation process repeated 10 times (10-by-10 CV) was carried out using the training set. In the evaluation phase, we used the test set to assess the quality of the results and discuss the practical implications of increased accuracy when implementing interventions to reduce no-shows. A public version of the experimentation code and a randomly generated database are available (Barrera et al., 2020). Different patients may be selected for targeting according to which classification algorithm is used. As discussed in Section 2.3.2, we use two measures to assess the quality of a given classification, coverage and risk. Therefore, with this evaluation approach, we aim at quantifying the potential impact of using our DSS.

2.4 Data collection and Initial Analyses

We analyse data from the South West cluster of the city. Forty-nine medical facilities offering primary care are located within this cluster. Four services: Oral Health (OH), Growth and Development (G&D), Young Adult Program (YAP) and Senior Program (SP), are studied as these cover 75% of scheduled appointments during 2017 and 2018. In many scoring models, segmentation of discrete variables results in more stable and parsimonious models (Thomas et al., 2017), so we have used decision trees to classify these categorical variables coarsely (for age and lead time) and one-hot encoding to represent them in the models. Table 2.7 presents a list of patient and appointment-level variables, their descriptions and the Cramer's V correlation coefficient with the outcome (show or no-show).

Our analysis also uses publicly available information relating to two of the above variables. First, using data from the National Administrative Department of Statistics (*Departamento Administrativo Nacional de Estadística*, DANE), we classify the zone in which each patient lives as low-income if 50% or more of its population belongs to the lowest two income strata: otherwise, it is classified as medium-income. We also use data provided by the National Police Office (Policia Nacional de Colombia, 2019) on reported criminal events affecting individual citizens since 2015 to determine the sociodemographic context of each healthcare facility.

Table 2.7 List of variables

Category	Variable	Description	Correlation Coefficient OH	G&D	YAP	SP
Patient	Gender	Gender of the patient (Male, Female)	0.000	0.000	0.000	0.000
	Age	Age of the patient at the moment of the appointment (years)	0.002	0.001	0.002	0.000
	Zone	Area of the city where the patient lives	0.008	0.017	0.008	0.008
Appointment	Lead time	Elapsed time between the date of the home visit and the appointment date (days)	0.015	0.018	0.008	0.005
	Month	Month in which the appointment was scheduled	0.009	0.015	0.012	0.009
	Day	Day of the week in which the appointment was scheduled	0.006	0.005	0.006	0.001
	Facility	Assigned healthcare facility	0.009	0.037	0.005	0.008

Table 2.8 summarizes basic information on 53,311 scheduled appointments during these two years, including the outcome (show or no-show). Oral Health has the greatest number of appointments (22,613, 42%) and Growth and Development the least, at 14%. No-show rates range from 21% to 39% for each service. At an aggregate level, there is no difference in gender between the no-show rates, but in Oral Health and Young Adult Program more females than males keep their appointments. With respect to age, the highest no-show rates are between 20 and 40 years and the lowest are among children under 10 years and adults over 50. It is also possible to see that smaller lead times yield lower no-show rates. The only exception to this behaviour is in Senior Program where no-show rates are slightly lower for appointments assigned more than 60 days in advance. Finally, Figure 2.1 shows the attendance levels, for each service, presented by day of the week and month of the year. While, on average, 92% of the patients keep their appointments on Sunday, this indicator decreases to 69% on Fridays. Attendance levels range from 58% to 82%, for each month, and its behaviour changes across the four services.

Table 2.8 Descriptive statistics

Category	OH			G&D			YAP			SP			**Total**		
Gender	Show	No-show		Show	No-show		Show	No-show		Show	No-show		**Show**	**No-show**	
Women	8,457	3,475	**29%**	2,629	965	**27%**	4,078	1,946	**32%**	3,294	1,067	**24%**	**18,458**	**7,453**	**29%**
Men	7,482	3,199	**30%**	2,650	999	**27%**	4,035	2,065	**34%**	5,365	1,605	**23%**	**19,532**	**7,868**	**29%**
Age (years)															
0-10	1,659	638	**28%**	5,197	1,918	**27%**	0	0	**--**	0	0	**--**	**6,856**	**2,556**	**27%**
10-20	2,860	1,186	**29%**	82	46	**36%**	5,856	2,530	**30%**	0	0	**--**	**8,798**	**3,762**	**30%**
20-30	1,467	789	**35%**	0	0	**--**	2,092	1,178	**36%**	0	0	**--**	**3,559**	**1,967**	**36%**
30-40	2,316	1,058	**31%**	0	0	**--**	165	91	**36%**	0	0	**--**	**2,481**	**1,149**	**32%**
40-50	2,964	1,209	**29%**	0	0	**--**	0	0	**--**	1,294	425	**25%**	**4,258**	**1,634**	**28%**
50-60	2,093	791	**27%**	0	0	**--**	0	0	**--**	3,232	1,014	**24%**	**5,325**	**1,805**	**25%**
Over 60	2,580	1,003	**28%**	0	0	**--**	0	0	**--**	4,133	1,233	**23%**	**6,713**	**2,236**	**25%**
Lead time (days)															
0-15	7,689	2,259	**23%**	3,329	929	**22%**	4,969	2,029	**29%**	4,070	1,068	**21%**	**20,057**	**6,285**	**24%**
15-30	2,079	1,061	**34%**	754	453	**38%**	902	562	**38%**	1,013	434	**30%**	**4,748**	**2,510**	**35%**
30-60	1,503	785	**34%**	373	166	**31%**	488	299	**38%**	901	309	**26%**	**3,265**	**1,559**	**32%**
Over 60	4,668	2,569	**35%**	823	416	**34%**	1,754	1,121	**39%**	2,675	861	**24%**	**9,920**	**4,967**	**33%**

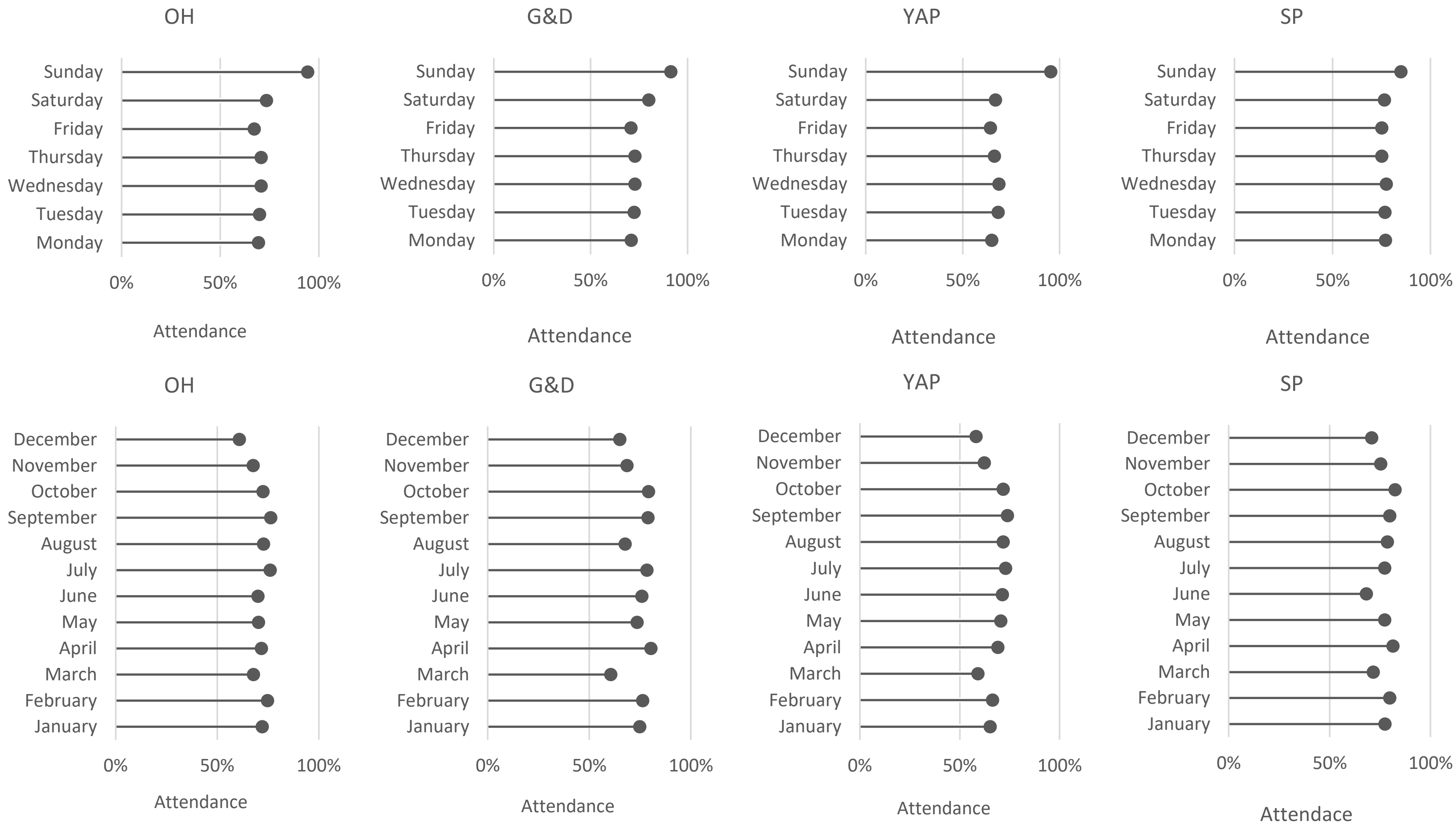

Figure 2.1 Attendance levels for each service

2.5 Results and discussion

We present the results organized in three sections. Firstly, we quantify the impact of each variable in the LASSO regression model on the no-show probability, and analyse the average coefficients obtained by a 10-by-10 cross validation process. Next, we quantify the added value of using RF and NN and compare the four modelling alternatives using the AUROC score. Finally, we analyse the impact of using these results as a decision support system and quantify changes in coverage and risk of an intervention when accuracy of prediction models increases.

2.5.1 LASSO regression model: variables affecting no-show probabilities

Females are more likely to keep their appointments except for SP (odds ratio OH: 1.03, G&D: 1.01, YAP: 1.08 and SP: 0.95). On the one hand, this result is highly context-dependent. Whereas some studies have reached the same conclusion (Cashman et al., 2007; Parente et al., 2018), others have reported that males have lower no-show rates (Ellis et al., 2017; Mander et al., 2018; Odonkor et al., 2017), or concluded that gender does not have impact in no-show probabilities (Daye et al., 2018; Shrestha et al., 2017). On the other hand, in developing countries it has been argued that, among socio-economically disadvantaged females, high no-show rates might be related to a lack of support from social networks and their responsibilities as caregivers (Frost et al., 2017; Magadzire et al., 2017; Topuzoğlu et al., 2007). This might explain the result for SP. In Bogotá it is common to find that women older than 60 years take care of their grandchildren while the parents work.

No-show probabilities change with the age of the patient. Figure 2.2 shows odds ratios (OR) for each age range in the four services. Since four models were run, one for each service, the reference values (OR = 1) must be independently interpreted. Firstly, in OH, patients between 22 and 33 years have the highest no-show probability (OR = 0.72) and it is not possible to identify any age range in which patients have particularly low no-show rates. Secondly, in G&D (between 0 and 13 years) and YAP (between 14 and 44 years), older patients are more likely to miss their appointments. This result is consistent with previously reported findings in primary care and paediatrics settings (Daye et al., 2018; McComb et al., 2017; Odonkor et al., 2017). Finally, age seems to have less impact among SP patients.

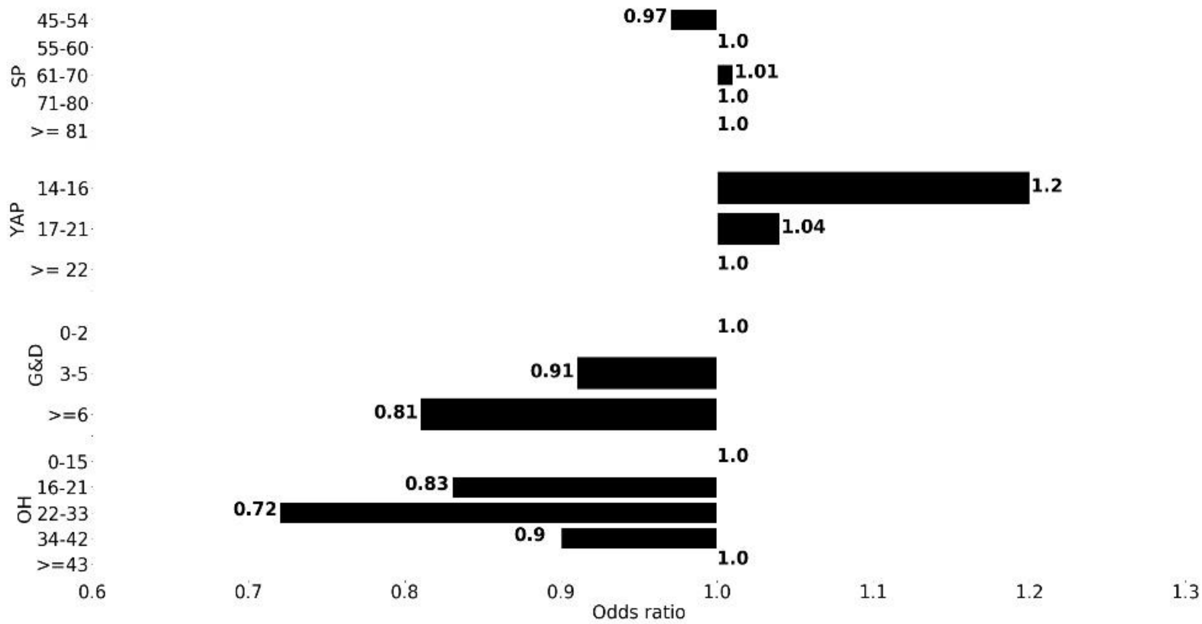

Figure 2.2 Odds ratio for each range of age

There is a relationship between the estimated income of the zone in which the patient lives and the no-show probability. In OH, 67% of zones with OR lower than one (i.e. higher no-show probabilities), are low-income zones. Additionally, 63% of zones with lower no-show probabilities have middle-income levels. This result might be associated with the patient's perception of oral health needs. Wallace and MacEntee (2012) found that, among low-income populations, dental care is perceived as desirable but more as a luxury than a necessity. The opposite scenario was found in SP: 75% of the zones in which OR is less than one and 25% of the zones with OR greater than one, have medium-income levels. Finally, for G&D and YAP, low-income zones represent the majority of both low and high no-show probability groups.

As expected, longer lead times increase no-show probabilities. Similar results have been reported in primary care settings (Ellis et al., 2017; McComb et al., 2017), and paediatric clinics (Topuz et al., 2018). As can be seen in Figure 2.3, the best attendance rates in OH occur when the lead-time ranges from 0 and 10 days, and the probability of no-shows reaches its maximum value after 15 days. Additionally, in older patients, the probability of attendance changes less with respect to lead time. Figure 2.3 also shows a higher attendance probability for appointments with lead times around 10 days in G&D and YAP. Although it is not possible to identity a reason for this behaviour, given the age of patients in these services, a companion (parent or carer) is often required to attend the appointment. Consequently, non-attendance may be due to challenges in coordinating these logistical aspects. These results demonstrate the non-linear nature of no-shows and support the use of analytical techniques for scheduling appointments.

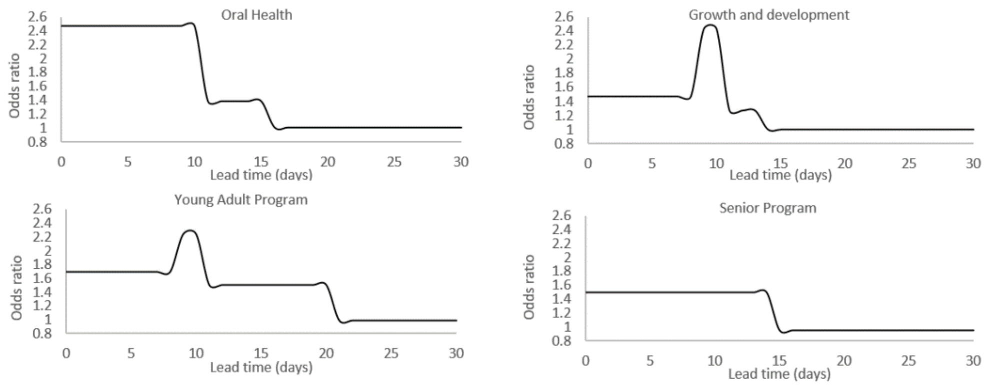

Figure 2.3 Odds ratio for each service when lead time is varied

We also find the date of the appointment affects the no-show probability. Previous studies have reported seasonal behaviours through the year (Odonkor et al., 2017; Parente et al., 2018) or variations depending on the day of the week (Do & Siegler, 2018; Harvey et al., 2017; Mohammadi et al., 2018). Table 2.9 shows the OR variations, for the four services, in each month of the year and each day of the week. As can be seen, in YAP the probability of no-show changes slightly in January, March and October. However, for the other months of the year and for all the days of the week, it remains constant. On the other hand, the service with the most changes throughout the year is SP with odds ratio varying between 0.61 and 1.22. This result is interesting because no-show probabilities show low sensitivity to factors such as age, area and lead-time in this service. The months of March, November and December seem to have higher levels of risk of no show. January, February and October have better behaviour. Regarding the days of the week, the best attendance levels are seen during the weekend.

Finally, we observe that there is a relationship between neighbourhood crime statistics and no-show probabilities. The four healthcare facilities with OR lower than one, across the four services, are in neighbourhoods with the highest number of incidents. Similarly, out of 49 facilities used in the program only two have OR greater than one, across all four services. These facilities are in neighbourhoods with the lowest incidence of crime in their respective districts.

Table 2.9 Average odds ratio for the appointment date

Month of the year	G&D	YAP	SP	OH
January	1.02	0.96	1.01	1.11
February	1.10	1.00	1.22	1.30
March	0.72	0.85	0.87	1.00
April	1.00	1.00	1.13	1.00
May	1.00	1.00	0.99	0.80
June	0.9	1.00	0.61	0.75
July	1.02	1.00	0.99	1.04
August	0.74	1.00	1.00	0.90
September	1.00	1.00	1.00	1.00
October	1.04	1.01	1.21	1.00
November	0.71	1.00	0.94	0.95
December	0.51	1.00	0.73	0.69
Day of the week	**G&D**	**YAP**	**SP**	**OH**
Sunday	1.06	1.00	1.37	3.50
Monday	0.96	1.00	1.00	0.93
Tuesday	1.00	1.00	1.00	0.96
Wednesday	1.00	1.00	1.00	1.00
Thursday	1.00	1.00	0.96	1.00
Friday	0.96	1.00	0.98	0.84
Saturday	1.35	1.00	1.00	1.03

Figure 2.4 presents the 15 variables with the greatest impact on no-show probabilities in each service. Firstly, attendance levels are higher on Saturdays (G&D) and Sundays (OH, YAP and SP). This result can be used to inform tactical decisions regarding the number of appointments that should be made available throughout the planning horizon. Secondly, ensuring reasonable lead

times can affect utilization levels. For the four services, it is possible to identify a maximum lead time that can be set as an objective in the scheduling process. Lastly, some months and facilities have relatively high no-show rates. This information can be used in the design of overbooking policies, since better estimates of no-show probabilities would help to reduce the undesirable side effects of this practice.

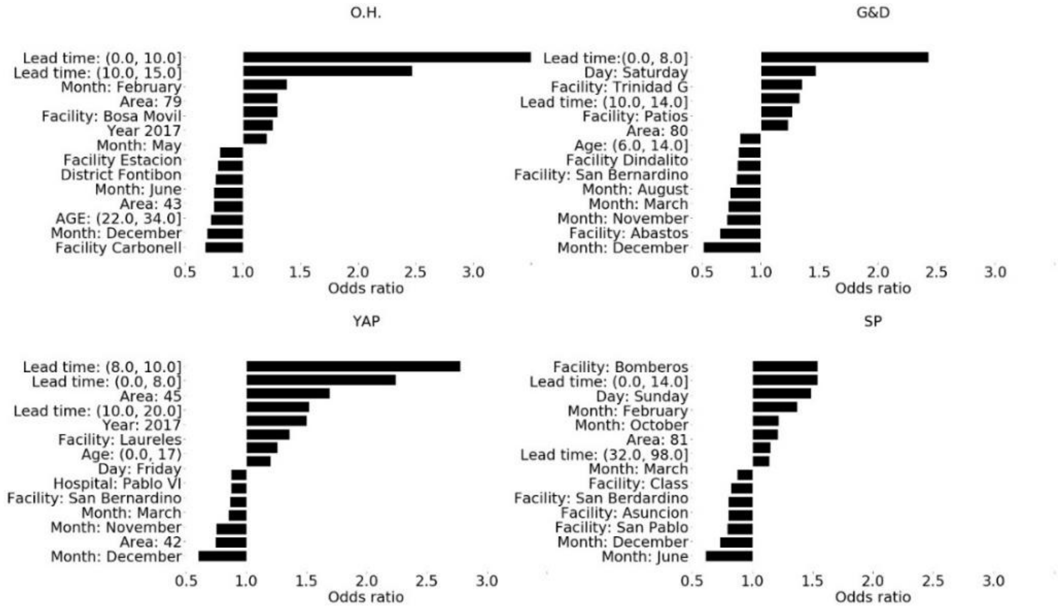

Figure 2.4 LASSO results: most relevant variables for each service

2.5.2 The added value of using other modelling approaches

Figure 2.5 presents the AUROC performance (Verbeke et al., 2017) of the four models. Each point in the graph represents the average and standard deviation of the AUROC in a repetition of 10-by-10 cross-validation (Verbeke et al., 2017). For all four services, the NN model has better average performance. The difference between RF and LR may suggest that the non-linear component of the relationship between the variables is not very strong, but still significant. Additionally, the average AUROC of both NN models indicates that variable interaction can be successfully modelled without using categorical embedding. Despite having low standard deviations, the amount of available data might not be sufficient to generate robust embeddings, and the disadvantage of increased variance is outweighed by better bias estimation with the increased number of dummy variables. Therefore, in our further analysis we consider only the NN with one-hot encoding (Okada et al., 2019).

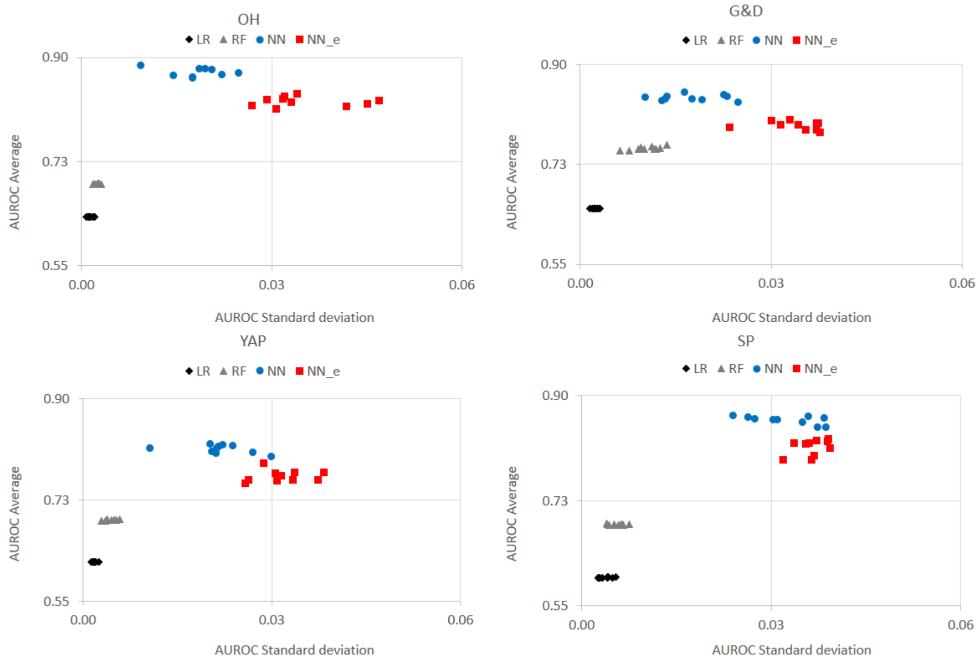

Figure 2.5 Model performance

2.5.3 The decision support system

In this section we analyse the implications of using our DSS to select patients and implement targeted interventions. As discussed in Section 3, SDS have specified that the developed DSS should allow program managers to divide patients into three groups. Group A will contain the 30% of patients estimated to have lowest no-show risk. Group B, the 40% of patients with intermediate risk and Group C will contain the remaining 30% of patients with the highest no-show probabilities. From the machine learning perspective, this means that two cut-off points are required. This process is called cut-off point tuning and is based on ROC performance measures (Verbeke et al., 2017).

Table 2.10 presents the coverage and risk for each service and for three models. As can be seen, in G&D, an intervention for 30% of patients could cover 80% of the no-shows, if the prediction of the NN is used. This percentage would decrease to 64% or 41% using RF or LR. This result is consistent across the four services. The average improvement in coverage using NN is 14% with respect to RF and 62% with respect to LR. Lastly, the risk of not implementing any action among patients with low no-show risk can be quantified. Using the NN classification, these patients represent between 2% and 3% of no-shows. On the other hand, using the RF prediction the highest risk is in OH and YAP where 9% of the no-shows are classified in group A. Finally, using logistic regression, the risk varies between 17% and 21%.

Table 2.10 Risk and Coverage for a potential intervention

	NN		RF		LR	
Service	Risk	Coverage	Risk	Coverage	Risk	Coverage
OH	2%	70%	9%	55%	17%	39%
G&D	2%	80%	3%	64%	17%	41%
YAP	3%	67%	9%	55%	20%	41%
SP	2%	75%	6%	61%	21%	40%

Despite the high accuracy of the NN prediction (i.e. risk of 2.25% and average coverage around 72%), using NN results might be challenging. It has been argued that decision makers need to understand the reasons underpinning a prediction in order to trust the results (Fong & Vedaldi, 2019; Shawi et al., 2019). Consequently, in an attempt to explain the results of the NN, we implement LRP (Bach et al., 2015). As a result, the importance of each of the variables in the classification of a patient in each category is obtained. According to Yang et al. (2018), one of the advantages of this technique, compared with sensitivity analysis, is the interpretability of the signs (and absolute values) of the weights. For example, when the weight is large and positive, the variable strongly supports the classification chosen by the NN, whereas if the weight is small and negative, the variable weakly suggests the opposite classification.

Figure 2.6 illustrates the results obtained for ten G&D patients. A column represents a patient, and the column heading the no-show probability. The blue cells represent positive coefficients and the red cells negative ones, shaded by the magnitude of the weight. Only those variables with at least one non-zero coefficient are shown for this group of patients. Our NN predicts that the first patient will not show up for his appointment (95% of no-show probability). The main reason for this conclusion is the month of the appointment, but lead time and age also support this classification. On the other hand, the day of the appointment, and the zone in which the patient lives support the opposite classification, i.e. that the patient would in fact attend. Moreover, the fact that the same variables have both positive and negative coefficients (regardless of the no-show probabilities) implies that the network is learning about the context. It means that the NN learns that it is not enough to know the gender of a patient to decide in which category they should be classified. For example, when running a regression model including the interaction of gender with age and day of the week, it is possible to observe slightly different results from those reported by the model without interaction. For G&D we found that females are more likely to miss appointments on Saturdays and Wednesdays (O.R. = 0.75 and 0.94).

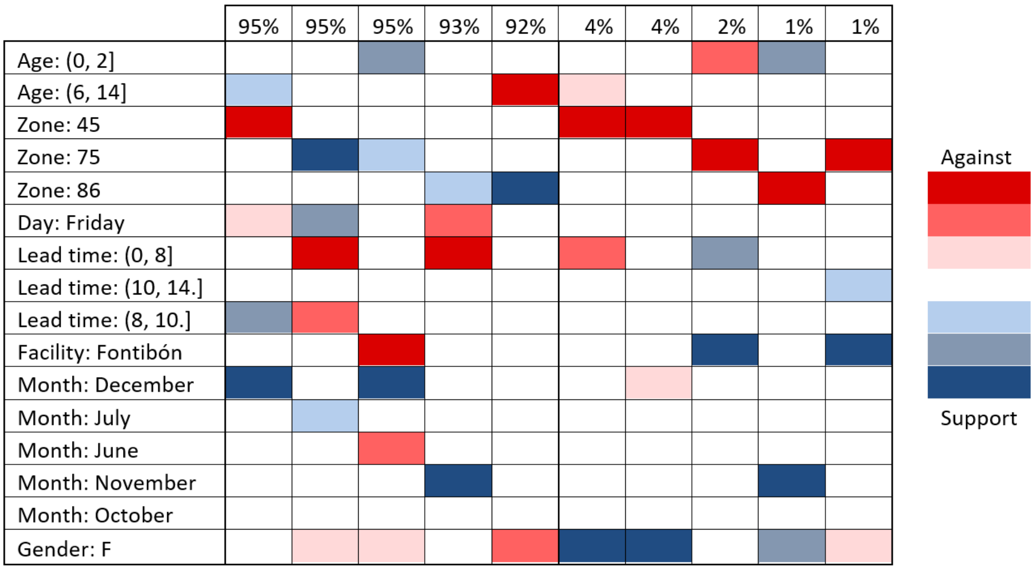

Figure 2.6 Heat map for G&D

This interpretation procedure can be used for any data-driven machine learning model, giving interesting insights which have real applications for decision support systems. The focus of the implementation of these processes must be on actionable combinations of parameters: if a relation between several variables is found (such as gender and day of the week), then an action can be performed for those specific groups. The use of such interpretability tools allows effects like these to be observed and revealed, which would otherwise be neglected.

2.6 Concluding remarks

This work has been developed with the active involvement of SDS. We conducted several workshops with program managers, operational analysts at the healthcare clusters, and community workers. This approach enabled us to develop a more comprehensive view of the program, identify a champion for the project within SDS, generate a shared vision of the main challenges and maintain stakeholders' engagement. Therefore, the discussion shifted from a resource allocation perspective to a better understanding of the underlying problem and the identification of restrictions that could prevent the implementation of changes in the operation. By the end of the workshops, they concluded that as the program covers a highly heterogenic population, more personalized strategies were required to reduce no-show behaviour. In this context, patient classification was identified as a key element to ensure the economic feasibility of any intervention strategy. Following this process we were able to reach an agreement on an appropriate design principle which captures the knowledge of our stakeholders. Consequently, our DSS aims at leveraging routinely collected data to inform such classification. During the feedback sessions, program managers stressed that they value that the results were easy to understand and have the potential to improve service quality.

In light of the promising results, at the time of writing SDS is starting a pilot intervention to modify patient behaviour. Using the DSS to predict no-show probabilities will improve the effectiveness of the intervention since the NN classifies around 80% of potential no-show cases to Group C, the 30% of patients designated to receive the most intensive, personalized, intervention. Therefore, as stated in our design principle, the design of this DSS can be seen as a necessary first step to reduce no-show behaviour in primary care and the future development of design knowledge (Baskerville et al., 2018). After an evaluation of the pilot is carried out, a web-based tool will be developed to enable models to be used in program operation.

Our objective is to use routinely collected data to predict no-show probabilities. However, in order to inform the discussion, we also use other sources of public information. Two findings are particularly relevant in developing country contexts. First, in Oral Health, 67% of zones with OR less than one (i.e. higher no-show probabilities), are low-income zones, and 63% of zones with lower no-show probabilities have middle-income levels. Second, the four healthcare facilities (out of 49) with OR less than one across all four services are in neighbourhoods with the highest number of reported crime incidents, whereas the two facilities with OR greater than one across all four services are in neighbourhoods with the lowest crime incidence in their respective districts. These exploratory results indicate that including socioeconomic data could potentially increase understanding of no-show behaviour. Further research is required to evaluate the cost/benefit of collecting such data and including these variables in the SDS information system.

Since this paper presents retrospective analysis of historical data, it is not possible to draw conclusions regarding the reasons for no-show behaviour. Therefore, the next step in this research is a mixed-method study to understand and model patients' decision-making processes. Semi-structured interviews are being conducted among no-show patients in order to learn from their experiences and identify access barriers. Moreover, we are analysing survey data to quantify the relationship between the no-show probability and the constructs of a health psychology model.

Modelling no-show behaviour in primary care settings is an active research area. The most common approach in the literature is multiple regression, but due to its limitations in accuracy, using the results to improve management practice can be problematic. Machine learning methods are gaining in popularity but have the drawback of being a 'black box' that managers may not trust. Our research shows the benefits of a two-pronged approach to overcome this. Firstly, using LRP to produce a heat map visualisation that makes the model results immediately understandable, and secondly, involving stakeholders in every stage of the design process. Additionally, despite the highest no-show rates worldwide being in developing countries, the problem has been mainly studied in North America and the United Kingdom (Dantas et al., 2018). The research presented here contributes to the literature by assessing the effectiveness of machine learning approaches using routine data to predict no-show behaviour among low-income patients in a developing country context.

Throughout this research, we have designed a process to construct a DSS for improving healthcare access powered with machine learning models. In general, the first stages of the process are replicable across all healthcare systems that wish to develop such a DSS. Steps such as the facilitated formulation of a design principle, data collection strategies, data processing steps, and the selection of models to use are relevant issues for every designer facing a similar challenge. Additionally, by using the schema proposed by Gregor, Chandra Kruse, and Seidel, our design principle also meets the five criteria for reusability: accessibility, importance, novelty, and effectiveness (Iivari et al., 2020). Therefore, we expect that other DSS designers can build from this experience when defining intervention groups. We believe that our results could help not only other designers in healthcare settings but also those dealing with limited resources in other contexts such as educational or social programs, where prioritization plays a key role in ensuring feasibility.

Chapter 3 Understanding No-show behaviour

Abstract

The global burden of cervical cancer remains a concern and higher early mortality rates are associated with poverty and limited health education. However, screening programs continue to face implementation challenges, especially in developing country contexts. In this study, we use a mixed-methods approach to understand the reasons for no-show behaviour for cervical cancer screening appointments among hard-to-reach low-income women in Bogotá, Colombia. In the quantitative phase, individual attendance probabilities are predicted using administrative records from an outreach program (N=23384) using both LASSO regression and Random Forest methods. In the qualitative phase, semi-structured interviews are analysed to understand patient perspectives (N=60). Both inductive and deductive coding are used to identify first-order categories and content analysis is facilitated using the Framework method. Quantitative analysis shows that younger patients and those living in zones of poverty are more likely to miss their appointments. Likewise, appointments scheduled on Saturdays, during the school vacation periods or with lead times longer than 10 days have higher no-show risk. Qualitative data shows that patients find it hard to navigate the service delivery process, face barriers accessing the health system and hold negative beliefs about cervical cytology.

3.1 Introduction

Despite being highly preventable, cervical cancer is the fourth leading cause of cancer death in women: in 2020, 341,831 women died worldwide of this disease (Sung et al., 2021). Additionally, incidence and early mortality rates of this type of cancer are associated with limited education and poverty (Black et al., 2019; Getachew et al., 2019; Kangmennaang et al., 2018; Makurirofa et al., 2019). While in North America, age standardised rates (ASR) of incidence and mortality are 6.1 and 2.1 per 100,000 women respectively (International Agency for Research on Cancer, 2021a), in

Colombia these indicators are 14.9 and 7.4 per 100,000 women (International Agency for Research on Cancer, 2021b). Therefore, early diagnosis and health education have been identified as key components in the effort to advance cervical cancer control worldwide (Broeders & Elfström, 2020). However, in many lower and middle-income countries (LMICs), screening programs still face implementation challenges (Canfell et al., 2020; Williams-Brennan et al., 2012). In Colombia, this disease is the leading reason of death by cancer among women between 30 and 59 years old in the country, and its burden continues to be a concern (Bermedo-Carrasco & Waldner, 2016; Pilleron et al., 2020).

In Bogotá, as part of a preventive-care strategy called *Acciones Colectivas en Salud* (ACS), the District Secretariat of Health (*Secretaría Distrital de Salud*, SDS) instituted a program to increase cervical cancer cytology uptake among hard-to-reach low-income women. Under this program, a group of community workers visit women who have not taken a cytology test during the last year, conduct basic training in cervical cancer risks and schedule a cytology appointment for them at the nearest healthcare facility. Over the last two years, the program has increased its coverage; however, no-show rates have reached levels of 46%. Therefore, no-show behaviour represents a challenge for program managers from both effectiveness and efficiency perspectives (Mikhaeil et al., 2019; Zebina et al., 2019). In this context, more information is needed to support the design of population-based strategies.

Quantitative and qualitative approaches have been used in recent studies to understand cancer screening uptake rates in developing countries. Black et al. (2019) and Nuche-Berenguer and Sakellariou (2019) review quantitative studies conducted in Uganda and Latin America, respectively. Both studies conclude that more research is needed in order to understand lower participation of low-income population in screening programs. To the best of our knowledge, no review of qualitative approaches has been published at the time of writing. However, qualitative studies have been undertaken in Tanzania (Mugassa & Frumence, 2020), Ethiopia (Brandt et al., 2019), Botswana (Matenge & Mash, 2018) and Nigeria (Modibbo et al., 2016), among others. In these four studies, detailed conversations with patients have enabled context-dependent barriers to be identified. Further, researchers conclude that interventions to increase cervical cancer screening uptake should be tailored to the local population, taking into account aspects such as levels of health education, religious affiliations, and personal beliefs of the patients. Although the emphasis on evidence-based research might explain the dominance of quantitative methods, the contribution of qualitative methods in health research is now increasingly accepted (Pope & Mays, 2020).

In this context, mixed-methods research has the potential to provide more complete information regarding no-show behaviour (Mugassa & Frumence, 2020; Williams-Brennan et al., 2012). According to Wisdom et al. (2012), the combined use of quantitative and qualitative methods can provide a more comprehensive picture of health services by capitalizing on the strengths of both approaches. Despite being a relatively new area, Guetterman et al. (2019) found that there is an increasing awareness of the relevance of mixed-methods research in order to address population and behavioural health problems. French et al. (2017), for example, used regression models to identify characteristics of children who missed their appointments and conducted phone interviews with GPs in order to understand their role and perceptions regarding low attendance levels.

The aim of this study is to understand this no-show behaviour by combining prediction and interpretation approaches. The prediction approach is premised on the idea that it is possible to use routinely collected historical data to produce a numerical estimate of the attendance probability for each individual patient. However, the retrospective nature and limitations of such data make it impossible to identify the reasons that could lead to a missed appointment (Y. S. Lee et al., 2018; McComb et al., 2017). The aim of the interpretation approach is to understand the phenomenon by studying patients' perceptions and their decision-making processes (Lyon & Reeves, 2006). Therefore, we use a qualitative approach to undertake an in-depth exploration of the perceived barriers to attendance (Lacy et al., 2004).

3.2 Methods

In this section, we first present the study context. Next, we discuss how the quantitative and qualitative phases interact and inform our conclusions. Then, for each phase, we describe the process of data collection and the analytical approach adopted. When pertinent, RECORD (The REporting of studies Conducted using Observational Routinely-collected health Data) (Benchimol et al., 2015) and SRQR (Standards for Reporting Qualitative Research) (O'Brien et al., 2014) guidelines are followed. Pontificia Universidad Javeriana (Faculty of Engineering's Research and Ethics Committee: FID-19-107), SDS (Ethics Committee for Health Research 2019EE47807) and the University of Southampton (Faculty of Social Sciences' Ethics and Research Committee ERGO ID 48583.A1) granted ethical approval for this study.

3.2.1 Study context

In Colombia, the cervical cancer screening program covers women between 25 and 65 years old, or younger in the presence of some risk factors (Bermedo-Carrasco et al., 2015). Currently, this program primarily relies on Pap smear tests following a 1-1-3 scheme (*Resolution 603280*, 2018; Torrado-García et al., 2020). This means that women should undergo annual cytology tests, and then change to a three-year interval after two consecutive negative results. Additionally, the screening is included in the national health insurance scheme and hence no out-of-pocket payment is required. Recent legislation has adopted the Human Papilloma Virus (HPV) test for women between 30 and 65 years old, as screening strategy (*Resolution 603280*, 2018). However, at the time of writing, we were not able to find any consolidated report about the HPV test piloting in the country.

In Bogotá, the cervical cancer screening component of ACS is designed to cover hard-to-reach women. For this program, SDS considers a woman to be hard-to-reach if despite being eligible, she has not undergone a Pap smear test over the last year. Additionally, to prioritize resource allocation for social programs, SDS uses a nation-wide adopted scoring system that classifies low-income citizens into four categories. The SISBEN[2] score ranges from 0 (extreme poverty) to 100 (wealthy) and is computed using self-reported information related to health, education, and housing, among others (Departamento Nacional de Planeacion, n.d.). ACS covers approximately 18% of the population with the lowest SISBEN score (Secretaría Distrital de Planeación, 2018).

3.2.2 Integration Approach

According to Fetters et al. (2013), in mixed-methods health research, integration might occur at three different levels: design, methods and interpretation. From a research design perspective, we use qualitative data to understand specific aspects of the quantitative findings. This is called an explanatory sequential approach. At the methods level, the quantitative findings inform the sample definition for the qualitative component. Therefore, at the methods level, we seek an integration through building. Lastly, results from both phases are reported independently and we analyse aspects of the problem that can be better understood as a result of integration. This is called integration through narrative using a continuous approach.

In our case, quantitative data are used to predict individual attendance probabilities and qualitative data are used to understand the patient experience. In order to build prediction models, we conduct statistical analysis using administrative records. Then, a series of semi-structured interviews are performed to understand the patient perspective regarding no-show behaviour. Therefore, in this research, integration occurs at two points: i) a patient is invited to take part of the interviews only if her no-show risk, according to the prediction models, was medium or high and ii) the results of the interviews are used to enhance the analysis of the prediction models.

3.2.3 Predicting attendance probabilities: the quantitative phase

We analysed data collected routinely by program managers (in SDS) to assess the performance of ACS. Between January 2017 and December 2019, appointments were scheduled for 23384 women

[2] Identification System of Potential Beneficiaries of Social Programs *(Sistema de Identificación de Potenciales Beneficiarios de Programas Sociales)*

aged between 21 and 65 years old. In each case, the outcome – show or no-show – was recorded. Table 3.1 presents the list of variables, grouped into two categories: patient and appointment-related information. We did not have access to poverty level data, marital status, or number of children for individual patients: these data are not held by SDS. For age and lead time we used decision trees to build categorical variables maximizing information value. This means that the categories (the number and the limits) were automatically selected by the algorithm to maximize inter-category difference and minimize intra-categories difference. This approach has also been found to generate more stable models (Thomas et al., 2017). SDS granted access to a fully anonymized database for our analysis. The data were accessed in August 2019 (all records from January 2017 to July 2019) and February 2020 (all records from August to December 2019). From this database, we randomly generated training (70%) and test (30%) sets.

Table 3.1: Variables used for prediction models

Category	Variable	Description
Patient	Age	Age of the patient at the moment of the appointment (years)
	Zone	Area of the city where the patient lives
	Poverty	Percentage of population living in poverty within the patient zone
Appointment	Lead time	Elapsed time between the date of the home visit and the appointment date (days)
	Month	Month in which the appointment was scheduled
	Day	Day of the week in which the appointment was scheduled

To estimate the probability of attendance, two well-known models were implemented, Least Absolute Shrinkage and Selection Operator (LASSO) regression (Tibshirani, 1996) and Random Forests (RF) (Breiman, 2001). Recent applications of LASSO in healthcare research include prediction of mortality rates (Zhang & Hong, 2017) and medication adherence (Zullig et al., 2019), among others. Additionally, for classification problems, RFs are less sensitive to outliers and eliminate the risk of overfitting (Ali et al., 2012) and thus improve the accuracy of the model. We conducted a parametric analysis on the penalization constant of the LASSO model and selected the one that maximizes the Area Under the Receiver Operating Curve (AUROC) while minimizing the number of selected variables. For classification proposes, a value of one was assigned to those patients attending their appointments. Therefore, higher odds ratios mean higher attendance probabilities.

To validate the model, we randomly divided the training set into 10 groups, used nine groups for training, and the other for testing. Then, the testing group was iteratively changed, and the procedure was repeated ten times, resulting in 100 experiments. This is called a 10-by-10 cross validation process (10-by-10 CV). We used the LASSO results to select the features included in the RF, optimized parameters using 30% of the training set and performed a 10-by-10 CV. The performance of both models was assessed using the average and standard deviation of the AUROC score (Verbeke et al., 2017) over the 100 experiments. LASSO and RF Scikit-Learn's implementations were used for our analysis (Pedregosa et al., 2011).

3.2.4 Understanding patient experience: the qualitative phase

The aim of the qualitative phase is to understand the patient experience and reasons for health-seeking behaviour. Data were collected through semi-structured interviews using purposeful sampling (Bradley et al., 2007; Sandelowski, 2000). We focused our analysis on patients with higher no-show risk, as their views can provide relevant information to design behavioural interventions (Gromisch et al., 2020). Therefore, patients who met the following three eligibility criteria were considered: i) having received a home visit and an appointment scheduled between October and December of 2019 (3140 patients), ii) additionally, had been classified as a medium or high no-show risk according to the prediction models (1099 patients) and iii) additionally, had failed to keep their appointments (857 patients). Program managers provided a list of 100 randomly selected patients that met the criteria; we were able to reach 75 patients by phone and, of these, 15 declined to participate.

Five community workers collected data using phone interviews in Spanish, between January and February 2020. A nine-item interview guide was designed using relevant literature and discussed with public health specialists and community workers at SDS, in one workshop (see

Appendix A). Before starting data collection, training took place in two workshops where the research project was presented, and each item of the interview guide was discussed. Since these community workers perform home visits as part of their normal jobs, they have had previous training on working with vulnerable populations and discussing health-related topics. In each phone call, basic information of the project was provided, the patient was invited to take part of the study and oral informed consent was obtained. Patients authorized the conversations to be recorded. A research assistant performed verbatim transcriptions of the audio files and one of the researchers checked quality of the transcription.

Data analysis was conducted in Spanish and facilitated using the Framework method (Spencer et al., 2014). Although different approaches can be adopted to analyse qualitative data, the Framework method is well-established for health multidisciplinary research projects, as it enables large data sets to be organized and compared (Dilgul et al., 2018). It has been argued that this method is particularly appropriate for research questions in which different views, in relation to a topic, are analysed and therefore a descriptive overview is required (Gale et al., 2013). Table 3.2 provides basic information of our approach in each of the seven stages proposed by Gale et al. (2013) to analyse qualitative healthcare data using the Framework method.

Table 3.2: Seven stages for analysis using the Framework method

	Stage	Our project
1	Transcription	A research assistant performed verbatim transcriptions of audio files and one of the authors checked quality of the transcription.
2	Familiarisation	Ten interviews were analysed by the coding team composed of three researchers.
3	Coding	As a pilot study, each member of the coding team analysed the first 20 audios and notes were compared.
4	Developing a working analytical framework	Both inductive and deductive analysis are performed.
5	Applying the analytical framework	Two members of the coding team coded each interview (n=60) using NVivo 12.
6	Charting data into the framework matrix	Computer-Aided Qualitative Analysis Software (NVivo 12)
7	Interpreting the data	Several virtual meetings.

To design the analytical framework, both inductive and deductive analysis were used. On the one hand, inductive coding enabled the identification of under-researched topics, as categories emerged from the data (Gellasch, 2019). On the other hand, deductive coding facilitated to take advantage of findings that have been previously documented in the research topic by using categories derived from the literature and prior experience (Bradley et al., 2007). The coding team (DB, AD, and VG) developed inductive first-order categories (i.e., emerging themes) using 10 interviews. Each researcher produced a preliminary list of categories, and these lists were analysed and discussed until consensus was reached.

Two literature searches were conducted, using SCOPUS and PubMed databases, to identify deductive first-order categories. Figure 3.1 provides details of each review using the PRISMA guidelines (Moher et al., 2009). We decided to limit our search using the title, abstract and key words option in SCOPUS and the title and abstract option in PubMed. First, we targeted journal papers, published in English, that use qualitative analysis in order to understand no-show behaviour in healthcare. We identified 55 papers published between 2004 and 2021. We note that of these 55, 40 were published after 2015 and only eight are on the topic of no-show behaviour in developing countries. Second, we aimed at identifying qualitative works studying cervical cancer screening uptake. We identified 37 papers published between 2005 and 2021. The majority of these works (62%) were conducted in developing country contexts.

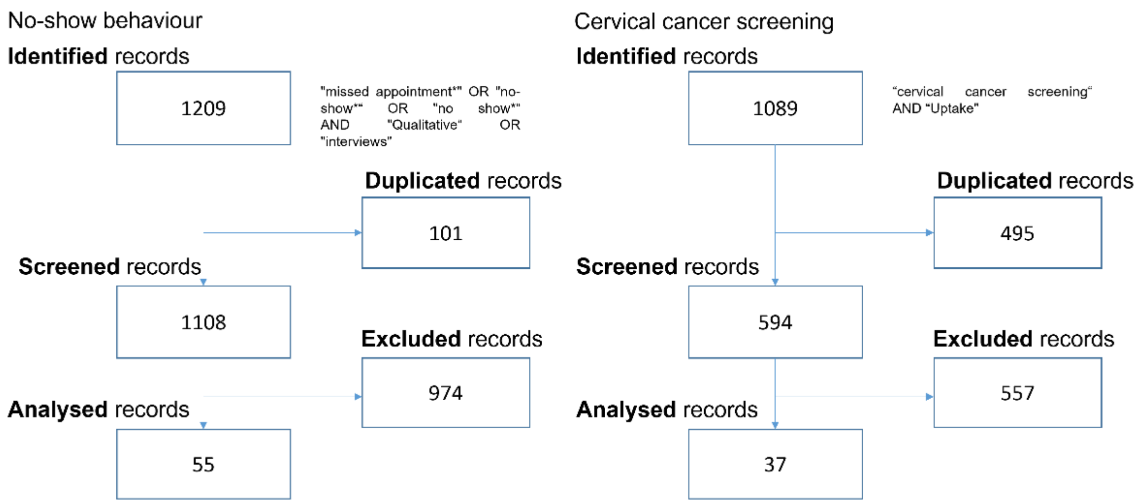

Figure 3.1 Literature searches

Drawing from the two literature searches, we found the Health Belief Model (HBM) (Rosenstock et al., 1988) to be an appropriate conceptual framework to build second order categories (i.e. groups of first-order categories). We were able to group all the first-order categories using the constructs of this mode. Further, the use of the HBM to understand behaviours and design population-based interventions in preventive care has been widely documented (Jones et al., 2014). The main idea is that the adoption of protective behaviours can be explained by what the patient perceives in terms of severity, benefits, susceptibility, and barriers. Therefore, we group the first-order categories using these constructs. Table 3.3 presents the resulting 44 categories of the analytical framework. Additionally, a description of each category and the list of references supporting the deductive categories are provided in Appendix B. The ten inductive categories were included at this stage. We believe that readers interested in healthcare no-show behaviour could find this framework useful to analyse qualitative data or inform instrument design in other contexts.

The three researchers of the coding team were involved in the analysis of each interview. First, we conducted a pilot using 20 transcriptions. In the pilot, each researcher coded independently and made notes of possible adjustments needed in the framework. These adjustments were then discussed in a joint meeting and a new version of the framework produced. Secondly, for each interview, two researchers were assigned to code independently and generate a preliminary version of the framework matrix using NVivo. Then, the third researcher analysed the resulting categories, identified differences, made notes, and formed a recommendation. All differences were analysed in joint meetings until consensus was reached among the three researchers. We were able to reach thematic saturation with our initial sample of 60 interviews, as no new categories emerged from the data, therefore no second round of interviews was required (Vasileiou et al., 2018). Lastly, a final version of the matrix was generated to inform discussions among all researchers.

Table 3.3: Analytical Framework Categories

Second order	First order	
Barriers	Access	
	1	Financial stress
	2	Inconvenient appointment slots
	3	Long lead times
	4	Geographical access
	5	Work Commitments
	Service delivery	
	6	Bad experiences with service delivery
	7	Bad experiences with home visit
	8	Communication
	9	Dismissive staff
	10	Lack of flexibility in service delivery
	11	Lack of information during the home visit
	12	Multiple appointments
	13	Poor care quality
-	14	Prefers to use other care
	15	Process design
	Personal	
	16	Family care
	17	Forgetfulness
	18	Health issues
	19	Lack of network support
	20	Language
	21	Migration
	22	Other priorities
	23	Religion
	24	Travel
Barriers	Protective behaviour	
	25	Anxiety
	26	Non-compliance with requirements
	27	Discomfort
	28	Embarrassment
	29	Gender of the health provider
	30	Pain
	31	Peer influence
Benefits	Protective Behaviour	
	32	Cancer diagnosis
	33	Health
	34	Lack of perceived benefits
	35	Lack of knowledge
	36	Screening program
	Service delivery	
	37	Satisfaction (home visit)
	38	Satisfaction (service delivery)
Susceptibility	39	Perceived susceptibility
	40	Denial
Severity	41	Fear of a bad result
	42	Fear of side effects
	43	Only uses emergency care
	44	Severity of the consequences

3.3 Results

This section starts with an analysis of the LASSO regression results and an assessment of the accuracy improvements achieved by RF. The qualitative findings then follow, with a discussion of the categories resulting from content analysis using our analytical framework.

3.3.1 Quantitative results

Table 3.4 presents the results of the LASSO regression model. This model has a moderate discriminatory power, and its results are not sensitive to the sample. The average AUROC score is 0.65 with a standard deviation of 0.001. This could indicate that the non-linear component of the relationship between the variables and the attendance probability is high. It is also possible that including additional patient information could lead to better performance. Variables such as income and education levels have been found to be good predictors of attendance for cervical cancer screening (Gemeda et al., 2020; Q. Li et al., 2020). However, our aim was to leverage routinely available data to inform patient prioritization by SDS. Therefore, the LASSO results are used to understand the characteristics of patients with higher no-show risk and to select the variables that should be used in the RF model.

There is a relationship between patient-related variables and attendance probability. The odds ratios for the zone in which the patient lives range from 0.47 (zone 65) to 4.48 (zone 11). Additionally, patients living in zones where poverty affects less than 18% of the population are three times more likely to attend their appointments than those living in the remaining zones. Lastly, the younger the patient, the higher her no-show risk.

Table 3.4 also shows a relationship between appointment-related variables and attendance probability. Regarding the appointment month, school vacation periods (January, March, June, and December) have lower odds ratios. Additionally, while patients are more likely to attend appointments on Sundays, Saturday appointments have a higher no-show risk. This might indicate that the requirement to take time off from work could act as a barrier to cytology uptake. Lastly, we find that longer lead times increase the risk of no-show.

Table 3.4: Results of the LASSO regression model.

Variable	Coefficient Average	Coefficient Percentile 5th	Coefficient Percentile 95th	Odds Ratio Average
Age (years)				
[21, 27]	-0.82	-0.85	-0.79	**0.44**
(27, 45]	-0.44	-0.46	-0.42	0.64
> 45				**1.00**
Zone				
11. San Cristobal	1.50	1.42	1.60	**4.47**
55. Diana Turbay	1.28	1.20	1.35	3.60
57. Gran Yomasa	-0.79	-0.85	-0.72	**0.45**
65. Arborizadora	-0.75	-0.87	-0.64	0.47
Poverty				
[0%, 18%]	1.10	1.05	1.16	**3.01**
> 18%				**1.00**
Lead time (days)				
(0, 9.0]	0.46	0.44	0.49	**1.58**
(9.0, 10]	0.13	0.08	0.19	1.14
> 10				**1.00**
Day				
Sunday	0.96	0.86	1.09	**2.61**
Monday	-0.02	-0.03	-0.01	0.98
Tuesday				1.00
Wednesday				1.00
Thursday	0.06	0.03	0.08	1.06
Friday	-0.07	-0.09	-0.05	0.93
Saturday	-0.20	-0.23	-0.17	**0.82**
Month				
January	-0.19	-0.22	-0.15	0.83
February	0.07	0.03	0.11	1.07
March	-0.29	-0.34	-0.26	0.74
April	0.38	0.32	0.45	**1.46**
May	0.04	0.01	0.08	1.04
June	-0.41	-0.45	-0.36	0.67
July	0.07	0.03	0.10	1.07
August	-0.03	-0.05	-0.01	0.97
September				1.00
October	-0.14	-0.17	-0.11	0.87
November	-0.24	-0.27	-0.21	0.78
December	-0.65	-0.67	-0.62	**0.52**

Values in bold indicate lowest and highest odds ratio in each category.

In terms of AUROC score, the use of RF adds value to the classification. Average score of the RF is 0.84 (29% higher that the LASSO AUROC score) with a standard deviation of 0.01. However, LASSO results are less sensitive to the sample and hence potentially more reliable when used for different data. One practical implication of an improvement in accuracy relates to the design of interventions to reduce no-show behaviour. Mass interventions aimed at the whole population are generally not cost-effective (Schwebel & Larimer, 2018) since a significant proportion of patients are likely to attend with no intervention at all. Initiatives can be made more cost-effective, and hence financially sustainable, by attempting to target those patients at greatest risk of no-show (Wu et al., 2019). Clearly, using a model that can accurately predict attendance probabilities in the design of such interventions would increase their cost-effectiveness.

Figure 3.2 shows the outcome when patients are assigned, in increasing order of attendance probability (calculated in three different ways: by LASSO, by Random Forest, and at random) to different sizes of intervention target group. For example, if it is only possible to include 30% of all patients in the intervention group, nevertheless over 70% of the no-show patients in our data would receive the intervention using the RF classification. This coverage would decrease to 41% if the LASSO model was used, and just 30% if the decision was made without the support of a classification model (i.e., patients were assigned to the intervention group at random). Conversely, we can also use Figure 3.2 to quantify the risk of a classification model, defined as the percentage of no-show patients who do not receive the intervention. For example, suppose the intervention is able to reach 50% of all patients. If the RF were used to make the selection, only 3% (100% - 97%) of the no-show patients would not have been included. This percentage would increase to 36% using LASSO, or 50% if patients were classified at random.

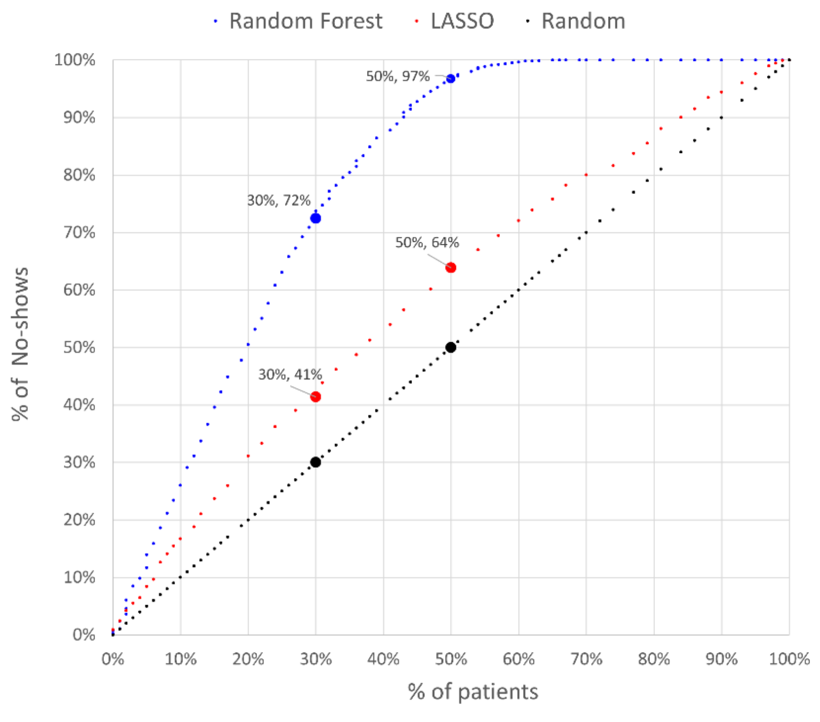

Figure 3.2 Model performance

3.3.2 Qualitative results

The aim of the interviews was to understand attendance barriers among patients with high and medium risk of no-show, as well as to identify some perceived benefits of the cytology and outreach programs. First-order categories are illustrated by quotes extracted from the interviews in Table 3.5. The final column of Table 3.5 shows the number of interviews in which each category was coded. In the rest of this section, we present the main qualitative findings.

Table 3.5: Quotes from the interviews

N	Category	Quote	Frequency
2	Category: Barriers - Access Inconvenient appointment slots	*I would say that [it is important to have] more service time. Sometimes you go to work at five or four thirty in the morning and you are back home at seven p.m. There is not service at nights and weekend appointments are always booked. It is difficult to keep an appointment*	5
3	Category: Barriers - Access Long lead times	*If you go [to the healthcare facility] they say that you need to call [to book an appointment]. Then you call, and they say there are not available slots. After a time, you just get tired and stop trying.*	12

15	Category: Barriers - Service delivery Process design	*It is not always clear what you need to do. Sometimes you need to carry out administrative paperwork and spend almost all day waiting in queues* *You need to go through administrative clearance for almost everything! I even took a mammogram a while ago and have no idea how to get the results or book an appointment.*	18
16	Category: Barriers - Personal Family care	*I have three children. For their appointments, I normally ask for some time off work. If I do the same [for mine] they would say I am always out. That is problematic.* *If you are a mom with small children, sometimes you just do not find anyone to take care of them*	11
17	Category: Barriers - Personal Forgetfulness	*Sometimes you forget because you are caught in the middle of so many things to do. It would be good if someone calls you to remind the appointment.*	11
28	Category: Barriers - Protective behaviour Embarrassment	*As a woman, I am embarrassed that someone examines that part of my body*	5
29	Category: Barriers - Protective behaviour Gender of the health provider	*Once I saw that a male nurse was performing the cytology at that facility. I decided to miss my appointment. I prefer to be examined by a woman*	2
32	Category: Benefits - Protective behaviour Cancer diagnosis	*It seems to me that having a cytology is essential. It is a way of preventing cancer and knowing what diseases one might have.*	17
37	Category: Benefits - Service delivery Satisfaction (home visit)	*The visit went well. She [the community worker] was kind, took my blood pressure and my weight. She even helped me with some appointments I needed*	28
38	Category: Benefits - Service delivery Satisfaction (service delivery)	*So far, the doctors I have seen are really good. I have been operated, hospitalized and the service is always good. I have felt supported*	32
39	Category: Susceptibility Perceived susceptibility	*It is important to have a cytology because one might develop cancer. My daughter was infected with human papillomavirus a while ago. She was timely diagnosed and thanks to God, there were no other consequences.*	4
41	Category: Severity Fear of a bad result	*Sometimes women are scared about getting a bad result.*	7
42	Category: Severity Fear of side effects	*I have heard that some healthy women end up with infections and bleeding after the cytology.*	5

Participants found it hard to navigate the service delivery process (see code 15 in Table 3.5). They felt that when attending a medical appointment, most of the time was spent in the waiting room or carrying out administrative paperwork. They also reported that it was common to have to provide the same information more than once to different staff within the same healthcare facility, or even to miss appointments because they were not properly briefed about the necessary administrative or clinical requirements. For example, some participants reported that even though they attended, they were not examined because they had had sexual intercourse the previous night. Lastly, a small number of participants commented on the (perceived) low quality of care they had experienced using that healthcare service.

There were barriers to accessing healthcare services. The most commonly raised concern was that it was difficult to book an appointment because lead times were long, healthcare facilities had inconvenient opening hours and call centres were permanently busy. This is particularly relevant in a context where most patients have informal jobs and are unable to attend appointments in working hours. For this reason, other participants mentioned difficulties in taking time off work, financial pressures, and problems with transport. Some quotes from interviewees affected by such problems are presented under categories 2 and 3 of Table 3.5.

Personal problems and beliefs about cervical cytology could also lead to a missed appointment (see quotes under categories 18, 19, 28 and 29 in Table 3.5). The most common personal problems were forgetfulness and family care responsibilities. Among the latter, some participants reported that they tend to prioritize medical appointments for other members of their family or were not always able to find someone to take care of their children during the appointments. Regarding the cytology test itself, some participants believed that the procedure would be painful or uncomfortable, or that they would feel anxiety or embarrassment. Moreover, some said that they were not able to attend because they were menstruating or had had sexual intercourse the day before the appointment. Two participants said that they decided not to attend because of the risk that a male nurse might examine them.

Despite the barriers described above, many participants reported that they were satisfied with the service they received, both in the healthcare facility and during the home visit (see categories 37 and 38 in Table 3.5). Most of them said that the community workers were kind and provided a direct way to overcome access barriers. Additionally, the home visits were informative. Most patients were aware of the purpose of the cytology test to diagnose cervical cancer and had a basic understanding of the screening program. However, some patients only had a general understanding of how screening could benefit their health, with no specific knowledge of the actual diseases that could be prevented.

Lastly, some comments related to susceptibility and severity. Some participants recognized that the purpose of the cytology test was to diagnose cancer, which could be interpreted as a sign of perceived susceptibility. However only three participants explicitly talked about their own risk of developing cancer. Moreover, those three participants had a family history of cancer or human papillomavirus infection. Additionally, fears of testing positive or of unpleasant side effects were stressed as possible reasons for missed cytology appointments. Table 3.5 presents some related quotes under categories 33, 40, 42 and 43.

3.4 Discussion

In this section we present a summary of our main findings, compare our study with others in the literature and consider implications for practice.

3.4.1 Main findings

Using routinely collected data, we were able to accurately predict individual attendance probabilities for cervical cancer screening appointments in Bogotá. First, we fitted a LASSO regression model to identify the characteristics of the higher no-show risk appointments. We found that younger patients living in zones with higher poverty levels are less likely to attend. Additionally, offering short lead times and Sunday appointments could increase screening uptake among hard-to-reach women in the city. Next, we used the LASSO results to select the variables to train an RF aimed at improving prediction accuracy. The resulting model has a good discrimination power and low variability in its performance (Average AUROC score 0.84 and standard deviation of 0.01). We used the RF results to inform the sample selection for a series of semi-structured interviews.

We interviewed 60 hard-to-reach women who received a home visit from the outreach program and had failed to attend their cytology appointments. Although most patients perceived the home visits to be informative, they found it hard to navigate the service delivery process and experienced access barriers. Qualitative data also enhanced the interpretation of the quantitative results. For example, the LASSO results show a relationship between the appointment date and the attendance probability. In the same vein, during the interviews some patients expressed that taking time off from work or childcare responsibilities might act as deterrents for screening uptake.

3.4.2 Comparison with other studies

Two of our quantitative results confirm what has been found in other cytology uptake studies: attendance probabilities change with the patient age and poverty. In Bogotá, we find the younger the patient, the higher her no-show risk. While some studies report similar behaviour in Ethiopia (Bante et al., 2019), or Kenya (Ng'Ang'A et al., 2018), in Tanzania younger patients are more likely to keep their appointments (Weng et al., 2020). Since this finding is context-dependent, it highlights the relevance of conducting research to inform public policy. We also find that, in zones where poverty affects less than 18% of the population, patients are three times more likely to attend. Several other studies have identified the same relationship between poverty and cervical cancer screening (Gatumo et al., 2018; Ilevbare et al., 2020; Ng'Ang'A et al., 2018; Weng et al., 2020). Moreover, during the interviews, some participants reported financial and transport difficulties in attending. Our qualitative results confirm the quantitative findings regarding financial difficulties.

We found a statistical relationship between the appointment date, i.e., day of week and month of year, and the attendance probability. In cervical cancer screening, most previous research has been devoted to exploring the impact of socio-demographic variables on attendance for screening (Williams-Brennan et al., 2012). The databases analysed in such studies normally include patients that do not have scheduled appointments. As our research was conducted within an outreach program, the context is slightly different. However, patients' lack of time has been described as a barrier for cytology uptake (Brown et al., 2019; Dunn & Tan, 2010). Our results can be also compared with previous work in no-show risk for primary care appointments. The existence of patterns in attendance probabilities according to the month of the year or day of the week has been documented previously (Cashman et al., 2007; Do & Siegler, 2018; Harvey et al., 2017; Parente et al., 2018). Two qualitative results might offer a context for these quantitative findings. First, a lower no-show risk on Sundays might be explained by the difficulties reported by some participants in taking time off work. Second, some participants stated that their childcare responsibilities caused them to miss appointments, which could explain why the no-show risk was higher during the school vacation months.

In our quantitative analysis, the attendance probability increases with the lead time. This is also found to be the case in studies of no-show behaviour for other primary care appointments (Ellis et al., 2017; McComb et al., 2017). Even in contexts where cultural barriers towards cervical cancer screening are overcome using education campaigns, offering timely access is a key component to increasing coverage (Black et al., 2019; Carr & Sellors, 2004). Confirming this quantitative finding, many of our participants stated that booking appointments is hard. They said that lead times were long (which could increase forgetfulness), and the healthcare facilities had inconvenient opening hours. These access problems were also found as a relevant barrier for screening programs in five other Latin American countries (Agurto et al., 2004).

Our qualitative study showed that participants found the home visits to be informative. Unsurprisingly, therefore, most participants either said they were aware that cytology is used to diagnose cancer or recognised the importance of regular cervical cytology. This result, however, is different from what has been found in many developing countries. Lack of knowledge regarding cervical cancer and screening programs has been identified as a key predictor of low uptake rates (see Table 3). Nevertheless, it must be noted that some participants explicitly stated that the importance of cytology was not discussed during the home visit. Additionally, only a few participants considered themselves personally to be at risk of developing cervical cancer. The belief that a disease is something faced by other people and not oneself is described by (Sundstrom et al., 2019) as *"othering"*, and leads people to underestimate the prevalence of the disease.

3.4.3 Implications for program management and public policy.

Our findings suggest a lack of coordination between the two components of the screening program, home visits and screening appointments. A great effort is made by the home visits team to reach patients who need screening, but although these patients are willing to take part in the screening program, they still face several access barriers. There is a need to offer agile scheduling and cancellation systems, shorter lead times and more flexible opening hours. Therefore, capacity management practices should be reviewed. Alternatives to the current operation might include: performing the cytology during the home visit (Arrossi et al., 2015), minimizing the impact of no-shows by overbooking (Parente et al., 2018), pooling resources within the program (Lewis et al., 2018) and offering open access scheduling policies for some healthcare facilities (Yang & Cayirli, 2020).

There is potential to overcome most of the perceived barriers by improving the service delivery process. On the one hand, community workers have a unique knowledge and understanding of the cultural context of the patient (Sivaram et al., 2018). Home visits could provide more standardized information about cervical cancer, the screening program, and the best way to navigate the healthcare system. Therefore, educational interventions for community workers (O'Donovan et al., 2019) and better design of information material for patients (Chan & So, 2020; Choi et al., 2020; So et al., 2019) could provide an interesting opportunity for the outreach program. On the other hand, drawing from our participants' experiences, there is a clear need to improve service quality at the healthcare facilities. Mechanisms to reduce waiting times for cytology

(Andreassen et al., 2017; Olwanda et al., 2018) and to improve the organization of the program (Chuang et al., 2019; Price et al., 2010) could increase satisfaction and attendance levels.

An impact evaluation should support future decision-making. After three years of running the outreach program, the District Secretariat of Health (*Secretaría Distrital de Salud*, SDS) has sufficient information to quantify its achievements in terms of early diagnosis. However, a model-based evaluation would enable different policy alternatives to be compared (Brennan et al., 2006; Briggs et al., 2004). While in developed countries cytology-based programs have achieved good results in decreasing morbidity and mortality of cervical cancer, in developing countries this is not always the case (Sivaram et al., 2018). A combination of alternative cervical cancer screening tests could enhance capacity and improve health outcomes in low resourced health systems (Denny et al., 2017). For example, a recent review concluded that self-sampling approaches have been found to increase acceptability of cervical cancer screening (Nishimura et al., 2021). In this context, by modelling the patient pathway from the home visit to treatment completion, a simulation model could support resource allocation and inform policy design.

3.4.4 Limitations

At the time of writing, three main limitations of this study are being addressed in ongoing projects. First, since we are using only routinely-collected quantitative data, the quantitative models predict attendance probabilities based only on a set of variables that has been designed for administrative purposes. Therefore, it was not possible to quantify the relationship between attendance probabilities and other variables thought to be highly predictive, such as patient income or the time of day of the appointment (Dantas et al., 2019; Mugassa & Frumence, 2020). Second, for both phases, the sample is limited by the inclusion of women who have participated in the outreach program managed by SDS. This program covers most of the low-income women in Bogotá, however, we do not know the perspectives or risk categories for other women in the city, or other parts of the country, that could inform public policy. Further, only patients with high no-show probabilities were included in the sample for the qualitative phase. Although their experiences are considered to be important to inform intervention design, insights from patients who missed their appointments despite having low no-show risk might be useful as well. Third, our findings suggest a relationship between the constructs of the HBM and no-show behaviour. However, this relationship is still to be quantified and a study with a representative sample is required.

3.5 Conclusion

This study has shown the benefits of combining a ‘black box’ approach, machine learning, with an in-depth qualitative methodology that can explore, and potentially explain, the results from the quantitative analysis. From a practical perspective, our findings indicate an urgent need to address the lack of alignment between the different phases of the cervical cancer screening program in Bogotá, and work to address this is currently under way.

Chapter 4 Assessing beliefs

Abstract

Background. Despite being a preventable disease, cervical cancer continues to be a public health concern, affecting mainly lower and middle-income countries. Therefore, in Bogotá a home-visit based program was instituted to increase screening uptake. However, around 40% of the visited women fail to attend their Pap smear test appointments. Using this program as a case study, this paper presents a methodology that combines machine learning methods, using routinely collected administrative data, with Champion's Health Belief Model to assess women's beliefs about cervical cancer screening. The aim is to improve the cost-effectiveness of behavioural interventions aiming to increase attendance for screening. The results presented here relate specifically to the case study, but the methodology is generic and can be applied in all low-income settings.

Methods. This is a cross-sectional study using two different datasets from the same population and a sequential modelling approach. To assess beliefs, we used a 37-item questionnaire to measure the constructs of the CHBM towards cervical cancer screening. Data were collected through a face-to-face survey (N = 1699). We examined instrument reliability using Cronbach's coefficient and performed a principal component analysis to assess construct validity. Then, Kruskal-Wallis and Dunn tests were conducted to analyse differences on the HBM scores, among patients with different poverty levels. Next, we used data retrieved from administrative health records (N = 23,370) to fit a LASSO regression model to predict individual no-show probabilities. Finally, we used the results of the CHBM in the LASSO model to improve its accuracy.

Results. Nine components were identified accounting for 57.7% of the variability of our data. Lower income patients were found to have a lower Health motivation score (p-value <0.001), a higher Severity score (p-value <0.001) and a higher Barriers score (p-value <0.001). Additionally, patients between 25 and 30 years old and with higher poverty levels are less likely to attend their appointments (O.R 0.93 (CI: 0.83-0.98) and 0.74 (CI: 0.66-0.85), respectively). We also found a

relationship between the CHBM scores and the patient attendance probability. Average AUROC score for our prediction model is 0.9.

Conclusion. In the case of Bogotá, our results highlight the need to develop education campaigns to address misconceptions about the disease mortality and treatment (aiming at decreasing perceived severity), particularly among younger patients living in extreme poverty. Additionally, it is important to conduct an economic evaluation of screening options to strengthen the cervical cancer screening program (to reduce perceived barriers). More widely, our prediction approach has the potential to improve the cost-effectiveness of behavioural interventions to increase attendance for screening in developing countries where funding is limited.

4.1 Background

Cervical cancer is a preventable disease. However, in 2018, it was the fourth leading cause of cancer death among women worldwide (Arbyn et al., 2020). Although the overall Age Standardized Incidence Rate (ASIR), per 100,000 women is 13.1, it ranges from 6.0 in Australia and New Zealand to 40.1 in Eastern Africa (Arbyn et al., 2020). In fact, both incidence and mortality rates are associated with poverty and limited health education (Amin et al., 2020; Tatari et al., 2020; X. Zhang et al., 2021). In 2018, around 84% of the cases and 88% of cervical cancer deaths occurred in poorly-resourced countries (Arbyn et al., 2020). Consequently, in 2020, the World Health Organization defined a set of goals to eradicate cervical cancer as a public health problem, emphasizing the need to improve human papillomavirus (HPV) vaccination coverage and screening uptake rates (Gultekin et al., 2020). Nevertheless, while in high income countries the implementation of screening and vaccination programs has been successful, for many lower and middle-income countries (LMICs) it still represents a major challenge (Canfell et al., 2020; Hinman & Orenstein, 2021; Pilleron et al., 2020; Diama B. Vale et al., 2021). In Colombia, the ASIR is 14.9 and mortality rates show geographical patterns affecting disproportionally low-income women (Hernández Vargas et al., 2020; International Agency for Research on Cancer, 2021b).

ACS *(Acciones Colectivas en Salud)* is an outreach program designed by the Health Office in Bogotá (*Secretaría Distrital de Salud*, SDS) to increase health service utilization among hard-to-reach populations. The main idea is to improve health outcomes by engaging low-income patients with eleven preventive care strategies. In this context, some of the ACS activities are devoted to increasing early cervical cancer detection by improving Pap smear test uptake among hard-to-reach women. Every month, a group of community workers identifies women who are not complying with the screening program, visits them at home, provides basic training in cervical cancer risks, and schedules a Pap smear test for them at the nearest healthcare facility. Despite this effort, around 40% of the visited patients end up missing their appointments. Therefore, more information is required to design interventions aimed at increasing attendance levels. Indeed, behavioural interventions informed by patient beliefs about screening have been found to increase uptake rates (Noman et al., 2021). Additionally, accurate predictions of individual no-show probabilities could improve resource allocation by identifying those patients who would benefit the most from such interventions (Wu et al., 2019).

The Health Belief Model (HBM) is a widely used conceptual framework in health behavioural research (Champion & Skinner, 2008). In its original version, introduced in the 1950s, the underlying theory is that the adoption of a protective health behaviour can be explained by the patient's perceptions of their susceptibility and the severity of the "threat", and the benefits of and barriers to the behaviour (Rosentock, 1960). Later, the model was extended to incorporate other categories (Champion & Skinner, 2008). Rosenstock et al. (1988), for example, proposed the inclusion of a Health Motivation category to assess the patient's incentive to behave and maintain general good health. More recently, Champion (1985) developed instruments to measure HBM constructs related to breast cancer behaviour. According to Ritchie et al. (2020), Champion's revised HBM (CHBM) has been found to explain between 25% and 89% of the variance in participation in mammography studies, in different contexts, over almost 40 years. Recent reviews on the use of the HBM to study cancer prevention behaviours can be found in (Lau et al., 2020; Naz et al., 2018; Ritchie et al., 2020) .

Guvenc et al. (2011) adapted the instruments of the CHBM to assess beliefs towards cervical cancer screening. Since then, several studies have adopted the CHBM as a conceptual framework to understand cervical cancer screening behaviours. As expected, the resulting scores for each construct are highly context dependent. For example, studies using Guvenc's scale have found susceptibility scores ranging from 2.2 in Saudi Arabia (Aldohaian et al., 2019a) to 4.8 in the USA (Smith & Mercado-Sierra, 2021). Consequently, two recent reviews have highlighted the need to conduct local empirical research to inform public policy and design tailored interventions, particularly among marginalized communities (De Cuevas et al., 2018; Maseko et al., 2019).

This study aims to inform the design of behavioural interventions to increase attendance levels for cervical cancer screening, among hard-to-reach low-income women in Bogotá. To achieve this, we propose a two-fold approach: cervical-cancer belief assessment and individual no-show probability prediction. A cross-sectional face-to-face survey of a random sample of ACS patients was conducted. Our analytical approach is three-fold: first, we study the reliability and construct validity of Guvenc's scale in our study context. Next, descriptive statistics and pairwise comparison of means are used to analyse the CHBM constructs. Finally, we develop a model to predict individual no-show probabilities using the survey results, patient sociodemographic information and appointment characteristics.

4.2 Methods

This section starts with a description of our study context. We provide basic information about the cervical screening program in Colombia and the definition of hard-to-reach women used by ACS in

Bogotá. The beliefs assessment then follows, describing the survey instrument, its validation, and data collection procedure. Finally, we present the proposed modelling approach to predict individual attendance probabilities.

4.2.1 Study context and sample.

In Colombia the coverage of the vaccination against the Human Papilloma Virus (HPV) remains low, despite being included in the free national immunization program (Vorsters et al., 2020). Therefore, cervical cancer control strategy is focused on early detection through screening. Women between 25 and 69 are eligible, following a 1-1-3 scheme. This means that screening is recommended annually and changed to a three-year interval after two consecutive annual negative results. Currently, the program is primarily based on cervical cytology and is included in the national health insurance, so no out-of-pocket payment is required when undergoing the examination (Bermedo-Carrasco et al., 2015; *Resolution 603280*, 2018). However, women do not receive any formal invitation to book a cytology appointment. Thus, the program relies on doctor recommendations and patient motivation. Although recent legislation recommended starting a transition to a HPV-test-based screening (*Resolution 603280*, 2018), the National Ministry of Health assessed operational barriers and decided to delay the pilot phase (*Resolution 276*, 2019). SDS considers a patient to be hard-to-reach if despite being eligible, she has not attended a screening appointment in the preceding year. Additionally, low-income populations are classified into four poverty levels to prioritize their participation in social programs. In this context, ACS only covers people belonging to the three most severe levels of poverty (High, Medium, and Low). Our study population are hard-to-reach women covered by ACS in Bogotá.

All items in the CHBM questionnaire used a three-point Likert scale: disagree, neutral and agree. The aim of the cross-sectional survey was to estimate the proportion of patients selecting each option. In December 2019, 43,500 hard-to-reach women were covered by ACS. In the absence of information about responses to any of the CHBM questions among this target population, the sample size was determined using an assumed proportion of 50% ‘yes’ responses to a hypothetical yes/no question, with confidence level 95% and error 2.5% (Eng, 2003). This gave a required sample of at least 1485 participants. Following a process of stratified random sampling, SDS eventually invited 1750 hard-to-reach women to take the survey. A total of 1699 women (97%) consented and SDS provided the anonymized answers. Although the women in our study population were designated hard-to-reach, they were willing to receive a home visit from the ACS team and were asked to take the survey at the end of the visit. This might offer an explanation for the high uptake, as no incentives were offered. Additionally, appointment information and socio-demographic data (i.e. age of the patient and poverty index) were retrieved from SDS information systems. Pontificia Universidad Javeriana (FID-19-107), SDS (2019EE47807) and the University of Southampton (ERGO ID 48583.A1) granted ethical approval for this study.

4.2.2 Assessing beliefs

We used the items of the CHBM questionnaire for cervical cancer screening and Pap smear test, developed by Guvenc et al. (2011). The statements were translated into Spanish and discussed with public health experts from SDS. As a result, taking into account the study context, six items were added to the list and five deleted. Hence, we used a 37-item survey (see Table 4.1) to assess the five constructs of the model: Susceptibility (4 items), Severity (7 items), Benefits (8 items), Health motivation (3 items) and Barriers (15 items). For data analysis, values of 1 (disagree), 3 (neutral) and 5 (agree) were assigned, following the convention in the literature (Aldohaian et al., 2019b). Construct validity was evaluated using principal component analysis and sample adequacy was assessed with the Kaiser-Meyer-Olkin (KMO) test. Finally, reliability of the scale was examined using item-rest subscale correlation and Cronbach's Alpha coefficients. We provide details of instrument validation in Appendix D.

Community workers collected data, at the end of home visits, between January and February 2020. Before data collection started, training took place in eight workshops with 280 community workers. During these workshops, the research project was presented and items of the instrument were analysed. As part of their enrolment process with SDS, community workers were previously trained in data collection, interaction with vulnerable communities and techniques to discuss health-related topics. Due to security concerns, it was decided that a printed version of the instrument should be used with each participant. Raw data were stored and anonymized by SDS. We used descriptive statistics to assess beliefs about cervical cancer screening. Pairwise comparison of means was performed to examine the effect of the participants poverty levels on each construct of the CHBM.

Table 4.1: CHBM Survey

Category	No	Statement
Susceptibility	1	It is likely that I will get cervical cancer in the future
Susceptibility	2	My chances of getting cervical cancer in the next few years are high
Susceptibility	3	I feel I will get cervical cancer sometime during my life
Susceptibility	4	I feel I will get cervical cancer sometime during my life because I have family history of cancer
Severity	5	The thought of cervical cancer scares me
Severity	6	When I think about cervical cancer, I feel worried
Severity	7	I am afraid to think about of cervical cancer
Severity	8	Problems I would experience with cervical cancer would last a long time
Severity	9	Cervical cancer would threaten a relationship with my husband, boyfriend, or partner
Severity	10	If I had cervical cancer my whole life would change
Severity	11	If I developed cervical cancer, I would not live longer than 5 years
Benefits	12	I want to discover health problems early
Benefits	13	Maintaining good health is extremely important to me
Benefits	14	I look for new information to improve my health
Benefits	15	I feel it is important to carry out activities which will improve my health
Benefits	16	Having regular Pap smear tests will help to find changes to the cervix, before they turn into cancer
Benefits	17	If cervical cancer was found at a regular Pap smear test its treatment would not be so bad
Benefits	18	I think that having a regular Pap smear test is the best way for cervical cancer to be diagnosed early
Benefits	19	Having regular Pap smear tests will decrease my chances of dying from cervical cancer
Motivation	20	I eat well-balanced meals for my health
Motivation	21	I exercise at least 3 times a week for my health
Motivation	22	I have regular health check-ups even when I am not sick
Barriers	23	I am afraid to have a Pap smear test for fear of a bad result
Barriers	24	I am afraid to have a Pap smear test because I don’t know what will happen
Barriers	25	I don’t know where to go for a Pap smear test
Barriers	26	I would be ashamed to lie on a gynaecologic examination table
Barriers	27	Undergoing a Pap smear test takes too much time
Barriers	28	Undergoing a Pap smear test is too painful
Barriers	29	Health professionals performing Pap smear tests are rude to women
Barriers	30	I have other problems in my life which are more important than having a Pap smear test
Barriers	31	I am too old to have a Pap smear test regularly
Barriers	32	Undergoing a Pap smear test is too uncomfortable
Barriers	33	I think that having a regular Pap smear test is required only if one has an active sexual life
Barriers	34	My religion does not allow me to undergo a Pap smear test
Barriers	35	Preparing for a Pap smear test can be inconvenient for me
Barriers	36	Undergoing a Pap smear test can cause problems with my partner
Barriers	37	I am too young to have a Pap smear test regularly

4.2.3 Predicting individual no-show probabilities

We analysed two data sets. First, SDS provided anonymised data from the 1699 surveyed patients (dataset 1). Table 4.2 presents the list of variables collected by ACS program managers, grouped into patient and appointment characteristics. These variables have been found to have good predictive value for medical appointment attendance (Dantas et al., 2018). Five of these variables (age, lead time, month, and day) were previously used to model no-show behaviour for preventive care appointments in Bogotá (Barrera Ferro et al., 2020). Second, we retrieved data from historical administrative records (dataset 2) relating to appointments scheduled for 23,384 women between 2017 and 2019 as part of the ACS program. Further details of the two datasets can be found in Appendix C, where it can be seen that the sociodemographic profiles of the women in both datasets are similar.

Table 4.2: Variables used for the LASSO model.

Category	Variable	Description	Highest no-show		Lowest no-show	
			Data set 1	Data set 2	Data set 1	Data set 2
Patient	Age	Age of the patient at the time of the appointment (years)	[30-49] 41%	<30 51%	>59 24%	>59 29%
	Poverty	Poverty level indicator defined by the national planning department	High 46%	High 40%	Medium 34%	Low 34%
Appointment	Lead time	Elapsed time between the date of the home visit and the appointment date (days)	≥16 39%	≥16 38%	[8-15] 30%	[8-15] 35%
	Month	Month in which the appointment was scheduled	January 42%	February 39%	February 33%	January 36%
	Day	Day of the week in which the appointment was scheduled	Saturday 38%	Saturday 44%	Monday 35%	Sunday 22%

The methodology is described in detail in (Barrera Ferro et al., 2020) and is summarised briefly here. For age and lead time we used decision trees to build categorical variables aiming at increasing model stability (Thomas et al., 2017). Additionally, one-hot encoding was used to represent all the variables in the models. To improve interpretability, we performed variable selection using a LASSO (Least Absolute Shrinkage and Selection Operator) regression model (Tibshirani, 1996). In cases with high correlation between independent variables, this model has been found to select only the best predictors and set the coefficients of the other variables to zero, avoiding multicollinearity problems (Muthukrishnan & Rohini, 2016). Finally, we randomly generated training (70%) and test sets (30%). Table 1 also shows the categories with the highest and lowest no-show rates, for each variable in each data set. For example, while in the data set 1 the patients between 30 and 49 years old have the highest no-show rate (41%), in the data set 2 the patients younger than 30 years old have a no-show rate of 51%. Detailed information about the samples, frequencies, and attendance levels for both data sets are provided in Appendix C.

To quantify the linear relationships between each variable and the no-show probability, we fitted a LASSO regression model. This model was proposed to overcome the accuracy and interpretability limitations of ordinary least-squares regression (Tibshirani, 1996) and has been widely used to predict appointment attendance (Dantas et al., 2018). In future, SDS will use individual no-show probabilities to classify patients into three groups: A, B and C. While patients in groups A (at high risk of no-show) and B (at medium risk) will receive different behavioural interventions, patients in group C (low risk) will not receive any intervention as they are likely to attend anyway. Therefore, we needed to select two cut-off points. This process is called cut-off point tuning and is based on ROC performance indicators (Verbeke et al., 2017). Consequently, the performance of the model was assessed using the average Area Under the Receiver Operating Characteristic (AUROC) score. This score ranges from 0 to 1, and can be interpreted as the average sensitivity of the classification considering all possible specificities (Verbeke et al., 2017).

We analysed average coefficients over 100 experiments. For each group of ten experiments, we randomly divided the data into ten groups, using nine for training and the other one for testing. Then, the testing group was iteratively changed. When this procedure is repeated 10 times, it is called a 10-by-10 cross validation process. Additionally, a parametric analysis was carried out to determine the penalty constant of the model. We decided to use the constant that maximizes AUROC score while maintaining the minimum possible number of variables. Scikit-

Learn's logistic regression was used in our analysis, setting the alpha value to 0 (Pedregosa et al., 2011).

To quantify the impact on accuracy, we conducted three experiments. For model 1, we used the variables presented in Table 1 for the surveyed patients (n= 1,699). For model 2, we used the same data set and included responses to the 37-item survey instrument. For model 3 a sequential approach was used as follows. First, we trained a model with the variables presented in Table 1, using information from Pap smear test appointments that were scheduled between 2017 and 2019 (dataset 2, n = 23,384). We hypothesized that by using these historical data the model would be better able to identify patterns of attendance. With this model, we predicted the no-show probability for each patient in the survey data set. Then, a second model was fitted using the first model prediction and the 37 items in the survey.

4.3 Results

We present our results organized in three sections. Firstly, an assessment of the beliefs is presented. Then, the LASSO regression results are summarized. We use average odds ratios (OR) to quantify the impact of each variable on the attendance probability. Finally, the performance of the prediction approach is assessed. We analyse the added value, in terms of AUROC score, of using a sequential approach to predict individual attendance probabilities.

4.3.1 Assessing beliefs

Figure 4.1 presents the distribution of the scores for the 37 items, grouped into nine components. We provide detailed results of the item reliability analysis and construct validation for the instrument in Appendix D. Response frequencies by item are provided in Appendix E. Using a scale from 1 (disagree) to 5 (agree), the average susceptibility score is 2.86, with 3.83 being the highest observed value (statement 1). When presented with the statement "*It is likely that I will get cervical* *cancer in the future",* 56% of the participants agreed. However, judging by the other three items in the category, most of the participants showed a low perceived susceptibility. More than 40% of the participants disagreed with statements 2, 3 and 4. Similarly, only one component is identified for the heath motivation category. The average score for health motivation is 3.52, with items ranging from 3.05 to 4.03 on average. While 71% of the participants agreed with statement 20 *"I eat well-balanced meals for my health"*, only 44% reported that they exercise at least 3 times a week for their health (statement 21).

Figure 4.1 also shows that severity items were grouped into two components (2 and 3). There is a difference between feeling anxiety about the idea of developing cervical cancer and being afraid of its possible consequences. The average score for component 2 is 4.27 and it includes items 5, 6 and 7. These items are all related to the general idea of cervical cancer. On average, 78% of the participants agreed with these three statements. However, severity score decreases when participants are asked about possible consequences of the disease. The average score for component 3 is 3.37, with values ranging from 2.82 to 4.14. Finally, statements 9 and 10 score bellow 3.0. While 42% of the participants disagreed with the statement *"Cervical cancer would threaten a relationship with my husband, boyfriend or partner"*, 43% provide the same answer for the statement *"If I developed cervical cancer, I would not live longer than 5 years"*.

Barriers statements are grouped into components 7, 8 and 9 with average scores of 2.63, 2.34 and 1.51, respectively. Component 7 includes statements 23 and 24 both related to being afraid to have a Pap smear test, either because of a possible bad result or because they do not know what might happen. Both statements have similar distribution of answers, among participants: around 35% agreed and 55% disagreed. Component 8 includes statements 28, 29 and 32. These statements are related to the experience of taking a Pap smear test. Among participants, the test is perceived as painful (38%) and uncomfortable (49%). Additionally, 19% of the respondents believed that the health professionals performing the test are rude to women. Lastly, component 9 included four statements: 34, 35, 36 and 37. Interestingly, these four items were added to the instrument as result of the discussion with SDS public health experts. However, on average, 83% of the participants disagreed with the statements.

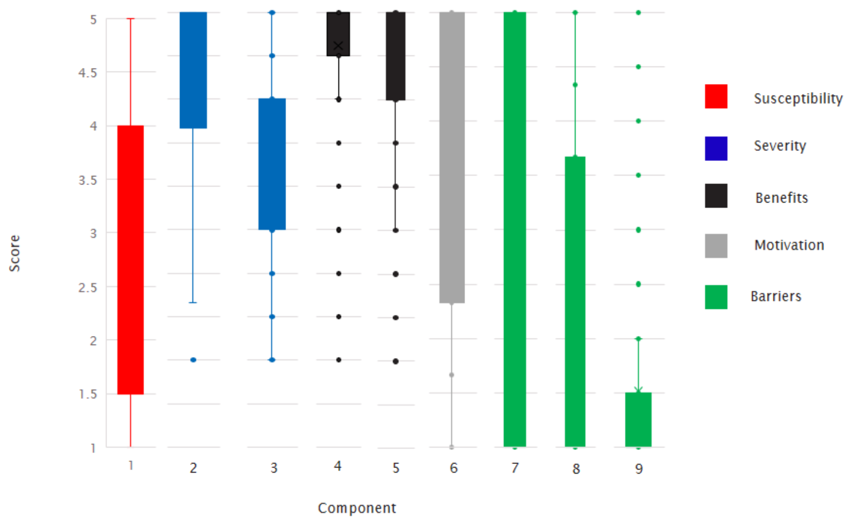

Figure 4.1 Distributions of the scores by component

There is a relationship between the scores of three constructs of the CHBM, severity, motivation and barriers, and the poverty level of the participant. Kruskal-Wallis tests show that there are statistically significant differences in the scores of severity (*p-value* <0.001), health motivation (*p-value* <0.0028) and barriers (*p-value* <0.001) between the three levels of poverty. Additionally, the Dunn tests show that participants at the higher level of poverty have lower health motivation score (*p-value* <0.001), highest severity score (*p-value* <0.001) and higher barriers score (p-value <0.001). There is no statistically significant difference among the scores of the other two groups of participants. Pairwise comparisons for the nine components lead to similar conclusions regarding the poverty levels. Appendix F presents the *p-values* for the Kruskal-Wallis test and the pairwise comparisons, using the Dunn test.

4.3.2 Variables affecting no-show probability.

This section presents the LASSO regression results. We report the odds ratios (5th percentile, 95th percentile and average) for the 100 experiments. While Table 4.3 presents the results for the HBM survey, Table 4.4 presents the results for the patient and appointment characteristics. Both tables present the results of the same LASSO model. To model the outcome, a value of one is assigned to those patients attending their appointments. Therefore, higher odds ratios (ORs) mean lower no-show probabilities. For example, patients who disagree with statement 1 are less likely to attend their appointments (OR 0.82) than those who are neutral to (OR 0.98) or agree (OR 1) with the same statement. This model has a good discriminatory power and its results are not sensitive to the sample. The average AUROC score is 0.79 with a standard deviation of 0.004.

There is a relationship between the CHBM constructs and the no-show probability. Table 4.3 summarises the ORs for the possible answers to 16 items of the survey. The other 21 items were found not to have a good predictive value for the attendance levels. Participants with higher perceived susceptibility are more likely to keep their appointments. Those who disagree with statements 1 and 3 have OR of 0.82 and 0.66, respectively. Additionally, patients with lower health motivation and perceived benefits are less likely to attend. The average ORs range from 0.54 to 1.09 for benefits and from 0.80 to 1.02 for health motivation.

Perceived severity and barriers affect the no-show probability. Patients who disagree with *being afraid to think about cervical cancer* are less likely to attend (OR 0.93). Surprisingly, those who do not worry about specific personal consequences of the disease have lower no-show probabilities (OR 1.26 and 1.27). Additionally, patients are more likely to attend if they are not afraid to have the test (OR 1.31), do not think that the test is painful (OR 1.23) or uncomfortable (1.42) and do not believe that the testing is only required for patients with an active sexual life (1.42). Lastly, patients have lower no-show probabilities if they are neutral to statements 29, 30 and 35.

Table 4.3: LASSO regression results: Health Beliefs Model survey.

CATEGORY	N	STATEMENT	Odds Ratio Disagree			Odds Ratio Neutral		
			95th	5th	Average	95th	5th	Average
Susceptibility	1	It is likely that I will get cervical cancer in the future	0.90	0.74	0.82	1.00	0.90	0.98
Susceptibility	3	I feel I will get cervical cancer sometime during my life	0.72	0.60	0.66	0.84	0.65	0.73
Severity	7	I am afraid to think about of cervical cancer	0.99	0.83	0.93	1.25	1.00	1.05
Severity	9	Cervical cancer would threaten a relationship with my husband	1.39	1.16	1.26	1.28	1.03	1.15
Severity	10	If I had cervical cancer my whole life would change	1.29	1.27	1.27	1.19	1.00	1.04
Benefits	13	Maintaining good health is extremely important to me	0.69	0.45	0.54	0.99	0.79	0.92
Benefits	17	If cervical cancer was found at a regular cytology its treatment would not be so bad	1.00	0.92	0.98	1.22	1.02	1.09
Motivation	21	I exercise at least 3 times a week for my health	1.00	0.95	0.99	0.97	0.81	0.89
Motivation	22	I have regular health check-ups even when I am not sick	0.87	0.75	0.80	1.11	1.00	1.02
Barriers	23	I am afraid to have a Pap smear test for fear of a bad result	1.42	1.21	1.31	1.80	1.32	1.52
Barriers	28	Undergoing a Pap smear test is too painful	1.36	1.11	1.23	1.12	1.00	1.02
Barriers	29	Health professionals performing Pap smear tests are rude to women	0.98	0.82	0.93	1.39	1.08	1.22
Barriers	30	I have other problems in my life which are more important than having a Pap smear test	1.00	0.86	0.95	1.59	1.13	1.32
Barriers	32	Undergoing a Pap smear test is too uncomfortable	1.58	1.27	1.42	1.26	1.00	1.05
Barriers	33	I think that having a regular Pap smear test is required only if one has an active sexual life	1.55	1.28	1.42	1.15	1.00	1.02
Barriers	35	Preparing for cytology can be inconvenient for me	1.00	0.83	0.95	1.48	1.04	1.22

We also find a relationship between patient and appointment characteristics and the attendance probability. As can be seen in Table 4.4, the age and the poverty level of the patient affect her attendance rate. The older the patient, the more likely they are to keep their appointment. Additionally, patients in the highest level of poverty have lower attendance probabilities. Table 4.4 also shows that reducing lead times might lead to better attendance levels. ORs range from 1 to 4.63 when the lead time is varied. Lastly, as the survey was conducted between

January and February 2020, the model is not able to find possible seasonal patterns on the attendance rates. The ORs for February appointments are only slightly higher than the ones for January.

Table 4.4: LASSO regression results: Patient and appointment characteristics.

Variable	Odds Ratio for attendance probability		
	5th	95th	Average
Age			
[25, 30)	0.83	0.98	0.93
[30, 59)	0.81	0.99	0.94
[59, 64)	1.62	2.29	1.96
>64	1.00	1.00	1.00
Poverty			
High	0.66	0.85	0.74
Medium	1.00	1.21	1.08
Low	1.00	1.00	1.00
Lead time			
<14	2.95	3.78	3.24
[14, 27)	4.00	5.40	4.63
[27, 39)	1.76	2.38	2.01
>39	1.00	1.00	1.00
Month			
January	0.95	1.00	0.99
February	1.16	1.02	1.06

4.3.3 Improving prediction accuracy.

In this section, we assess the performance of the three modelling approaches to predict individual attendance probabilities. Figure 4.2 summarizes the results of 300 experiments. Each point in the graph represents the average and standard deviation of the AUROC score for a group of ten experiments. Model 1 predicts the attendance probability using only patient and appointment variables presented in Table 1. Model 2 includes the same variables and the results from the HMB survey. Lastly, model 3 follows a sequential approach, combining data from 23,384 Pap smear appointments and the survey results.

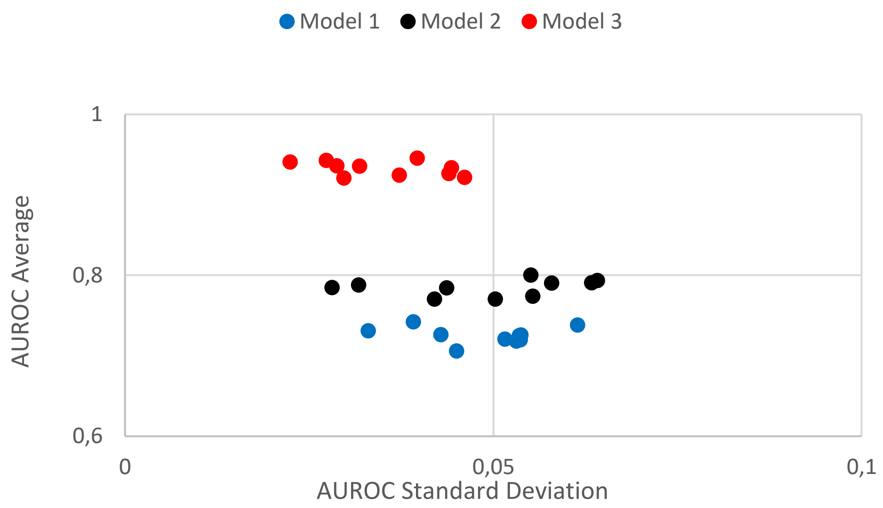

Figure 4.2 Model performance

Assessing patient beliefs towards cervical cancer screening adds value to the prediction process. By using the survey results, it is possible to increase the average AUROC score from 0.71 to 0.79. Arguably, collecting and processing this information is expensive. However, these results improve the understanding of the no-show phenomena and could be used to inform the design of interventions to increase attendance levels. This is particularly relevant in the context of hard-to-reach patients. Additionally, the performance of model 3 shows that it is possible to train one model with administrative data (routinely collected) and select a representative sample of patients to assess their beliefs. This strategy increases the AUROC score up to 0.9.

4.4 Discussion

Compared to other studies using Guvenc's scale, our results suggest that hard-to-reach women from Bogotá have lower perceived susceptibility (Daryani et al., 2016; Mabotja et al., 2021; Nigussie et al., 2019; Samami et al., 2021; Smith & Mercado-Sierra, 2021), higher perceived severity (Aldohaian et al., 2019a; Daryani et al., 2016; Kocaöz et al., 2018; Mabotja et al., 2021; Maharjan et al., 2020; Nigussie et al., 2019; Samami et al., 2021; Smith & Mercado-Sierra, 2021), higher perceived benefits (Daryani et al., 2016; Kocaöz et al., 2018; Mahajan et al., 2020; Maharjan et al., 2020; Nigussie et al., 2019; Samami et al., 2021; Smith et al., 2018) and lower perceived barriers

(Aldohaian et al., 2019a; Demirtas & Acikgoz, 2013; Kocaöz et al., 2018; Maharjan et al., 2020; Reis et al., 2012; Samami et al., 2021), towards cervical cancer screening. Recent reviews concluded that these beliefs have been less researched in Latin America (Liebermann et al., 2018; Williams-Brennan et al., 2012). However, we identified among our participants three beliefs that have hampered the implementation of cervical cancer screening programs in other countries of the region. Firstly, for 32% of our participants there is a relationship between cancer history in the family and the susceptibility of developing cervical cancer (Gajardo & Urrutia, 2017; Urrutia S, 2012). Secondly, 28% of the women believe that undergoing a Pap smear test is not required if one does not have an active sexual life (Agurto et al., 2004; Paz Soldan et al., 2008; Urrutia S, 2012). Lastly, 41% of the surveyed patients think that a cervical cancer diagnosis might threaten the relationships with their husbands, boyfriends or partners (Agurto et al., 2004; Liebermann et al., 2020; Victoria et al., 2020).

Our regression results also confirm what has been found in previous research, in LMIC contexts outside Latin America. In Bogotá, patients are more willing to undergo a Pap smear test if they perceive themselves at risk of developing cervical cancer or understand the benefits of the screening program. Similarly, perceived susceptibility was associated with higher uptake rates in Ghana (Ampofo et al., 2020), Ethiopia (Nigussie et al., 2019) and Iran (Mehraban et al., 2018). Additionally, higher perceived benefits were found to encourage screening behaviours in Nepal (Maharjan et al., 2020), Ghana (Ampofo et al., 2020) and Ethiopia (Gemeda et al., 2020). In a recent review, Simbar et al. (2020) concluded that training-based interventions are able to modify perceived susceptibility and benefits, leading to behavioural changes. Therefore, education among participants with higher no-show risk in Bogotá should aim at increasing perceived susceptibility.

We also find that poverty affects patients' beliefs and attendance probabilities. Participants in the most severe level of poverty have lower perceived health motivation, higher perceived severity, higher perceived barriers and are less likely to keep their appointments. The relationship between poverty levels and cervical cancer screening behaviour (Arrossi et al., 2008; Ilevbare et al., 2020; Ng'Ang'A et al., 2018; Paz Soldan et al., 2008; Weng et al., 2020), or no-show rates (Daye et al., 2018; French et al., 2017; Lu et al., 2017; Mohammadi et al., 2018), has been widely documented (Dantas et al., 2018). However, little has been discussed about the differences in beliefs among women suffering different levels of poverty. Targeting marginalized communities with tailored interventions could improve screening uptake (Amin et al., 2020; Musa et al., 2017; Pilleron et al., 2020). Therefore, our results suggest the need to develop new information material for lower income patients in Bogotá.

Cancer worries decrease attendance probability. The underlying assumption of the CHBM is that perceived susceptibility acts as an enabler for protective health behaviours. Indeed, several studies have found that perceived severity is associated with better cervical cancer screening uptake rates (Annan et al., 2019; Brandt et al., 2019; Guvenc et al., 2011; Mabotja et al., 2021; Maharjan et al., 2020). However, our results show that participants who believe that a cervical cancer diagnosis would threaten their relationships (41%) or change their whole life (74%), and participants who are afraid of a bad result (36%) are less likely to attend. Recent research has theorized that there is a difference between general (about the disease) and specific (about the consequences) cancer worries (Quaife et al., 2018). In this context, it is possible that while worrying about developing cancer motivates early diagnosis behaviours, some specific worries about the consequences act as deterrents to screening attendance (Murphy et al., 2018; Vrinten et al., 2017). Our results highlight the need to develop education campaigns to address misconceptions about the disease mortality and treatment.

There is a potential for improving attendance rates among hard-to-reach women in Bogotá by decreasing lead times. ORs range from 1 to 4.63 (IC 4-5.4) when the lead time is decreased. This relationship has been previously found in other no-show studies for healthcare appointments (Parente et al., 2018; Rosenbaum et al., 2018; Srinivas & Ravindran, 2018). Further, while offering timely access to screening services is a key component in implementation success (Black et al., 2019; Carr & Sellors, 2004), access problems are one of the main barriers towards cervical cancer screening in Latin America (Agurto et al., 2004). It has been argued that in poorly-resourced systems, cytology-based screening programs are less effective than using a combination of different types of test (Denny et al., 2017; Sivaram et al., 2018). Our results highlight the need to conduct an economic evaluation of alternatives to strength the cervical cancer screening program in Bogotá. For example, including HPV testing and self-sampling have shown positive impacts in Argentina, Brazil and Mexico (Arrossi, 2019; Arrossi et al., 2021; Flores et al., 2011; Diama Bhadra Vale et al., 2021).

The main limitations of this study are related to the sample. First, we aimed at assessing beliefs among hard-to-reach women in Bogotá. Therefore, sampling among ACS participants is considered to be a good strategy. However, we are not able to draw conclusions about other relevant groups in the city. Further research on women outside the program could also inform public policy. Second, data were collected at the end of the home visit. Consequently, it is not possible to quantify the impact of the basic training provided by ACS community workers among our participants. However, we believe that the information provided by this assessment can be used to strengthen the program and ultimately improve health outcomes. Lastly, data were collected between January and February 2020. In Bogotá, the first confirmed case of COVID-19 was reported in March 2020 and restrictions on social distance were adopted two weeks later. Data collection was completed before the public became aware of the pandemic so we are confident this did not influence responses, but it is not possible to draw any conclusions on how the (widely available) information on the virus may subsequently have affected the health-seeking behaviours of our study population.

4.5 Conclusion

Our methodological approach has the potential to improve the cost-effectiveness of behavioural interventions to increase screening uptake among hard-to-reach women in any setting. Generally, behavioural strategies aimed at the whole population are not cost-effective (Schwebel & Larimer, 2018; Weaver et al., 2019; Wu et al., 2019). Further, using mass interventions such as phone or text reminders might ignore the underlying reasons for the no-show behaviour among hard-to-reach populations (Brouwers et al., 2011; Spadea et al., 2010). Therefore, by accurately predicting individual attendance probabilities, it is possible (and financially sustainable) to design tailored interventions for marginalized communities in low-resourced settings. More importantly, for each cohort of patients the model can be used to predict individual attendance probabilities and classify patients into different intervention groups. By doing so, costly behavioural interventions can be reserved for those with higher no-show risk. In this context, scores of the beliefs assessment can be used to select the most appropriate behavioural approach for each group. We have also shown that, following a sequential approach, it is possible to identify patients with higher no-show risk by exploiting a combination of routinely-collected data and a sample-based beliefs assessment. In Bogotá, interventions for younger patients living in extreme poverty should be prioritized. Additionally, educational campaigns should be designed to address misconceptions about the disease mortality and treatment. Although it is important to convey a message about susceptibility, communication should be careful so not to reinforce anxiety among the patients.

Chapter 5 Improving fairness

Abstract

Over the last decade, due to the growing availability of data and computational resources, machine learning (ML) approaches have started to play a key role in the implementation of affirmative-action policies and programs. The underlying assumption is that resource allocation can be informed by the prediction of individual risks, improving the prioritization of the potential beneficiaries, and increasing the performance of the system. Therefore, there is an interest in ensuring that biases in the data or the algorithms do not lead to treating some individuals unfavourably. Particularly, the notion of group-based fairness seeks to ensure that individuals will not be discriminated on the basis of their group's protected characteristics. This work proposes an optimization model to improve fairness in ML-enabled affirmative actions, following a post-processing approach. Our case study is an outreach program to increase cervical cancer screening among hard-to-reach women in Bogotá, Colombia. The computational experimentation shows that it is possible to address ML bias while maintaining high levels of accuracy.

5.1 Introduction

Affirmative actions are designed to avoid discrimination against part of the population on the basis of gender, ethnic group or socio-economic background, among others (Crosby et al., 2006). According to Chavkin (1997), these type of policies and programs have two main goals: social justice and efficiency. While in the former the objective is to balance the playing field for those who have been discriminated against; in the later, the idea is to take advantage of the practical implications of their effective inclusion. Although there is an open debate on the possible unintended consequences of this approach (Ellison & Pathak, 2021), there is also compelling evidence about the positive impact of affirmative actions in different contexts such as education (Aygun & Bó, 2017; Rotem et al., 2021) or inclusion in the workplace (Beaurain & Masclet, 2016). Perhaps more importantly, as discrimination continues to be a concern, these type of policies are still needed and expected to be in place for the decades to come (Crosby et al., 2006).

Over the last years, due to the availability of data and computational resources, machine learning (ML) approaches have started to play a key role in the implementation of such affirmative-action policies and programs. Ye et al. (2019), for example, used ML techniques to help the New York City government to identify buildings where tenants might face landlord harassment, in order to prioritize resource allocation for an outreach educational program. In the same vein, ML has been used to improve students drop-out prevention (Maldonado et al., 2021) reduce patients no-show behaviour (Barrera Ferro et al., 2020) and improve the understanding of the community needs in developing countries contexts (Conforti et al., 2020). In a recent review, Shi et al. (2020) analysed published work under the broader concept of Artificial Intelligence for Social Good (AI4SG). According to the authors, while there is a growing interest on solving social problems using AI, the deployment remains a challenge. Therefore, more work providing evidence of short-to-medium impact is needed.

In this context, it is important to ensure that biases in the data or the algorithms do not lead to treating some individuals unfavourably (Oneto & Chiappa, 2020). Therefore, assessing and accounting for AI fairness has become increasingly important among researchers and decision makers (Mehrabi et al., 2021) and a large number of metrics have been developed to quantify fairness and mitigate bias in ML (Caton & Haas, 2020). Verma and Rubin (2018), for example, collected different definitions of fairness for the algorithmic classification problem and analysed them using a regression classifier trained on a credit data set. In this review, the authors conclude that an assessment of which fairness definition is appropriate needs to be conducted on a case-by-case basis.

This work proposes an optimization approach to improve fairness in ML-enabled affirmative actions. We study the case in which a set of interventions will be adopted to foster a desired outcome among a target population. From the operational perspective, the decision of who will take part in each intervention is made based on the predicted individual probabilities of achieving the outcome without intervention. Therefore, the bi-objective model maximizes accuracy and minimizes inequality of the classification. Our case study is an outreach program to increase cervical cancer screening among hard-to-reach women in Bogotá, Colombia.

5.2 Related Work

Due to the increasing interest in detecting and mitigating Artificial Intelligence bias, different reviews have aimed at synthetizing recent work in the field, providing analysis frameworks and identifying future research challenges (Caton & Haas, 2020; Feuerriegel et al., 2020; Mehrabi et al., 2021; Oneto & Chiappa, 2020). Therefore, in this section emphasizes the use of optimization to improve fairness in the algorithmic classification problem. To organize our discussion, we adopt a widely accepted framework that classifies works according to when the bias is addressed, into three categories: pre-processing, in-processing and post-processing (Caton & Haas, 2020; Mehrabi et al., 2021).

In the pre-processing approach, the objective is to eliminate the discrimination by transforming the data. Tae & Whang (2021), for example, study the case in which the bias is tackled by gathering additional data. They argue that indiscriminate collection, although it might be feasible, is not cost-effective. Therefore, an optimization model is proposed to determine the minimum amount of new data required, for each class. By exploiting the learning curves of the classification algorithm, this approach improves both accuracy and fairness.

A second alternative is to redesign the classification algorithm to remove the discrimination, this is called in-processing. According to Mehrabi et al. (2021), several authors have used optimization models to improve classification fairness during the algorithm training. Dwork et al. (2012) study individual-based fairness, the idea that two *similar* individuals should be classified *similarly,* and its relationship with statistical parity, a notion of group-based fairness. They propose mathematical model to maximize accuracy subject to a fairness constraint and a bicriteria approach to maximize accuracy while minimizing individual-based unfairness, subject to a group-based fairness constraint. In the same vein, Valdivia et al. (2021) propose a methodology to explore the trade-off between accuracy and fairness. They argue that in most in-processing approaches fairness is used as a constraint of the optimization problem, leading to solutions that ignore a wide space of potentially good alternatives. Consequently, a bicriteria model is proposed and a pareto front generated using a nondominated sorting genetic algorithm II approach.

Lastly, in the post-processing approach the objective is to improve fairness by making changes after the classification algorithm is trained. Hadi et al. (2019), for example, aim at improving resource allocation on a healthcare communications network, using a ML-enabled patient classification. In this work, the classification process leverages health-status data to predict individual stroke risks. Therefore, the notion of fairness is based on the idea of assigning high-performance resources to patients with higher risk levels. However, possible bias on the patient classification itself is not discussed. Similarly, Yan et al. (2021) propose a ML-informed model to optimally allocate inspection resources for the shipping industry. The underlying idea is that it is possible to increase fairness in the ship inspection process, by using ML techniques to predict possible deficiencies on each ship.

This work adds to the body of research by proposing a bi-objective model to tackle classification bias, using a post-processing approach. Our technique integrates the effort to improve fairness with the decision-making process, including potential user requirements. In our case study, we model capacity constraints for each intervention group. However, this can be easily extended to model, for example, cost and impact of each intervention to support tactical decisions.

5.3 Problem context and motivation

Despite been a highly preventable disease, cervical cancer remains a public health problem. In 2020, 604,127 new cases were diagnosed, and 341,831 women died of this type of cancer, worldwide (International Agency for Research on Cancer, 2021a). Therefore, the World Health Organization defined three goals to reduce its age standardized incidence rate (ASIR) to less than 4 per 100.000 women, by 2030 (Gultekin et al., 2020). One of these goals is to reach a 70% screening coverage with a high-performance test. However, although in high-income countries screening programs have been successful in reducing mortality, in lower and middle-income countries this is not the case (Canfell et al., 2020; Diama B. Vale et al., 2021). In fact, 84% of the cases and 88% of cervical cancer deaths, reported in 2018, occurred in poorly resourced countries (Arbyn et al., 2020). In Colombia, the ASIR increased from 12.57 in 2018 to 14.9 in 2020 and there is evidence of geographical patterns indicating a disproportional incidence among low-income women (Hernández Vargas et al., 2020; International Agency for Research on Cancer, 2021b; Pilleron et al., 2020).

Consequently, Bogotá's health office *(Secretaría Distrital de Salud, SDS)* instituted a program to increase early cervical cancer diagnosis by promoting screening uptake among low-income women who have failed to undergo a Pap smear test, despite being eligible. Under this program, a group of community workers visit patients at their homes, conduct basic training in cervical cancer risks and schedule for them a screening appointment at the nearest healthcare facility. Despite this effort, the no-show rate for the appointments is around 40%. Therefore, SDS is interested in designing two interventions to increase uptake. While the first intervention is personalized and highly resource intensive, the second one is a mass strategy aimed at improving coverage. To ensure cost-effectiveness and financial sustainability of the system, there is a capacity constraint for each strategy. In this context, the population would be divided into three groups: a group who would receive the personalized intervention (Group A), a group who would receive the mass intervention (Group B) and a group that would not receive any intervention at all (Group C).

To support the classification process, a machine learning algorithm is trained to predict individual attendance probabilities. Figure 5.1 presents the distribution of a population according to their predicted probabilities, their actual attendance (show/no show) and an example of the classification, using the data described in section 5.5. For example, for the 6% of patients for whom the algorithm gave between 10% and 20% probability of attendance, 5% did not actually attend while 1% did attend; however, all the patients with a predicted probability of attendance between 90% and 100% did actually attend. Figure 5.1 also shows that the classification can be made based on the predicted probability of attendance. If the machine learning algorithm has good predictive power, by assigning those patients with predicted probability of attendance less than some threshold value to group A and those with predicted probability greater than some other threshold value to group C it is possible to maximize the cost-effectiveness of the interventions.

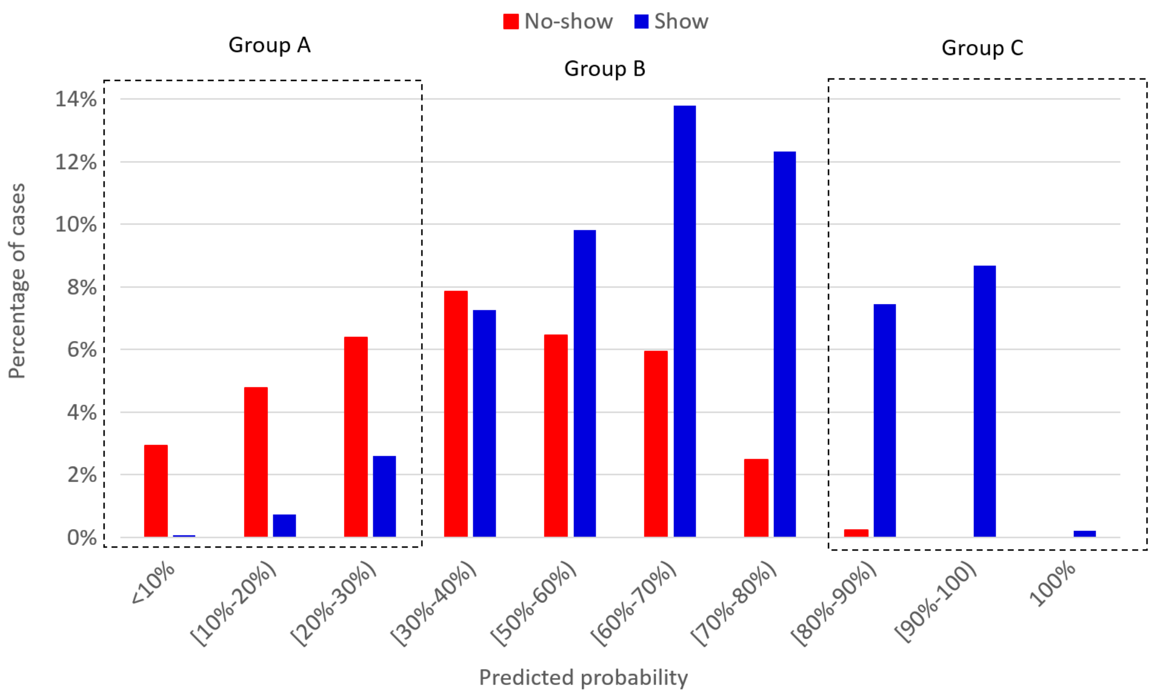

Figure 5.1. Distribution of the number of show and no-show patients according with the predicted probability

However, when part of the targeted population belongs to a group associated with a sensitive attribute (i.e., socio-economic background or age) this scenario might change. Hereafter, we will refer to such group as the protected class. The selection of the protected class depends on the context and the goals of the decision makers. One of the objectives in fair AI is to avoid (when possible) discrimination against this class (Verma & Rubin, 2018). Therefore, the notion of group-level fairness is linked to the distribution of the prediction errors among both the protected and unprotected classes (Feuerriegel et al., 2020). Figure 5.2 presents the distribution of the population of Figure 5.1, when the lowest-income patients are considered as a protected class. As can be seen, when both groups are unevenly distributed across the different ranges of probability, using the same threshold values for both groups could lead to a different distribution of the prediction errors. For example, suppose all the patients with predicted attendance probability higher than 70% are assigned to Group C (the no-intervention group). In this case, Group C would include less than 1% of the no-show patients in the unprotected class, but more than 3% of the no-show patients in the protected class.

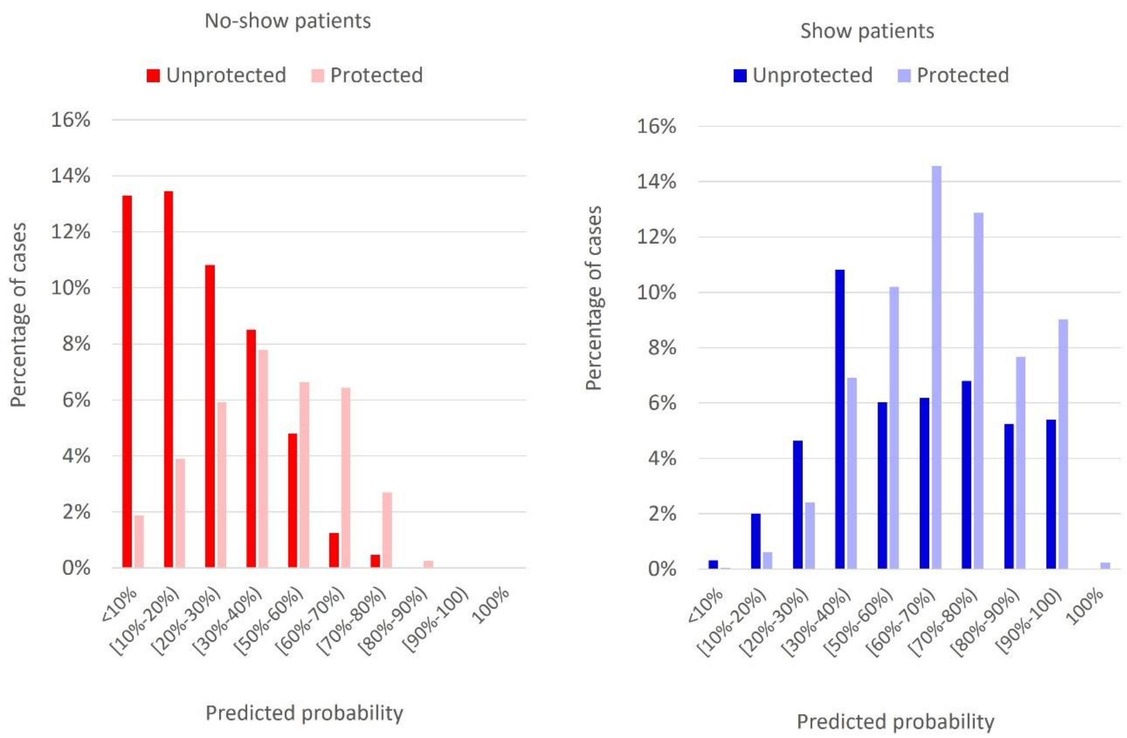

Figure 5.2. Distribution of the number of show and no-show patients according with their predicted probability and class

In this context, two definitions of fairness are relevant: predictive equality and equal opportunity. According to Verma and Rubin (2018), a classifier is said to guarantee *predictive equality* if the false positive error rate (FPR) is the same in both protected and unprotected classes.

Conversely, if the false negative error rate (FNR) is the same for both classes, an algorithm is said to guarantee *opportunity equality*. In our context, a false positive is an individual that the algorithm predicted would attend, but was in fact a no-show; a false negative is the opposite. When the k top-ranked candidates are selected for each group (i.e., choosing the k candidates with the highest attendance probability to be in Group C), we are using the same threshold for both classes. Although this approach might increase accuracy, it overlooks the distribution of the prediction errors. Therefore, we propose a mathematical model to support the classification process.

5.4 Mathematical Model

Our integer programming model optimizes two objective functions. On the one hand, we maximize accuracy, measured as the total number of correctly classified cases. On the other hand, we minimize the maximum difference between the prediction error rates of both classes. Here, we present the model used to select the patients who will be in Group C and thus will not receive any intervention. This group should contain those patients with the greatest probabilities of attending the appointment. However, the model can be easily adapted to solve the classification problem for Group A, patients who receive the personalised intervention. After solving both optimization problems, all remaining patients will be assigned to Group B. Consequently, to solve the problem for Group C, only the patients with attendance probabilities higher than 50% will be included. In the formulation below, a *positive case* is a predicted show, and a *negative case* is a predicted no-show. Note that in practice, the 'capacity' L2 of Group C will be determined by the actual capacities of Groups A and B.

Sets

I Set of patients

J Set of classes (Protected, Unprotected)

Parameters

$$p_i = \begin{cases} 1 & \text{if the patient } i \in \mathbf{I} \text{ is a positive case} \\ 0 & \text{Otherwise} \end{cases}$$

$$n_i = \begin{cases} 1 & \text{if the patient } i \in \mathbf{I} \text{ is a negative case} \\ 0 & \text{Otherwise} \end{cases}$$

$$c_{ij} = \begin{cases} 1 & \text{if the patient } i \in \mathbf{I} \text{ belongs to the class } j \in \mathbf{J} \\ 0 & \text{Otherwise} \end{cases}$$

$$a_{ik} = \begin{cases} 1 & \text{if the patients } i \in \mathbf{I} \text{ and } k \in \mathbf{I} \text{ belong to the same class} \\ 0 & \text{Otherwise} \end{cases}$$

Pr_i Predicted attendance probability of the patient $i \in \mathbf{I}$

$$b_{ik} = \begin{cases} 1 & \text{if } Pr_i \leq Pr_k \; i \in \mathbf{I} \text{ and } k \in \mathbf{I} \\ 0 & \text{Otherwise} \end{cases}$$

TP_j Number positive cases in the class $j \in \mathbf{J}$

TN_j Number negative cases in the class $j \in \mathbf{J}$

L_2 Maximal number of patients that can be classified as a positive case

Decision Variables

$$X_i = \begin{cases} 1 & \text{if the patient } i \in \mathbf{I} \text{ is classified as a positive case} \\ 0 & \text{Otherwise} \end{cases}$$

$W =$ Maximum difference between the false positive rates of the two classes

$V_j =$ Threshold for the class $j \in \mathbf{J}$

$Y_j =$ Proportion of the patients of the class $j \in \mathbf{J}$ classified as positive cases

Model formulation

$$f_1:\ Maximize \sum_{i\in\mathbf{I}} X_i p_i \tag{1}$$

$$f_2: minimize\ W \tag{2}$$

$$\sum_{i\in\mathbf{I}} X_i \leq L_2 \tag{3}$$

$$\frac{\sum_{i\in\mathbf{I}} X_i n_i c_{ij}}{TN_j} - \frac{\sum_{i\in\mathbf{I}} X_i n_i c_{il}}{TN_l} \leq W \qquad \forall\, j \in \mathbf{J}, \forall l \in \mathbf{J}\ \mathrm{j} \neq \mathrm{l} \tag{4}$$

$$X_i \geq a_{ik} b_{ik} X_k \qquad \forall\, i \in \mathbf{I}, \forall\, k \in \mathbf{I} \tag{5}$$

$$V_j \geq (1 - X_i)\ c_{ij} pr_i \qquad \forall\, i \in \mathbf{I}\ , \forall\, j \in \mathbf{J} \tag{6}$$

$$\frac{\sum_{i\in\mathbf{I}} X_i c_{ij}}{TN_j + TP_j} = Y_j \qquad \forall\, j \in \mathbf{J} \tag{7}$$

$$X_i \in \{0,1\} \qquad \forall\, i \in \mathbf{I} \tag{8}$$

$$W \geq 0 \tag{9}$$

$$V_j \geq 0 \qquad \forall\, j \in \mathbf{J} \tag{10}$$

The first objective function (1) maximises the number of correctly classified show patients. The second objective function (2) minimizes the predictive inequality. The set of constraints (3) ensures the desired capacity for Group C. Constraints (4) compute the predictive inequality as the maximum difference between the FPR of both classes. Constraints (5) ensure that if a patient is classified as a show, all the patients with an equal or higher probability are classified as a show as well, within each class. Constraints (6) define the threshold for each class. Lastly, constraints (7) compute the proportion of patients that are classified as show, and assigned to Group C, for each class.

5.5 Computational experiments

We analysed data retrieved from the SDS information system. Between 2017 and 2019, a total of 23384 appointments were scheduled under the home visits program. Table 5.1 presents the list of variables recorded by program managers, classified into patient and appointment related. For age and lead time we used decision trees to build categorical variables maximizing information value. For the experimentation, we selected three definitions of protected class: the lowest-income patients, the youngest patients, and the oldest patients. From this database, we randomly generate training (s_1, 70%) and test (s_2, 30%) sets.

Table 5.1: Variables used for prediction models

Category	Variable	Description
Patient	Age	Age of the patient at the moment of the appointment (years)
	Poverty	Patients are classified into four levels of poverty
Appointment	Lead time	Elapsed time between the date of the home visit and the appointment date (days)
	Month	Month in which the appointment was scheduled
	Day	Day of the week in which the appointment was scheduled

Two prediction modelling approaches were implemented. To quantify linear relationships between each variable and the attendance probability, we used a Least Absolute Shrinkage and Selection Operator (LASSO) regression model. This model was proposed by Tibshirani (1996) to overcome the accuracy and interpretability limitations of the Ordinary least squares model (OLS). Recent applications of LASSO in healthcare research include no-show prediction (Tong et al., 2020) and medication adherence (Zullig et al., 2019), among others. We conducted a parametric analysis on the penalty constant and use a 10-fold cross validation process, repeated 10 times (10-by-10 CV). To improve accuracy, we model variable interactions using a Random Forest (RF). For classification problems, RFs are less sensitive to outliers and eliminate the risk of overfitting (Ali et al., 2012). We decide to use weight class balancing, inform feature selection using LASSO results and perform parameter optimization using 20% of the training set.

Two experiments were conducted with the mathematical model. First, to quantity the trade-off between fairness and accuracy, we used an epsilon constraints approach (Haimes et al., 1971). The accuracy was defined as objective and the fairness was transformed into a constraint, bounded by the ε parameter. Additionally, we divided the original training set (s_1) into a two new training (s_3,70%) and test (s_4, 30%) sets. After training the classification algorithms, we predicted individual attendance probabilities for each patient on the s_4 set and solved the optimization problem. The model was implemented and solved to optimality using Xpress IVE. As a result, a pareto front was generated for each definition of protected class and for each classification algorithm. Second, we discussed the results of the mathematical model with program managers at SDS and selected one of solutions on the pareto front. Using this information, we divided the patients on the s_2 set. The quality of the solution was compared to the one obtained by selecting the k patients with highest predicted attendance probability in each group.

5.6 Results

We present the results organized into two sections. First, we analyse the trade-off between accuracy and fairness, in the context of our case study. Next, we use these results to quantify the impact of using our approach when selecting patients for each intervention group.

5.6.1 Accuracy vs Fairness.

Table 5.2 presents three solutions for each optimization problem. As we explained in Section 5.4, to deal with the bi-objective model, the accuracy (f_1) was selected as objective and the fairness (f_2) was transformed into a constraint, bounded by an ε parameter. The idea is to quantify the trade-offs between both objectives. Therefore, the first solution solves the single-objective problem, maximizing accuracy. For each case, we report both objective functions: the optimal number of corrected classified patients (f_1^*) and the difference between the prediction error rates (f_2). Then, the second solution minimizes inequality. We report the optimal level of accuracy f_1^* given that $f_2 = \varepsilon = 0$. Lastly, in the third solution we aim at illustrating the changes produced in f_1 when a small change in f_2 is allowed. We report f_1^* given that $f_2 = \varepsilon \leq 0.1\%$. For groups A and B, maximum capacities of 1500 and 2000 patients (approximately 30% and 40% of the s_4 set) were assumed, respectively. When using the LASSO regression model, all the youngest patients (one of the three protected classes) have a predicted attendance probability below 50%. Therefore, for this class, only the optimization model for Group A was solved.

Table 5.2: Mathematical model results

Protected class	Prediction model	Optimization model	Solution 1 f_1^*	Solution 1 f_2	Solution 2 $f_1^* \mid f_2 = 0$	Solution 3 $f_1 \mid f_2 \leq 0.1\%$
Oldest patients	Random Forest	Show - Group C	1354	9%	565	1350
	LASSO	Show - Group C	1137	48%	512	1100
Youngest patients	Random Forest	Show - Group C	1369	10%	552	1337
	LASSO	Show - Group C	-	-	-	-
Lowest-income patients	Random Forest	Show - Group C	1364	19%	600	1281
	LASSO	Show - Group C	1098	31%	1075	1077
Oldest patients	Random Forest	No-show - Group A	1043	32%	687	1040
	LASSO	No-show - Group A	634	53%	606	608
Youngest patients	Random Forest	No-show - Group A	1044	13%	959	1040
	LASSO	No-show - Group A	683	62%	383	607
Lowest-income patients	Random Forest	No-show - Group A	1035	27%	958	1033
	LASSO	No-show - Group A	799	43%	550	578

Table 5.2 also shows that the two objective functions on the first solution change, when the definition of the protected class is varied. On average (over the three definitions of protected class), if the RF prediction is used, 1362 (91%) out of the 1500 patients assigned to Group C would have attended their appointments without any intervention. This average decreases to 74% when the decision is made based on the LR prediction. Similarly, while the RF prediction would allow to assign

an average of 1040 no-show patients to Group A, this value would decrease to 705 patients using the LR prediction. As expected, all these solutions have high levels of inequality. The differences between the prediction errors rage from 9% to 62%. On average, levels of predictive inequality are lower (23%) that the levels of opportunity inequality (38%).

On average, eradicating the inequality in the prediction generates a 33% reduction in accuracy. However, this indicator is highly variable. For example, if the youngest patients are selected as the protected class, decreasing the predictive inequality from 10% to 0% generates a 60% reduction in accuracy (from 1369 to 552 correctly classified patients using the RF prediction). See the row of youngest patients, using RF and group C model. However, if the protected class are those patients with lowest-income levels, it is possible to eradicate 31% of the predictive inequality (group C model) by sacrificing only 2% of the accuracy (from 1098 to 1077 correctly classified patients, using the LR prediction). Interestingly, on average, despite the predictive inequality (group C model) being lower (23%) than the opportunity inequality (group A model, 38%), the accuracy sacrifice needed to eradicate the former is higher (46% and 22%, respectively).

Table 5.2 also shows that, in most cases, it is possible to achieve a 0.1% difference between the prediction error rates by sacrificing less than 10% of the accuracy. In fact, in four cases (36%) the number of correctly classified patients changes less than 1% and in other three cases (27%), less than 5%. Additionally, between the solutions two $(f_1|f_2 = 0)$ and three $(f_1|f_2 = 0.1\%)$ of Table 5.1, it is possible to find multiple pareto solutions and quantify the impact on accuracy of different levels of expected inequality.

Figure 5.3 presents the four pareto fronts generated when the lowest-income patients are selected as protected class. The green and purple series represent the mathematical model results using the RF and LR predictions, respectively. For example, the first green panel presents 14 solutions for the Group C model, using the RF prediction. On the one hand, the highest possible level of accuracy is 91%. Maximizing this objective function, 1364 (out of 1500) patients classified in group C would attend their appointments without any intervention. However, this solution has a 19% of predictive inequality (the difference between the prediction errors of both classes). On the other hand, it is also possible to have a solution with the same prediction error for both classes (0% of predictive inequality), by decreasing the number of correctly classified patients from 1364 to 600. We also generated 12 solutions to quantify the trade-off between the two objective functions and support the decision making process. By using the pareto front, decision makers can select the maximum level of accuracy they are willing to sacrifice in order to improve the fairness of the solution. For example, it is possible to have a 5% of predictive inequality with 91% of accuracy (1361 patients) or 0.1% of predictive inequality with an 85,4% of accuracy (1281 patients).

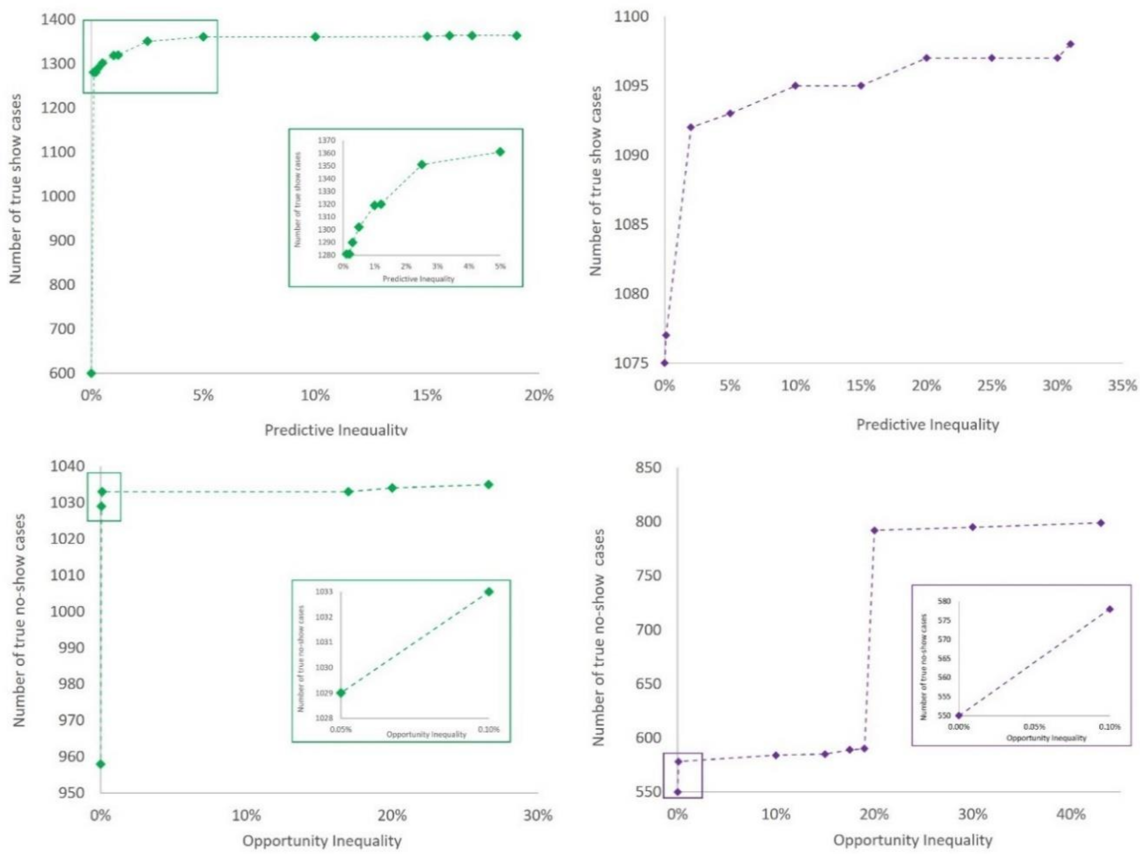

Figure 5.3. Pareto front for the lowest-income patients.

5.6.2 Improving Fairness.

Figure 5.4 shows the AUROC performance of the two prediction models. Each point represents the average and standard deviation of the AUROC score for one repetition of the 10-by-10 cross validation process. As can be seen, both models have low levels of variability. This means that their predictive power is consistent when different data sets are used. Additionally, the difference between the LASSO and the RF results might indicate that the non-linear component on the relationships between the variables and the attendance probability is high. Therefore, we use the result of the RF prediction to quantify the impact of using the mathematical model approach to improve fairness in the classification.

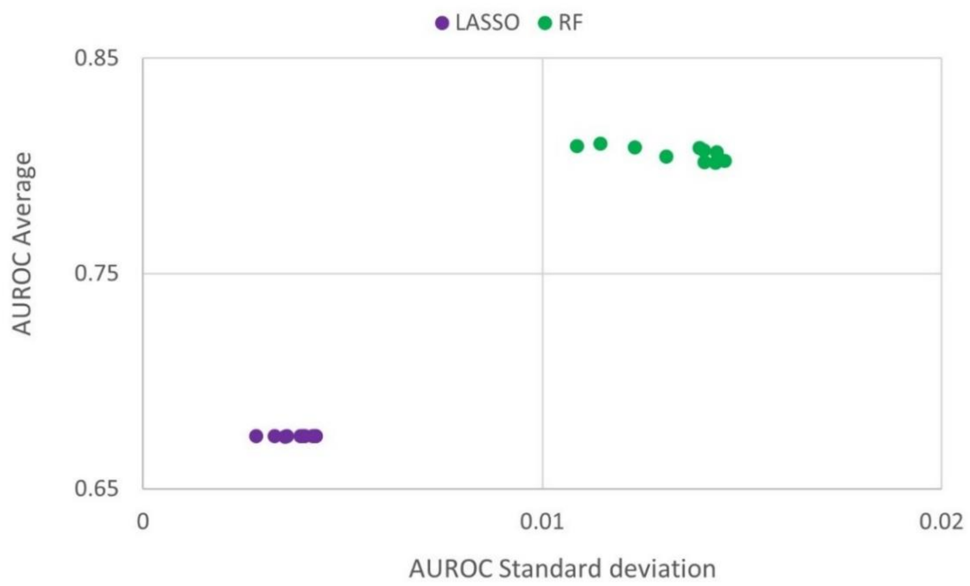

Figure 5.4. AUROC standard deviation and average for each model.

Using the results of the RF prediction, we classified all patients in the set s_2. Figure 5.5 compares the solutions obtained using the same classification threshold with the solutions obtained by using the mathematical model. We present the values of both objective functions for the three definitions of protected class. As an example, consider the case in which the protected class are the youngest patients. If the 2100 patients with the highest attendance probability are assigned to Group C (approximately 30% of the set s_2), this group would include 1938 correctly classified patients and a 12% level of predictive inequality (i.e., the difference between the FPRs). However, if the group assignment decision were to be based on the results of the mathematical model, it would be possible to correctly classify 2035 show patients while reducing predictive inequality to 1%.

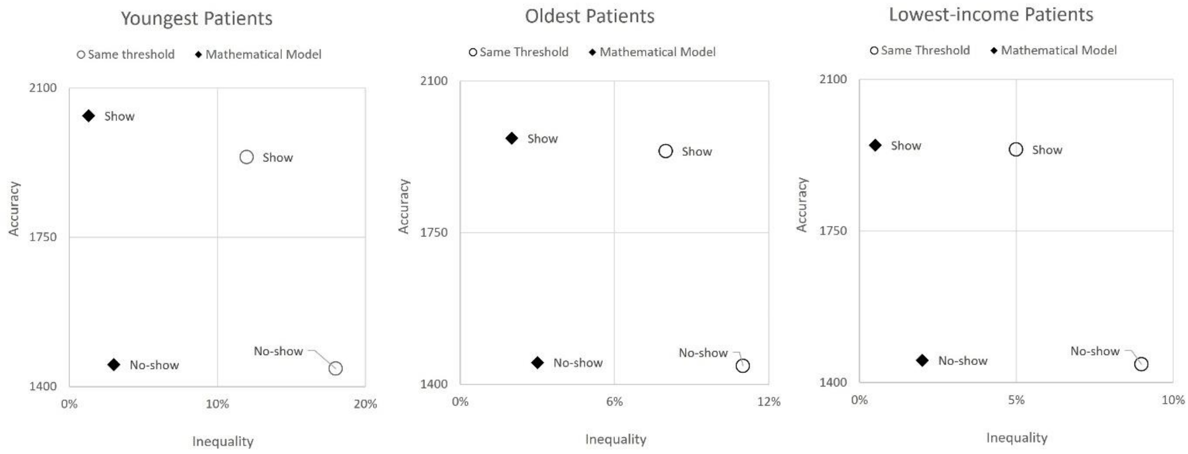

Figure 5.5: Impact of the mathematical model.

As can be seen, by using the mathematical model, it is possible to improve the fairness of the solution without sacrificing accuracy. While the average opportunity inequality (i.e., the difference between the FNRs) if the k top-ranked patients are assigned to Group A is 13% and 1442 patients are correctly classified, 1451 no-show patients are correctly classified with a 3% predictive inequality, using the mathematical model. Similarly, for the Group C, the opportunity inequality can be reduced by 85% (from 8% to 1%) while increasing the number of correctly classified show patients by 2% (from 1938 to 1948).

From the program management perspective, this means that it is possible to include up to 73% of the no-show patients in a high-cost intervention, covering only 30% of the total population and having low levels of inequality. The relevance of this result is twofold. On the one hand, behavioural interventions aimed at increasing cancer screening uptake are more effective when tailored to patients’ beliefs (Bhochhibhoya et al., 2021; Musa et al., 2017; Noman et al., 2021). Therefore, being able to accurately predict no-show probabilities can inform intervention design and increase impact. On the other hand, health psychology constructs such as the perceived susceptibility or severity of cervical cancer (associated with the adoption of protective health behaviours), might vary according to the levels of income and the age of the patient (Weng et al., 2020) in addition to factors (such as educational attainment) identified in the health psychology literature but rarely captured in routine health data. By reducing inequality, we are ensuring that traditionally marginalized groups are proportionally represented in the intervention.

5.7 Concluding remarks

In this paper, we have shown that by following an optimization-based post-processing approach it is possible to address ML bias while maintaining high levels of accuracy in the algorithmic classification problem. In contexts where the protected class is under-represented in the data set, even highly accurate prediction algorithms might map members of the protected class to a different distribution of the outcome probabilities. Therefore, using the same threshold for both classes (protected and unprotected) would lead to a different distribution of the prediction errors. By allowing different thresholds to be used for each class, it is possible to reduce the difference between the prediction errors and correct the discrimination against the members of a particular group. These results were consistent across three different definitions of protected class in our case study and are particularly relevant when ML approaches are being used to inform decisions that potentially affect members of traditionally discriminated communities.

Additionally, our bi-objective model enables decision makers to understand and quantify the trade-off between accuracy and group-based fairness that they face on a particular problem. Further, the post processing approach connects the prediction task with the next step in the decision-making process. This means that it is possible to model tactical or operational decisions that will be informed by the predicted probability of the outcome. There are at least two benefits of this methodology: the possibility of including stakeholders' knowledge in the design of a decision support system, and the capacity to avoid the replication of discriminatory patterns on data-driven planning decisions. This is particularly important where routine administrative data are used in making such decisions.

Our work could be extended in a number of ways. Firstly, different definitions of fairness could be explored. For example, it would be useful to understand the implications of improving individual fairness in the resource allocation problem. According to Dwork et al. (2012) the underlying assumption the behind individual fairness is that *similar* inputs should produce *similar* model outputs for everyone. At the same time, considering individual characteristics opens the discussion about the difference between equity and equality as a possible line of future work. Secondly, we have formulated and solved a deterministic version of the optimization problem. We believe this is appropriate due to the low variance of the prediction performance. However, understanding the impact that variability in the prediction errors might have on the final threshold selection could improve decision making. Therefore, simulation-optimization approaches and heuristics to reduce computational effort could be explored. Lastly, more research is needed using this approach in different problem settings with diverse data characteristics to better understand the relationship between data characteristics and performance of this technique so that we can understand when this methodology can be applied for the best gain.

Chapter 6 Assessing impact: Ongoing work

6.1 Introduction

Health technology assessment (HTA) is a systematic process to evaluate the social, economic, organizational and ethical issues of a health intervention or technology (World Health Organization, 2019). Since such an evaluation requires multiple sources of uncertainty to be assessed, modelling approaches have been recognized as a powerful tool to support the decision making process (Briggs et al., 2004). Brennan, Chick, and Davies (2006) define a model-based evaluation as a formal quantified comparison, among multiple options, synthesising sources of evidence on costs and benefits. Although different modelling approaches can be used, at least three main arguments can be made to support the use of simulation. Firstly, simulation models have the ability to incorporate the dynamics and complexities of a particular health care system (Marshall, Burgos-Liz, Ijzerman, Osgood, et al. 2015). Secondly, output analysis enables patterns and trends to be used to inform policy design (Marshall, Burgos-Liz, Ijzerman, Crown, et al. 2015). Thirdly, virtual simulation environments can be used to conduct experiments considered unethical or impracticable in real settings (Brailsford, Harper, and Sykes 2012).

In this chapter, we discuss how to use simulation to assess the impact of an outreach program as a preventive care strategy for cervical cancer, among hard-to-reach women in Bogotá. Since high no-show rates for screening appointments are a distinctive feature, we include health-seeking behaviour in our modelling approach. The intervention is premised on the idea that educating women regarding cervical cancer risks and scheduling for them a screening appointment, will increase uptake. Although the program has been functioning since 2017, formal impact assessment is yet to be conducted. In March 2020, Bogotá's Mayor declared an emergency status for the city, and lockdown measures were put in place. Therefore, all preventive healthcare programs were paused for two years, and resources were assigned to tackle the COVID-19 pandemic. Consequently, at the time of writing, data collection for this model is still in progress.

We present the current status of this part of the research, including a validated conceptual model, and discuss future lines of work to support decision making.

6.2 Study context

6.2.1 Cervical cancer

Cervical cancer is the abnormal growth of cells in a woman's cervix in an uncontrolled way. In 99% of the cases, this disease is linked to the infection with high-risk or oncogenic human papillomaviruses (HPV), the most common sexually transmitted infection (World Health Organización.WHO, n.d., 2020). Although most cases of HPV resolve spontaneously, the persistent infection might lead to a precancerous lesion called cervical intraepithelial neoplasia (CIN). When detected, CINs are classified into 3 levels depending on how much tissue looks abnormal: CIN1 (mild), CIN2 (moderate), and CIN3 (severe) (American Cancer Society, n.d.). Most patients will not need a treatment for a CIN; however, CIN2 and CIN3 can turn into invasive cancers. It takes between 15 to 20 years for cervical cancer to develop in a woman with a normal immune systems and between 5 to 10 years if the immune system is compromised (American Cancer Society, n.d.). Therefore, this disease is preventable and it is curable if detected early and treated (World Health Organización.WHO, 2020).

Although the overall Age Standardized Incidence Rate (ASIR) for cervical cancer, per 100,000 women is 13.1, it ranges from 6.0 in Australia and New Zealand to 40.1 in Eastern Africa (Arbyn et al., 2020). Further, in 2018, around 84% of the cases and 88% of cervical cancer deaths occurred in low and middle-income countries (LMICs). However, there is no indication that the higher rates of incidence and mortality among LMICs are attributable to differences in the infection rates of oncogenic HPV types (World Health Organización.WHO, 2020). In fact, both incidence and mortality rates are associated with poverty, limited health education and barriers accessing health services

(Amin et al., 2020; Tatari et al., 2020; X. Zhang et al., 2021). This scenario is particularly concerning as the COVID-19 pandemic increased screening disparities (Wentzensen et al., 2021) and the cancer burden is expected to increase in the next 10 years in some regions such as Latin America (Piñeros et al., 2022).

In this context, the Word Health Organization launched a strategy aimed at achieving an ASIR lower than 4 per 100,000 women. This would imply the elimination of cervical cancer as a public health problem, and is based on three pillars: HPV vaccination, screening, and treatment of precancerous lesions. By 2030, the goal is to reach 90% of vaccine coverage by the age of 15, 70% of women screened with a high-performance test and 90% of women with precancer treated. Nevertheless, while in high income countries the implementation of screening and vaccination programs has been successful, for many LMICs it still represents a major challenge (Vale et al., 2021). It has been found that this can be explained by the existence of cultural factors acting as deterrents for the adoption of preventive care behaviours, among others (Barrera Ferro et al., 2022; Liebermann et al., 2018).

6.2.2 Cervical cancer prevention in Bogotá, Colombia.

In Colombia, cervical cancer control strategy is focused on early detection through screening. Although the HPV vaccine is included in the free national immunization program, the coverage remains low (Vorsters et al., 2020). Therefore, prevention relies on Pap smear tests following a 1-1-3 scheme (*Resolution 603280*, 2018; Torrado-García et al., 2020). This means that women should undergo annual cytology tests, and then change to a three-year interval after two consecutive negative results. Women between 25 (or younger in the presence of some risk factors) and 65 years old are eligible and screening is included in the national health insurance scheme, hence no out-of-pocket payment is required (Bermedo-Carrasco et al., 2015). Nevertheless, different authors have reported quality problems with the cytology tests (Cendales et al., 2010; Murillo et al., 2011) and access inequalities for women living under conditions of poverty, in rural areas, or with low education levels (Hernández Vargas et al., 2020, 2021). In this context, recent legislation has adopted the Human Papilloma Virus (HPV) test for women between 30 and 65 years old as screening strategy (*Resolution 603280*, 2018). The gradual implementation of this new guideline should have started in 2019 and was expected to improve cancer control (Vorsters et al., 2020). However, the National Ministry of Health assessed and identified operational and logistical barriers for the piloting phase and delayed its beginning to 2020 (*Resolution 276*, 2019). At the time of writing, we were not able to find any consolidated report about the HPV test piloting in the country.

In Bogotá, as part of a preventive-care strategy called *Acciones Colectivas en Salud* (ACS), the District Secretariat of Health (*Secretaría Distrital de Salud*, SDS) instituted a program to increase cervical cancer cytology uptake among hard-to-reach low-income women. Under this program, a group of community workers visit women who are overdue for screening, conduct basic training in cervical cancer risks and schedule a cytology appointment for them at the nearest healthcare facility. However, although patients value the contact with the community workers and find the visits informative, there is a lack of coordination between home visits and screening appointments teams. A great effort is made by the home visits team to reach patients who need screening, but even when these patients are willing to take part in the screening program, they find it hard to navigate the service delivery process and face barriers accessing the health system. Consequently, over the last years no-show rates have reached levels of 46% (Barrera Ferro et al., 2022).

Figure 6.1 is a graphical representation of the care pathway for cervical cancer in Bogotá. For management purposes, the city is divided into four clusters with independent resources. In each cluster, a nurse oversees the service delivery process. Figure 6.1 was drawn in consultation with team leaders at each cluster and ACS program managers at SDS. As can be seen, the activities can be grouped into four phases. Firstly, hard-to-reach women are contacted by the ACS team. Community workers visit patients at their homes, provide basic training on cervical cancer risks and schedule for them a cytology appointment, at the nearest healthcare facility. The objective of this phase is to increase screening uptake. Then, in the second phase, patients are expected to undergo sample collection and obtain their results after 3 days. If the cytology shows an abnormal growth of cells, the patient is contacted by phone to collect her results and attend a colposcopy appointment, this is phase three of the process. During this appointment, a course of treatment is decided. Some patients will be treated during the appointment and start disease management. If required, a biopsy is conducted and after having diagnosis confirmation the patient is referred to oncology services. Cancer treatment is the last phase of the process.

6.3 Simulation model: work in progress

The objective of this model is to assess the impact of ACS. The program is premised on the idea that basic education on cervical cancer risks has the potential to increase screening attendance levels. Hence, we aim at quantifying the changes in the number of early diagnosed and treated patients, due to the home-visits educational intervention. At the same time, the model will be used to understand the potential impact of other behavioural interventions or changes in the screening program. For example, it has been found that increased perceived severity of cervical cancer and long lead times might act as a deterrent for screening uptake in Bogotá (Barrera Ferro et al., 2022). Therefore, the model outputs can be used to assess cost effectiveness and improve resource allocation.

Agent Based Simulation (ABS) enables the long-term progression of a disease to be modelled in order to assess the impact of potential interventions (Veloso, 2013). According to Li et al. (2016), this feature overcomes the main limitation of Markov model-based evaluations. Further, using ABS modelling, it is possible to relate individual behaviours to the patterns of the system (Utomo et al., 2022). Therefore, this approach can be used to determine how small changes in individual behaviour may influence population-level health-outputs (Currie et al., 2020). Applications include the evaluation of screening policies for diabetic retinopathy (Day et al., 2013) and the early-stage cancer interactions with the immune system (Figueredo et al., 2014), among others.

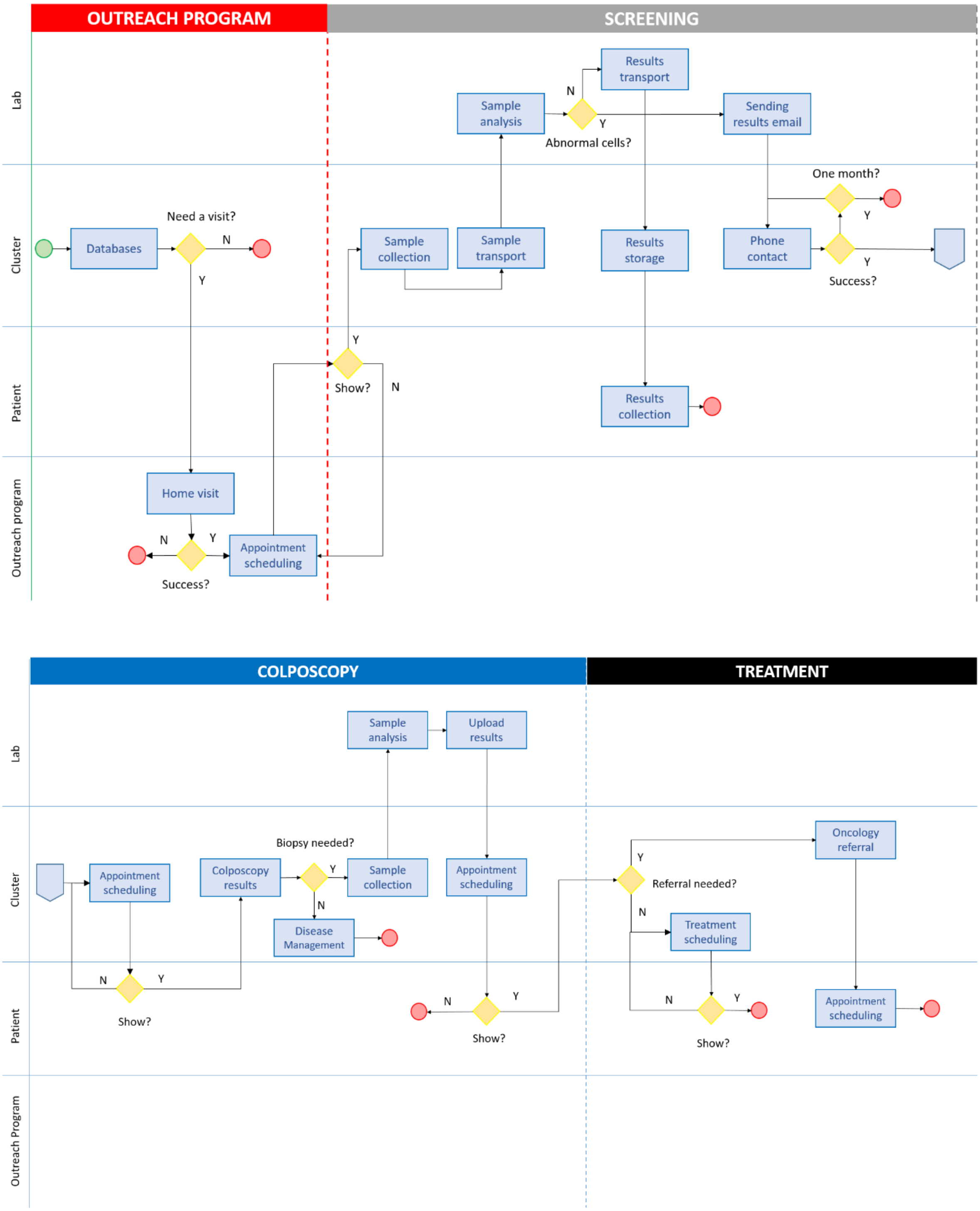

Figure 6.1: Care pathway for cervical cancer in Bogotá

We model evolution of a cohort of hard-to-reach patients in Bogotá. For ACS, SDS considers a woman to be hard-to-reach if despite being eligible, she has not undergone a Pap smear test over the last year. Additionally, to prioritize resource allocation for social programs, SDS uses a nation-wide adopted scoring system that classifies low-income citizens into four categories. The SISBEN[3] score ranges from 0 (extreme poverty) to 100 (wealthy) and is computed using self-reported information related to health, education, and housing, among others (Departamento Nacional de Planeacion, n.d.). ACS covers approximately 18% of the population with the lowest SISBEN score (Secretaría Distrital de Planeación, 2018).

Figure 6.2 represents the progression of the disease. All patients are assumed to start in a healthy state. They could either remain healthy or get infected with HPV. In most cases, infected patients will return to a healthy state without receiving any medical intervention. However, some infections will progress to develop a CIN1 lesion. Transitions from a precancerous-lesion state (CIN1, CIN2, or CIN3) follow the same logic: If the patient attends the screening appointment, the lesion can be detected and treated. In that case, the patient will return to a healthy status. However, some diagnosed patients will refuse treatment and the disease could progress to the next status. If the patient decides not to undergo screening, the disease will remain undetected and could progress to the next state or resolve by itself. Lastly, for some CIN3 patients, the disease will progress to an invasive cancer. Cancer can also be detected during routine screening and consequently be treated.

[3] Identification System of Potential Beneficiaries of Social Programs *(Sistema de Identificación de Potenciales Beneficiarios de Programas Sociales)*

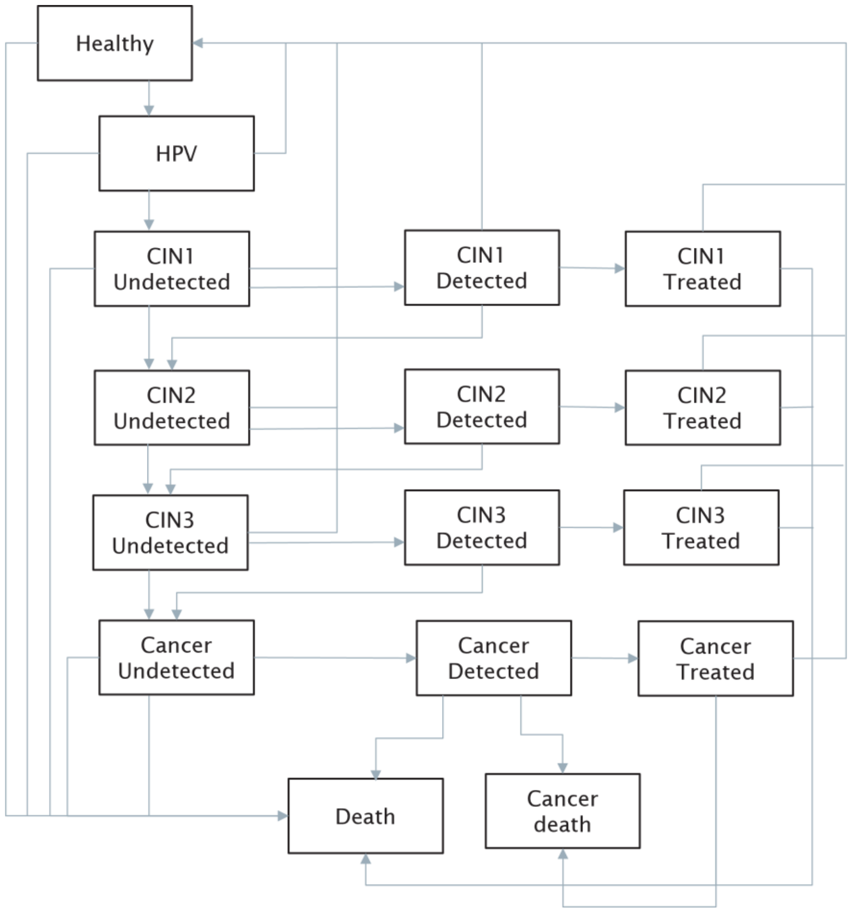

Figure 6.2: Cervical cancer progression

At any given stage of the disease, the probability of accessing treatment depends on the screening state. Figure 6.3 presents the transitions between screening states, in a 1-1-3 scheme. All women are assumed to start as eligible. If the patient attends the first screening appointment, her state changes to screened (1). Otherwise, she remains eligible. From screened (1), all patients attending a second (consecutive) screening appointment change to screened (2). However, if a patient misses the second appointment, she becomes eligible for screening again. After two consecutive attended screening appointments, the patient becomes ineligible for a three-year period. After that, her status change to eligible 2 and should be screened again. If she attends, her state changes to screened (3) and becomes ineligible again. In this context, the no-show behaviour needs to be modelled. It is possible to have accurate predictions of the individual no-show probability using the age of the patient, her income level, and the appointment lead time (Barrera Ferro et al., 2022).

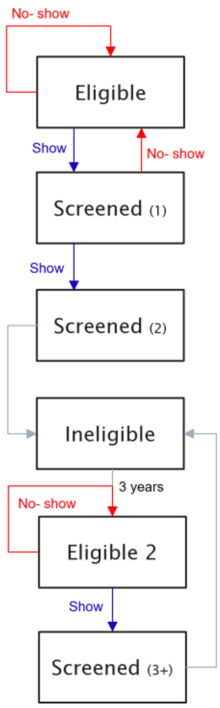

Figure 6.3: Screening states for a patient

At the time of writing, the next stages of model development are in progress. Although the model logic has been reviewed with program managers and two experts in gynaecological oncology, a computer model has not yet been developed. Databases of screening appointments attendance, after the COVID-19 pandemic, are being consolidated by ACS program managers. The idea is to look for possible changes in the no-show patterns identified by Barrera Ferro et al. (2022). Additionally, data about HPV, CIN and cancer incidence and mortality among hard-to-reach women in Bogota are being consolidated by the insurance company. Lastly, SDS started a pilot to implement HPV-based screening in the city. Information about attendance, acceptability and resource consumption is being recorded. All data sources are expected to be available for this research by December 2022. The plan is to develop and verify the computer model in parallel with these final stages of data collection, so that validation and experimentation can start early in 2023.

6.4 What if scenarios

The conceptual model presented in this chapter will be used as a baseline to understand the potential impact of changes in the screening program in Bogotá. SDS is interested in examining the following areas:

Self-sampling. Different studies have found that self-sampling increases cervical cancer screening coverage among hard-to-reach women. Therefore, it would be possible to offer a sample collection with during the home visit, particularly for those women with a higher no-show probability. An economic evaluation of the strategy is required. The results will inform discussions around the number and characteristics of the patients that will be offered self-sampling as an alternative.

HPV testing. Cytology-based screening is set to be replaced by HPV testing in Colombia. Therefore, the screening scheme will change from a 1-1-3 scheme to a one HPV test every 5 years. However, due to capacity constraints, is highly likely that both types of screening will work for the next years to come. Therefore, it is important to generate insights about how the system will respond to different goals of implementation of the HPV test in Bogotá.

Assessing the impact of behavioural interventions. It has been found that education campaigns could increase perceived susceptibility or decrease perceived severity of cervical cancer among hard to reach women. In this context, resource allocation can be informed by an assessment of the possible impact of such interventions. The model results can be used to conduct economic evaluation.

Chapter 7 Conclusions and future work

This section starts with an overview of the thesis, the research topic, methods, and case study are presented. The main contributions then follow, we summarize what each paper adds to the body of research in the field. Finally, we discuss some limitations and lines for future work.

7.1 Overview

This thesis has studied no-show behaviour for medical appointments, and it is structured as a Research Paper PhD. We have used administrative health records and collected both qualitative and quantitative data. Our analytical approach comprises the use of logistic regression, machine learning algorithms and optimization as well as content analysis, for the qualitative component. Four papers have been written and are presented in Chapters 2, 3, 4 and 5. Three of these papers have been published and the other one is under review. Although each paper addresses a different aspect of the problem, when linked, they can be used to support planning decisions and ultimately, improve health outcomes.

The case study is a preventive care program designed to overcome access barriers affecting low-income patients in Bogotá, Colombia. Therefore, throughout the study we have worked in close collaboration with different teams of program managers, operational analysts, community workers and healthcare professionals from the local health authority (SDS). We have met with SDS regularly, both online during the pandemic and in person, for the past four years. Our results have informed discussions around the design of the cervical cancer pathway in the city and have opened new research questions. At the time of writing, new projects on breast cancer screening and treatment adherence among patients living with chronic diseases are being considered for funding in collaboration with SDS.

7.2 Main contributions

In the first paper, we have assessed the effectiveness of machine learning algorithms to improve accuracy of the regression models, for no-show prediction. Using routinely-collected administrative data, we were able to generate good predictions of individual no-show probabilities. Then, given the added value of using Neural Networks (in terms of AUROC score), we implemented Layer-wise Relevance Propagation (LRP) in a novel context to generate trust in its prediction. Lastly, we identified both patients and appointment characteristics associated with lower attendance probabilities. For program managers, this result highlighted the need for developing targeted behavioural interventions and reviewing the capacity management practices in the program.

In the second paper, we have shown the benefits of combining machine learning, with an in-depth qualitative methodology to understand no-show behaviour. Our mixed-methods approach was designed to explore, and potentially explain, the results from the quantitative analysis. This is particularly relevant in contexts where the quantitative available data is collected with administrative purposes, as it is often the case in health services research. Using the inductive coding of 60 interviews and two literature searchers, we proposed a Health Beliefs Model-based conceptual framework to analyse qualitative data related to attendance behaviour in medical appointments. From the application point of view, our findings indicated an urgent need to address the lack of alignment between the different phases of the cervical cancer screening program in Bogotá.

In the third paper, we have validated the use of the Health Beliefs Model to explain and predict no-show behaviour for cervical cancer screening appointments, among low-income hard-to-reach women in Bogotá. Using a 37-item survey, we were able to quantify the relationship between the no-show probability and each of four constructs of the model: susceptibility, severity, benefits, and barriers. We found that, by exploiting a combination of routinely-collected data and a sample-based beliefs assessment, it is possible to improve the accuracy of the no-show prediction. Therefore, the proposed methodological approach has the potential to improve the cost-effectiveness of behavioural interventions for healthcare attendance in any setting. According to our results, in Bogotá interventions for younger women living under extreme poverty conditions should be prioritized.

In the fourth paper, we have proposed a novel optimization-based post-processing approach to address ML bias in the algorithmic classification problem. Particularly, we studied the notion of group-based fairness to ensure that individuals will not be discriminated on the basis of their group’s protected characteristics. Our integer programming model optimizes two objective functions. On the one hand, we maximize accuracy, measured as the total number of correctly classified cases. On the other hand, we minimize the maximum difference between the prediction error rates. We found that, by allowing different thresholds to be used for each class, it is possible to reduce the difference between the prediction errors and correct the discrimination against the members of a particular group while maintaining high levels of accuracy. Additionally, our solution approach allows decision makers to quantify the trade-offs between the two objective functions and assess the maximum level of accuracy they are willing to sacrifice to improve fairness of the classification.

7.3 Limitations

We acknowledge several limitations of this research:

- The data we have used to train the prediction models was collected for administrative purposes. Therefore, we did not have access to some variables that have been found to be good predictors of attendance.
- Data collection was aimed at assessing no-show probabilities of cervical cancer appointments for hard-to-reach women in Bogotá. Therefore, sampling among ACS

participants is considered to be a good strategy. However, we are not able to draw conclusions about other relevant groups in the city.

- Primary data collection was carried out between July 2019 and February 2020. In Bogotá, the first confirmed case of COVID-19 was reported in March 2020 and restrictions on social distance were adopted two weeks later. It is not possible to draw any conclusions on how the (widely available) information on the virus may subsequently have affected the health-seeking behaviours of our study population.
- It is possible that new attendance patterns have emerged after the pandemic. Therefore, it is important to collect new data and train the prediction models to check the validity of the results in this new scenario. However, the methods and models can be easily adapted.
- The methods we have discussed are widely applicable and no-show behaviour is a problem beyond low-income settings. However, the insights we have generated from SDS data cannot be translated to other contexts. Therefore, further research studying different health seeking behaviours or other settings could use our modelling approach to inform public policy and intervention design.
- The model presented in Chapter 5 solves the deterministic version of the problem. However, understanding the impact that variability in the prediction errors might have on the final threshold selection could improve decision making.
- Updating the developed models requires computational skills; this might present a problem with the implementation. We are currently applying for funding to develop web-based tools that can be used for the daily operation of the program. We aim at building a set of tools that can be easily adopted by SDS managers.

- Using the models and interpreting the results might require basic OR knowledge. Through the research process, questions around possible mechanisms to develop basic OR skills among SDS managers were discussed. This was identified as a first step towards consolidating the adoption of OR models within SDS. At the time of writing, an international Healthcare OR school is being planned. The school will be held at Pontificia Universidad Javeriana and SDS will enrol 10 managers.

7.4 Future work.

In Chapter 6 we have discussed our plans to conduct a formal impact assessment of ACS in cervical cancer diagnosis. Since model-based evaluation allows multiple sources of uncertainty to be assessed, we proposed a simulation approach. This is an ongoing work, and the results will allow SDS to evaluate potential changes on the care pathway in Bogotá.

Our results have highlighted the need for a change in capacity management practices. At present, SDS aims at offering a screening appointment withing 3 days after the home visit. However, lead-times can even be longer than 39 days. This is problematic as long lead-times not only decrease attendance but also increase perceived barriers. In this context, it is important to understand how different distributions of the lead-time might impact the number of early detected and treated cases. Therefore, we believe there is an opportunity to include patient behaviour in the tactical and operational models for outpatient services, such ACS.

Our approach to reduce ML bias has proved to be effective for the studied context. However, further research is needed using this approach in different problem settings. The idea is to better understand the relationship between data characteristics and performance of this technique, so that we can conclude when this methodology can be applied for the best gain.

Appendix A Interview guide (Supplement to Chapter 3)

Question 1: Could you describe your experience using health services, over the last three years?

Question 2: On (insert date) a community worker visited your home. Could you describe the visit?

Question 3: Do you think is important having a cervical cytology? Why?

Question 4: According to our records, you did not attend the cytology appointment that was scheduled on (insert date). Could you tell me why?

Question 5: In your opinion, which other reasons could prevent a patient to keep her cytology appointment?

Question 6: Have any of your close friends or relatives had a cytology? If so, what have they told you about this experience?

Question 7: During the home visit, did the community worker discussed with you the importance of having a cytology? Do you remember what did she/he tell you?

Question 8: What do think it can be done to increase cytology uptake?

Question 9: Is there anything else you want to tell me about the experience of having a cervical cytology?

Appendix B Analytical framework (Supplement to Chapter 3)

First order categories

Second order	First order			Description
Barriers	Access			
		1	Financial stress	Economic constrains such as out-out-pocket payments.
		2	Inconvenient appointment slots	Patient finds it difficult to attend an appointment on the available slots.
		3	Long lead times	The time elapsed between the appointment scheduling and the actual appointment date is too long.
		4	Geographical access	Patients finds it difficult to reach the appointment facility location.
		5	Work Commitments	Work obligations make it difficult to attend medical appointments.
	Service delivery			
		6	Bad experiences with service delivery	Prior negative experiences while using healthcare services.
		7	Bad experiences with home visit	Negative experiences during ACS home visits.
		8	Communication	Confusing or absent information about appointments or exams.
		9	Dismissive staff	Rude or disrespectful behaviours from health care providers.
		10	Lack of flexibility in service delivery	Incapability to adapt or modify the service delivery process according to the patient's needs.
		11	Lack of information during the home visit	Incomplete or confusing information, during home, about the exam or the service delivery.
		12	Multiple appointments	Patient has multiple appointments to attend at the same day.
		13	Poor care quality	Patients perceive a low quality in the health services.
		14	Prefers to use other care	Patients attend to other medical service or types of healthcare approaches.
		15	Process design	Challenges related to the steps or requirements to book or attend an appointment.
	Personal			
		16	Family care	Demands on women's time including child-care and housework.
		17	Forgetfulness	Patients forget the appointment.
		18	Health issues	The patient is experiencing health problems and decided not to attend.

Second order	First order			Description
		19	Lack of network support	Women do not have the support of their partner or family to carry out the exam.
		20	Language	Inability to communicate effectively due to lack of fluency in the language.
		21	Migration	Patients move to another city or country.
		22	Other priorities	Women decided to prioritize another task over the appointment.
		23	Religion	Religious beliefs prevent them from attending the exam.
		24	Travel	Patient was traveling at the appointment’s date.
Barriers	Protective behaviour			
		25	Anxiety	Feelings of anxiety towards the procedure.
		26	Non-compliance with requirements	Failure to comply with the requirements for screening (i.e., having had sexual intercourses on the last 24 hours).
		27	Discomfort	Perception that the screening procedure is uncomfortable.
		28	Embarrassment	Feelings of embarrassment about the cervical examination.
		29	Gender of the health provider	Women's preferences regarding the gender of the health care provider.
		30	Pain	Perception that the screening procedure is painful.
		31	Peer influence	Experiences of friends or peers influences the preferences for screening.
Benefits	Protective Behaviour			
		32	Cancer diagnosis	Recognition of the possibility of diagnosing cancer.
		33	Health	Belief that screening is beneficial for health.
		34	Lack of perceived benefits	Patient does not perceive benefits on screening participation.
		35	Lack of knowledge	Patient does not know what screening is, why is important or have received misleading information.
		36	Screening program	Patient does not have information about the screening program.
	Service delivery			
		37	Satisfaction (home visit)	Patient satisfaction with the home visit.
		38	Satisfaction (service delivery)	Patient satisfaction with the healthcare service delivery.
Susceptibility		39	Perceived susceptibility	Patient perception of her own risk of developing cervical cancer.
		40	Denial	Patients deny they might need medical attention.

Second order	First order		Description
Severity	41	Fear of a bad result	Fear of the outcome of the test.
	42	Fear of side effects	Fear of experiencing undesirable and unintended effects of the test.
	43	Only uses emergency care	Lack of familiarity with preventative health and tendency to seek health services only when ill.
	44	Severity of the consequences	Patient perceives that the consequences of developing cervical cancer are severe.

References supporting the analytical framework categories

Second order	First order		No-Show behaviour studies	Cervical cancer screening studies
Barriers	Access			
	1	Financial stress	(Cameron et al., 2014; Freed et al., 2013; Gashu et al., 2021; Heaman et al., 2015; Leijdesdorff et al., 2021; Morris et al., 2009; Ofei-Dodoo et al., 2019; Pegon-Machat et al., 2009; Sherbuk et al., 2020; Topuzoğlu et al., 2007; Wolf et al., 2020; M. Yang et al., 2020)	(Adedimeji et al., 2021; Binka et al., 2019; Christie-de Jong & Reilly, 2020; Hasahya et al., 2016; H. Lee et al., 2019; Mkhonta & Shirinde, 2021; Moss et al., 2021; Onyenwenyi & McHunu, 2018; Roux et al., 2021; Schoenberg et al., 2013; Vasudevan et al., 2020)
	2	Inconvenient appointment slots	Inductive category*	Inductive category*
	3	Long lead times	(Alderson et al., 2021; Ballantyne et al., 2019; Bollinger et al., 2011; Cavallaro et al., 2018; Chamberlin et al., 2021; Christie-Johnston et al., 2020; Denberg et al., 2005; Dilgul et al., 2018; Freed et al., 2013; Gellasch, 2019; Gombe et al., 2020; Heaman et al., 2015; Lam et al., 2016; Leijdesdorff et al., 2021; D. Marshall et al., 2016; Martin et al., 2005; Minick et al., 2018; Schwennesen et al., 2016; Sheppard et al., 2013; Sherbuk et al., 2020; Sinclair & Alexander, 2012; Strutton et al., 2016; Topuzoğlu et al., 2007; Touch & Berg, 2016)	(Adedimeji et al., 2021; Adewumi et al., 2021; Binka et al., 2019; Brandt et al., 2019; Christie-de Jong & Reilly, 2020; Curmi et al., 2016; Francis et al., 2013; Gu et al., 2018; H. Lee et al., 2019; Logan & McIlfatrick, 2011; Malhotra et al., 2016; Matenge & Mash, 2018; Mkhonta & Shirinde, 2021; Moss et al., 2021; Munthali et al., 2015; Roux et al., 2021; Vahabi & Lofters, 2016; Vasudevan et al., 2020)
	4	Geographical access	(Alanazy et al., 2019; Ballantyne et al., 2019; Bollinger et al., 2011; Cameron et al., 2014; Cavallaro et al., 2018; Cibulka et al., 2012; Copeland et al., 2017; Denberg et al., 2005; Dilgul et al., 2018; DuMontier et al., 2013; Eades & Alexander, 2019; Fägerstad et al., 2019; Feitsma et al., 2012; Freed et al., 2013; French et al., 2017; Gashu et al., 2021; Gombe et al., 2020; Heaman et al., 2015; Jefferson et al., 2019; Klatte et al., 2019; Lacy et al., 2004; Magadzire et al., 2017; Minick et al., 2018; Morris et al., 2009; Ofei-Dodoo et al., 2019; Poll et al., 2017; Saleh et al., 2021; Sheppard et al., 2013; Sherbuk et al., 2020; Strutton et al., 2016; Topuzoğlu et al., 2007; Touch & Berg, 2016; Wolf et al., 2020)	(Greibe Andersen et al., 2020; Gu et al., 2018; H. Lee et al., 2019; Malhotra et al., 2016; Matenge & Mash, 2018; Moss et al., 2021; Munthali et al., 2015; Onyenwenyi & McHunu, 2018; Rasul et al., 2016; Roux et al., 2021; Vahabi & Lofters, 2016)

Second order	First order		No-Show behaviour studies	Cervical cancer screening studies
	5	Work Commitments	(Alanazy et al., 2019; Alderson et al., 2021; Britton & Robinson, 2016; Cameron et al., 2014; Chamberlin et al., 2021; Cibulka et al., 2012; Copeland et al., 2017; Eades & Alexander, 2019; Feitsma et al., 2012; French et al., 2017; Klatte et al., 2019; Lam et al., 2016; Ofei-Dodoo et al., 2019; Saleh et al., 2021; Sinclair & Alexander, 2012; Touch & Berg, 2016; Wolf et al., 2020; Zanardelli & Robinson, 2019)	(Christie-de Jong & Reilly, 2020; Matenge & Mash, 2018; Vasudevan et al., 2020)
Barriers	Service delivery			
	6	Bad experiences with service delivery	(Ballantyne et al., 2019; Cameron et al., 2014; Campbell et al., 2015; Dahl et al., 2018; Heaman et al., 2015; Lacy et al., 2004)	(Borrull-Guardeño et al., 2021; Christie-de Jong & Reilly, 2020; Gu et al., 2018; Hasahya et al., 2016; Mkhonta & Shirinde, 2021; Roux et al., 2021; Sadler et al., 2013; Schoenberg et al., 2013; Vasudevan et al., 2020)
	7	Bad experiences with home visit	Inductive category*	Inductive category*
	8	Communication	(Alderson et al., 2021; Ballantyne et al., 2019; Cibulka et al., 2012; Dilgul et al., 2018; DuMontier et al., 2013; Fägerstad et al., 2019; Freed et al., 2013; Gashu et al., 2021; Hussain-Gambles et al., 2004; Jefferson et al., 2019; Llovet et al., 2018; Lou et al., 2016; D. Marshall et al., 2016; Martin et al., 2005; Morris et al., 2009; Saleh et al., 2021; Sheppard et al., 2013; Sinclair & Alexander, 2012; Zanardelli & Robinson, 2019)	(Gu et al., 2018; Roux et al., 2021; Schoenberg et al., 2013; Vasudevan et al., 2020)
	9	Dismissive staff	(Alanazy et al., 2019; Ballantyne et al., 2019; Campbell et al., 2015; DuMontier et al., 2013; Heaman et al., 2015; M. Yang et al., 2020)	-
	10	Lack of flexibility in service delivery	Inductive category*	Inductive category*
	11	Lack of information during the home visit	Inductive category*	Inductive category*

Second order	First order		No-Show behaviour studies	Cervical cancer screening studies
	12	Multiple appointments	(Christie-Johnston et al., 2020; Touch & Berg, 2016)	-
	13	Poor care quality	(Alanazy et al., 2019; Lam et al., 2016)	-
	14	Prefers to use other care	(Alanazy et al., 2019; Magadzire et al., 2017)	(Kue et al., 2020; Onyenwenyi & McHunu, 2018)
	15	Process design	(Jefferson et al., 2019; Minick et al., 2018; Touch & Berg, 2016)	(Christie-de Jong & Reilly, 2020; Gu et al., 2018; Onyenwenyi & McHunu, 2018; Vahabi & Lofters, 2016; Vasudevan et al., 2020)
Barriers	Personal			
	16	Family care	(Alanazy et al., 2019; Ballantyne et al., 2019; Chamberlin et al., 2021; DuMontier et al., 2013; Feitsma et al., 2012; Heaman et al., 2015; Klatte et al., 2019; Magadzire et al., 2017; Ofei-Dodoo et al., 2019; Poll et al., 2017; Saleh et al., 2021; Sheppard et al., 2013; Sinclair & Alexander, 2012; Touch & Berg, 2016; Wolf et al., 2020; M. Yang et al., 2020)	(Logan & McIlfatrick, 2011; Rasul et al., 2016; L. P. Wong et al., 2008)
	17	Forgetfulness	(Alderson et al., 2021; Ballantyne et al., 2019; Cibulka et al., 2012; Copeland et al., 2017; DuMontier et al., 2013; Fägerstad et al., 2019; Feitsma et al., 2012; French et al., 2017; Gashu et al., 2021; Heaman et al., 2015; Hussain-Gambles et al., 2004; Lam et al., 2016; Magadzire et al., 2017; Ofei-Dodoo et al., 2019; Strutton et al., 2016; Touch & Berg, 2016)	-
	18	Health issues	(Ballantyne et al., 2019; Britton & Robinson, 2016; Cameron et al., 2014; Chamberlin et al., 2021; Denberg et al., 2005; Feitsma et al., 2012; Gashu et al., 2021; Klatte et al., 2019; Llovet et al., 2018; Ofei-Dodoo et al., 2019; Poll et al., 2017; Touch & Berg, 2016; M. Yang et al., 2020)	-

Second order	First order		No-Show behaviour studies	Cervical cancer screening studies
	19	Lack of network support	(Gashu et al., 2021; Gombe et al., 2020; Heaman et al., 2015; Minick et al., 2018; Poll et al., 2017; Smith-Miller et al., 2020; Topuzoğlu et al., 2007; Zanardelli & Robinson, 2019)	(Adedimeji et al., 2021; Greibe Andersen et al., 2020; Modibbo et al., 2016; Munthali et al., 2015; Oketch et al., 2019; Onyenwenyi & McHunu, 2018; Vasudevan et al., 2020)
	20	Language	(Wolf et al., 2020)	(Kue et al., 2020; Raymond et al., 2014; Vahabi & Lofters, 2016; Y. Zhang et al., 2017)
	21	Migration	(Wolf et al., 2020)	-
	22	Other priorities	(Ballantyne et al., 2019; Cameron et al., 2014; Cibulka et al., 2012; Copeland et al., 2017; Denberg et al., 2005; Martin et al., 2005; Poll et al., 2017)	-
	23	Religion	(Alanazy et al., 2019; Cavallaro et al., 2018; Gombe et al., 2020; Rossell et al., 2017)	(Rasul et al., 2016; Raymond et al., 2014)
	24	Travel	(Chamberlin et al., 2021; DuMontier et al., 2013; Gombe et al., 2020)	-
Barriers	Protective behaviour			
	25	Anxiety	(Akre et al., 2010; Britton & Robinson, 2016; Denberg et al., 2005; DuMontier et al., 2013; Strutton et al., 2016)	-
	26	Non-compliance with requirements	Inductive category*	Inductive category*
	27	Discomfort	(Fägerstad et al., 2019)	-
	28	Embarrassment	-	(Adewumi et al., 2021; Binka et al., 2019; Borrull-Guardeño et al., 2021; Christie-de Jong & Reilly, 2020; Greibe Andersen et al., 2020; Hasahya et al., 2016; Kue et al., 2020; Logan & McIlfatrick, 2011; Matenge & Mash, 2018; Ogunsiji et al., 2013; Rasul et al., 2016; Sadler et al., 2013; L. P. Wong et al., 2008)

Second order		First order	No-Show behaviour studies	Cervical cancer screening studies
	29	Gender of the health provider	-	(Adewumi et al., 2021; Binka et al., 2019; Gu et al., 2018; Hasahya et al., 2016; Logan & McIlfatrick, 2011; Malhotra et al., 2016; Mkhonta & Shirinde, 2021; Modibbo et al., 2016; Munthali et al., 2015; Oketch et al., 2019; Onyenwenyi & McHunu, 2018; Vahabi & Lofters, 2016; Vasudevan et al., 2020; L. P. Wong et al., 2008)
	30	Pain	-	(Adewumi et al., 2021; Binka et al., 2019; Busingye et al., 2012; Curmi et al., 2016; Hasahya et al., 2016; Logan & McIlfatrick, 2011; Malhotra et al., 2016; Matenge & Mash, 2018; Ogunsiji et al., 2013; Oketch et al., 2019; Sadler et al., 2013; L. P. Wong et al., 2008)
	31	Peer influence	(Alanazy et al., 2019; Fägerstad et al., 2019; Heaman et al., 2015; Topuzoğlu et al., 2007)	(Greibe Andersen et al., 2020; Rasul et al., 2016)
Benefits		Protective Behaviour		
	32	Cancer diagnosis	Inductive category*	Inductive category*
	33	Health	Inductive category*	Inductive category*
	34	Lack of perceived benefits	(Alanazy et al., 2019; Cameron et al., 2014; Campbell et al., 2015; Copeland et al., 2017; Dahl et al., 2018; Eades & Alexander, 2019; Hussain-Gambles et al., 2004; Leijdesdorff et al., 2021; Pegon-Machat et al., 2009; Poll et al., 2017; Schwennesen et al., 2016; Sheppard et al., 2013; Topuzoğlu et al., 2007)	(Adedimeji et al., 2021; Borrull-Guardeño et al., 2021; Busingye et al., 2012; Curmi et al., 2016; Laranjeira, 2013; H. Lee et al., 2019; Malhotra et al., 2016; Matenge & Mash, 2018; Ogunsiji et al., 2013; Sadler et al., 2013; L. P. Wong et al., 2008)
	35	Lack of knowledge	-	(Adedimeji et al., 2021; Adewumi et al., 2021; Binka et al., 2019; Borrull-Guardeño et al., 2021; Brandt et al., 2019; Busingye et al., 2012; Christie-de Jong & Reilly, 2020; Curmi et al., 2016; Filade et al., 2017; Greibe Andersen et al., 2020; Hasahya et al., 2016; Kue et al., 2020; Laranjeira, 2013; H. Lee et al., 2019; Logan & McIlfatrick, 2011; Matenge & Mash, 2018; Modibbo et al., 2016; Munthali et al., 2015; Ogunsiji et al., 2013; Rasul et al., 2016; Raymond et al., 2014; Roux et al., 2021; Sadler et al., 2013; Schoenberg et al., 2013; Vahabi & Lofters, 2016; L. P. Wong et al., 2009)

Second order	First order		No-Show behaviour studies	Cervical cancer screening studies
	36	Screening program	Inductive category*	Inductive category*
Benefits	Service delivery			
	37	Satisfaction (home visit)	Inductive category*	Inductive category*
	38	Satisfaction (service delivery)	Inductive category*	Inductive category*
Susceptibility	39	Perceived susceptibility	-	(Adedimeji et al., 2021; Filade et al., 2017; Laranjeira, 2013; Ogunsiji et al., 2013; Oketch et al., 2019; Schoenberg et al., 2013)
	40	Denial	(Gellasch, 2019; Llovet et al., 2018)	-
Severity	41	Fear of a bad result	(Bollinger et al., 2011; Campbell et al., 2015; Dahl et al., 2018; Freed et al., 2013; Llovet et al., 2018; Sheppard et al., 2013; Sinclair & Alexander, 2012; Strutton et al., 2016)	(Adewumi et al., 2021; Binka et al., 2019; Borrull-Guardeño et al., 2021; Christie-de Jong & Reilly, 2020; Hasahya et al., 2016; Kue et al., 2020; Malhotra et al., 2016; Modibbo et al., 2016; Onyenwenyi & McHunu, 2018; Rasul et al., 2016; Vahabi & Lofters, 2016; Vasudevan et al., 2020; L. P. Wong et al., 2008)
	42	Fear of side effects	-	(Busingye et al., 2012; Hasahya et al., 2016; Modibbo et al., 2016)
	43	Only uses emergency care	(Alanazy et al., 2019; Dahl et al., 2018)	-
	44	Severity of the consequences	(Eades & Alexander, 2019; Gombe et al., 2020; Saleh et al., 2021; Schwennesen et al., 2016)	(Adewumi et al., 2021; Binka et al., 2019; Brandt et al., 2019; Christie-de Jong & Reilly, 2020; Filade et al., 2017; Greibe Andersen et al., 2020; Hasahya et al., 2016; Matenge & Mash, 2018; Oketch et al., 2019; Rasul et al., 2016; Raymond et al., 2014; Roux et al., 2021; Vahabi & Lofters, 2016; Vasudevan et al., 2020; L. P. Wong et al., 2008, 2009)

Appendix C Descriptive statistics of the data sets (Supplement to Chapter 4)

Variable	Data set 1 (n=1699)			Data set 2 (n=23370)		
	Show	No-show	No-show (%)	Show	No-show	No-show (%)
Age						
<30	230	123	7%	1370	1458	6%
[30,39]	202	141	8%	2762	2041	9%
[40,49]	232	144	8%	3824	2395	10%
[50,59]	242	146	9%	3981	1794	8%
>59	158	51	3%	2672	1073	5%
Poverty						
High	149	128	8%	1325	907	4%
Medium	677	345	20%	9750	6056	26%
Low	238	132	8%	3534	1798	8%
Leadtime						
<=3	112	62	4%	599	356	2%
[4,7]	168	99	6%	1617	1009	4%
[8,15]	270	115	7%	4019	2194	9%
>=16	514	329	19%	8374	5202	22%
Month						
January	29	21	1%	1233	694	3%
February	648	315	19%	1197	751	3%
March	387	269	16%	1218	752	3%
April				1093	659	3%
May				1169	692	3%
June				1245	779	3%
July				1227	735	3%
August				1239	754	3%
September				1259	720	3%
October				1255	747	3%
November				1290	750	3%
December				1184	728	3%
Day						
Monday	20	11	1%	2150	1259	5%
Tuesday	162	90	5%	3020	1756	8%
Wednesday	224	130	8%	2712	1591	7%
Thursday	202	102	6%	2638	1456	6%
Friday	197	114	7%	2666	1681	7%
Saturday	175	108	6%	1250	968	4%
Sunday	84	50	3%	173	50	0%

Appendix D Instrument validation (Supplement to Chapter 4)

First, we present the results of the principal component analysis (the Kaiser Mayer Olkin test result is 0.86 and the *p-value* for Bartlett's test is below 0.001). Nine components are identified with an eigenvalue greater than one, accounting for 57.7% of the variability. While no item has a loading value greater than 0.3 outside the intended category, five items did not meet the criteria for inclusion in any of the components (25, 26, 27, 30 and 31). All these items belong to the Barriers category of the instrument. Finally, for three categories, more than one component can be identified: Severity (two components), Benefits (two components) and Barriers (three components). As can be seen in the following Table, the three Barriers components explain 30% of the variability.

Component	Category	Statement	Eigenvalue	Proportion*
1	Susceptibility	1, 2, 3, 4	2.05	5.5%
2	Severity	5, 6, 7	2.57	6.9%
3	Severity	8, 9, 10, 11	1.08	2.9%
4	Benefits	12, 13, 14, 15	1.54	4.2%
5	Benefits	16, 17, 18, 19	1.42	3.8%
6	Motivation	20, 21, 22	1.22	3.3%
7	Barriers	23, 24	1.48	4.0%
8	Barriers	28, 29, 32	3.82	10.3%
9	Barriers	34, 35, 36, 37	6.16	16.7%

*Proportion of the variability explained by each component

Then, we discuss the results for the item reliability tests. For each statement, mean, standard deviation, coefficient of variation, correlation with the other items in the same category and Cronbach's alpha coefficient (if the item is deleted) are provided. On the one hand, statements in the Barriers category have the highest average variability. Coefficients of variation for this category range from 0.63 to 0.83, with an average of 0.76. Items 25, 27, 30, 31, 34 and 35 have coefficients of variation above 0.8. On the other hand, the perceived benefits are more similar among the participants. Coefficients of variation for this category range from 0.19 to 0.36, with an average of

0.24. Additionally, items 13 and 15 have coefficients of variation below 0.2. Average coefficients of variation for susceptibility, severity and motivation are 0.65, 0.44 and 0.51, respectively.

Category	No.	Statement	Mean	SD	Mean/SD	Correlation*	Alpha
Susceptibility	1	It is likely that I will get cervical cancer in the future	3.47	1.83	0.53	0.57	0.73
Susceptibility	2	My chances of getting cervical cancer in the next few years are high	2.72	1.83	0.67	0.66	0.68
Susceptibility	3	I feel I will get cervical cancer sometime during my life	2.78	1.84	0.66	0.63	0.7
Susceptibility	4	I feel I will get cervical cancer sometime during my life because I have family history of cancer	2.45	1.82	0.74	0.47	0.78
Severity	5	The thought of cervical cancer scares me	4.26	1.46	0.34	0.57	0.68
Severity	6	When I think about cervical cancer, I feel worried	4.25	1.44	0.34	0.61	0.67
Severity	7	I am afraid to think about of cervical cancer	4.32	1.41	0.33	0.62	0.67
Severity	8	Problems I would experience with cervical cancer would last a long time	3.54	1.72	0.49	0.44	0.71
Severity	9	Cervical cancer would threaten a relationship with my husband, boyfriend, or partner	2.99	1.83	0.61	0.32	0.74
Severity	10	If I had cervical cancer my whole life would change	4.14	1.55	0.37	0.38	0.72
Severity	11	If I developed cervical cancer, I would not live longer than 5 years	2.83	1.75	0.62	0.31	0.74
Benefits	12	I want to discover health problems early	4.59	1.15	0.25	0.39	0.7
Benefits	13	Maintaining good health is extremely important to me	4.76	0.88	0.19	0.51	0.68
Benefits	14	I look for new information to improve my health	4.38	1.32	0.3	0.4	0.7
Benefits	15	I feel it is important to carry out activities which will improve my health	4.75	0.89	0.19	0.54	0.67
Benefits	16	Having regular Pap smear tests will help to find changes to the cervix, before they turn into cancer	4.67	0.98	0.21	0.46	0.69
Benefits	17	If cervical cancer was found at a regular Pap smear test its treatment would not be so bad	4.11	1.48	0.36	0.34	0.73
Benefits	18	I think that having a regular Pap smear test is the best way for cervical cancer to be diagnosed early	4.66	1.02	0.22	0.46	0.69

Category	No.	Statement	Mean	SD	Mean/SD	Correlation*	Alpha
Benefits	19	Having regular Pap smear tests will decrease my chances of dying from cervical cancer	4.52	1.21	0.27	0.35	0.71
Motivation	20	I eat well-balanced meals for my health	4.04	1.59	0.39	0.43	0.53
Motivation	21	I exercise at least 3 times a week for my health	3.06	1.84	0.6	0.46	0.48
Motivation	22	I have regular health check-ups even when I am not sick	3.45	1.83	0.53	0.4	0.56
Barriers	23	I am afraid to have a Pap smear test for fear of a bad result	2.66	1.85	0.7	0.42	0.88
Barriers	24	I am afraid to have a Pap smear test because I don't know what will happen	2.59	1.86	0.72	0.48	0.88
Barriers	25	I don't know where to go for a Pap smear test	2.08	1.7	0.81	0.5	0.87
Barriers	26	I would be ashamed to lie on a gynaecologic examination table	2.39	1.82	0.76	0.55	0.87
Barriers	27	Undergoing a Pap smear test takes too much time	1.91	1.55	0.81	0.62	0.87
Barriers	28	Undergoing a Pap smear test is too painful	2.72	1.87	0.69	0.51	0.87
Barriers	29	Health professionals performing Pap smear tests are rude to women	2.04	1.59	0.78	0.54	0.87
Barriers	30	I have other problems in my life which are more important than having a Pap smear test	1.83	1.48	0.81	0.56	0.87
Barriers	31	I am too old to have a Pap smear test regularly	1.73	1.43	0.83	0.57	0.87
Barriers	32	Undergoing a Pap smear test is too uncomfortable	3.09	1.93	0.63	0.44	0.88
Barriers	33	I think that having a regular Pap smear test is required only if one has an active sexual life	2.26	1.77	0.78	0.52	0.87
Barriers	34	My religion does not allow me to undergo a Pap smear test	1.52	1.23	0.81	0.62	0.87
Barriers	35	Preparing for a Pap smear test can be inconvenient for me	1.61	1.31	0.82	0.65	0.87
Barriers	36	Undergoing a Pap smear test can cause problems with my partner	1.54	1.22	0.79	0.61	0.87
Barriers	37	I am too young to have a Pap smear test regularly	1.38	1.02	0.74	0.46	0.88

* Item- rest correlation

In order to identify poorly-functioning items, we adopted the criteria defined by Guvenc et al. (2011). Statements with a correlation below 0.3 with category scores, or showing an increase greater than 0.1 in the Cronbach's coefficient, if deleted, should be removed. Only six items have a correlation below 0.4: three severity items (9, 10 and 11) and three benefits items (12, 17 and 19). However, as shown in Table 1 they all are above 0.3. Additionally, Cronbach's coefficients for each category are: Susceptibility 0.74, Severity 0.74, Benefits 0.73, Health motivation 0.62 and Barriers 0.82. As can be seen in Table 1, there is no statement that increases the coefficient of its category above 0.1 when it is removed. Therefore, all the items met the inclusion criteria

Appendix E Survey results (Supplement to Chapter 4)

Category	No.	Statement	Agree		Neutral		Disagree	
			N	%	N	%	N	%
Susceptibility	1	It is likely that I will get cervical cancer in the future	958	56%	182	11%	559	33%
Susceptibility	2	My chances of getting cervical cancer in the next few years are high	606	36%	252	15%	841	49%
Susceptibility	3	I feel I will get cervical cancer some time during my life	638	38%	240	14%	821	48%
Susceptibility	4	I feel I will get cervical cancer some time during my life because I have family history of cancer	538	32%	159	9%	1002	59%
Severity	5	The thought of cervical cancer scares me	1325	78%	119	7%	255	15%
Severity	6	When I think about cervical cancer, I feel worried	1310	77%	145	9%	244	14%
Severity	7	I am afraid to think about of cervical cancer	1350	79%	119	7%	230	14%
Severity	8	Problems I would experience with cervical cancer would last a long time	918	54%	320	19%	461	27%
Severity	9	Cervical cancer would threaten a relationship with my husband, boyfriend, or partner	703	41%	285	17%	711	42%
Severity	10	If I had cervical cancer my whole life would change	1265	74%	135	8%	299	18%
Severity	11	If I developed cervical cancer, I would not live longer than 5 years	579	34%	393	23%	727	43%
Benefits	12	I want to discover health problems early	1486	87%	74	4%	139	8%
Benefits	13	Maintaining good health is extremely important to me	1572	93%	51	3%	76	4%
Benefits	14	I look for new information to improve my health	1356	80%	156	9%	187	11%
Benefits	15	I feel it is important to carry out activities which will improve my health	1557	92%	69	4%	73	4%
Benefits	16	Having regular Pap smear tests will help to find changes to the cervix, before they turn into cancer	1503	88%	109	6%	87	5%
Benefits	17	If cervical cancer was found at a regular Pap smear test its treatment would not be so bad	1195	56%	250	11%	254	33%
Benefits	18	I think that having a regular Pap smear test is the best way for cervical cancer to be diagnosed early	1512	36%	87	15%	100	49%
Benefits	19	Having regular Pap smear tests will decrease my chances of dying from cervical cancer	1444	38%	101	14%	154	48%
Motivation	20	I eat well-balanced meals for my health	1205	70%	170	15%	324	15%
Motivation	21	I exercise at least 3 times a week for my health	743	89%	263	5%	693	6%
Motivation	22	I have regular health check-ups even when I am not sick	946	85%	193	6%	560	9%
Barriers	23	I am afraid to have a Pap smear test for fear of a bad result	609	71%	189	10%	901	19%

Category	No.	Statement	Agree		Neutral		Disagree	
			N	%	N	%	N	%
Barriers	24	I am afraid to have a Pap smear test because I don't know what will happen	593	44%	164	15%	942	41%
Barriers	25	I don't know where to go for a Pap smear test	401	56%	119	11%	1179	33%
Barriers	26	I would be ashamed to lie on a gynaecologic examination table	522	36%	136	11%	1041	53%
Barriers	27	Undergoing a Pap smear test takes too much time	298	35%	173	10%	1228	55%
Barriers	28	Undergoing a Pap smear test is too painful	644	24%	174	7%	881	69%
Barriers	29	Health professionals performing Pap smear tests are rude to women	325	31%	233	8%	1141	61%
Barriers	30	I have other problems in my life which are more important than having a Pap smear test	259	18%	183	10%	1257	72%
Barriers	31	I am too old to have a Pap smear test regularly	240	38%	140	10%	1319	52%
Barriers	32	Undergoing a Pap smear test is too uncomfortable	829	19%	115	14%	755	67%
Barriers	33	I think that having a regular Pap smear test is required only if one has an active sexual life	468	15%	136	11%	1095	74%
Barriers	34	My religion does not allow me to undergo a Pap smear test	158	14%	125	8%	1416	78%
Barriers	35	Preparing for a Pap smear test can be inconvenient for me	184	49%	146	7%	1369	44%
Barriers	36	Undergoing a Pap smear test can cause problems with my partner	149	28%	161	8%	1389	64%
Barriers	37	I am too young to have a Pap smear test regularly	89	9%	149	7%	1461	83%

Appendix F Kruskal-Wallis (Supplement to Chapter 4)

Category	Component	Kruskal-Wallis	Dunn test		
			H-M	H-L	M-H
Susceptibility	1	0.11			
Severity	2	0.001	0.02	0.001	0.1
Severity	3	0.001	<0.001	<0.001	0.16
Benefits	4	0.83			
Benefits	5	0.54			
Health motivation	6	0.002	0.015	0.003	0.3
Barriers	7	0.012	0.001	<0.001	0.21
Barriers	8	0.001	0.001	<0.001	0.49
Barriers	9	0.001	<0.001	<0.001	0.11

H: High, M: Medium and L: Low levels of poverty

List of References

Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Mohamed, N. A. E., & Arshad, H. (2018). State-of-the-art in artificial neural network applications: A survey. *Heliyon*, *4*(11), e00938. https://doi.org/10.1016/j.heliyon.2018.e00938

Ade, S., Trébucq, A., Harries, A. D., Ade, G., Agodokpessi, G., & Wachinou, P. (2016). Follow-up and tracing of tuberculosis patients who fail to attend their scheduled appointments in Cotonou , Benin : a retrospective cohort study. *BMC Health Services Research*, 1–7. https://doi.org/10.1186/s12913-015-1219-z

Adedimeji, A., Ajeh, R., Pierz, A., Nkeng, R., Ndenkeh, J. J., Fuhngwa, N., Nsame, D., Nji, M., Dzudie, A., Anastos, K. M., & Castle, P. E. (2021). Challenges and opportunities associated with cervical cancer screening programs in a low income, high HIV prevalence context. *BMC Women's Health*, *21*(1), 1–14. https://doi.org/10.1186/s12905-021-01211-w

Adewumi, K., Nishimura, H., Oketch, S. Y., Adsul, P., & Huchko, M. (2021). Barriers and Facilitators to Cervical Cancer Screening in Western Kenya: a Qualitative Study. *Journal of Cancer Education*. https://doi.org/10.1007/s13187-020-01928-6

Agurto, I., Bishop, A., Sánchez, G., Betancourt, Z., & Robles, S. (2004). Perceived barriers and benefits to cervical cancer screening in Latin America. *Preventive Medicine*, *39*(1), 91–98. https://doi.org/https://doi.org/10.1016/j.ypmed.2004.03.040

Ahmadi-Javid, A., Jalali, Z., & Klassen, K. J. (2017). Outpatient appointment systems in healthcare: A review of optimization studies. *European Journal of Operational Research*, *258*(1), 3–34. https://doi.org/10.1016/j.ejor.2016.06.064

Akre, C., Michaud, P. A., & Suris, J. C. (2010). "I'll look it up on the Web first": Barriers and overcoming barriers to consult for sexual dysfunction among young men. *Swiss Medical Weekly*, *140*(23–24), 348–353.

Alanazy, W., Rance, J., & Brown, A. (2019). Exploring maternal and health professional beliefs about the factors that affect whether women in Saudi Arabia attend antenatal care clinic appointments. *Midwifery*, *76*, 36–44. https://doi.org/10.1016/j.midw.2019.05.012

Alderson, H., Spencer, L., Scott, S., Kaner, E., Reeves, A., Robson, S., & Ling, J. (2021). Using behavioural insights to improve the uptake of services for drug and alcohol misuse. *International Journal of Environmental Research and Public Health*, *18*(13).

https://doi.org/10.3390/ijerph18136923

Aldohaian, A. I., Alshammari, S. A., & Arafah, D. M. (2019a). Using the health belief model to assess beliefs and behaviors regarding cervical cancer screening among Saudi women: A cross-sectional observational study. *BMC Women's Health*, *19*(1), 1–12. https://doi.org/10.1186/s12905-018-0701-2

Aldohaian, A. I., Alshammari, S. A., & Arafah, D. M. (2019b). Using the health belief model to assess beliefs and behaviors regarding cervical cancer screening among Saudi women: A cross-sectional observational study 11 Medical and Health Sciences 1117 Public Health and Health Services. *BMC Women's Health*, *19*(1), 1–12. https://doi.org/10.1186/s12905-018-0701-2

Ali, J., Ahmad, N., & Maqssod, I. (2012). Random Forests and Decision Trees. *International Journal of Computer Science Issues*, *9*(5), 272–278.

Alwasel, A., Fakhimi, F., & Stergioulas, L. (2019). Modelling and Simulation for Behavioural Analysis in Healthcare. *OR 61*. https://www.theorsociety.com/media/4400/or61-timetable-and-abstracts-02092019-rw.pdf?mc_cid=12efde5d34&mc_eid=%5BUNIQID%5D

American Cancer Society. (n.d.). *What Is Cervical Cancer?* Retrieved June 18, 2022, from https://www.cancer.org/cancer/cervical-cancer/about/what-is-cervical-cancer.html

Amin, R., Kolahi, A. A., Jahanmehr, N., Abadi, A. R., & Sohrabi, M. R. (2020). Disparities in cervical cancer screening participation in Iran: a cross-sectional analysis of the 2016 nationwide STEPS survey. *BMC Public Health*, *20*(1), 1–8. https://doi.org/10.1186/s12889-020-09705-2

Ampofo, A. G., Adumatta, A. D., Owusu, E., & Awuviry-Newton, K. (2020). A cross-sectional study of barriers to cervical cancer screening uptake in Ghana: An application of the health belief model. *PLoS ONE*, *15*(4), 1–16. https://doi.org/10.1371/journal.pone.0231459

Andreassen, T., Weiderpass, E., Nicula, F., Suteu, O., Itu, A., Bumbu, M., Tincu, A., Ursin, G., & Moen, K. (2017). Controversies about cervical cancer screening: A qualitative study of Roma women's (non)participation in cervical cancer screening in Romania. *Social Science and Medicine*, *183*, 48–55. https://doi.org/10.1016/j.socscimed.2017.04.040

Annan, F. M., Oppong Asante, K., & Kugbey, N. (2019). Perceived seriousness mediates the influence of cervical cancer knowledge on screening practices among female university students in Ghana. *BMC Women's Health*, *19*(1), 1–8. https://doi.org/10.1186/s12905-019-0842-y

Arbyn, M., Weiderpass, E., Bruni, L., de Sanjosé, S., Saraiya, M., Ferlay, J., & Bray, F. (2020). Estimates of incidence and mortality of cervical cancer in 2018: a worldwide analysis. *The Lancet Global Health*, *8*(2), e191–e203. https://doi.org/10.1016/S2214-109X(19)30482-6

Arras, L., Montavon, G., Müller, K.-R., & Samek, W. (2017). Explaining Recurrent Neural Network Predictions in Sentiment Analysis. *Proceedings of the 8th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis*, 159–168. https://doi.org/10.18653/v1/W17-5221

Arrossi, S. (2019). The impact of the HPV test in screening programs in Latin America: The case of Argentina. *Salud Publica de Mexico*, *61*(1), 86–94. https://doi.org/10.21149/9257

Arrossi, S., Paolino, M., Laudi, R., & Thouyaret, L. (2021). Changing the paradigm of cervical cancer prevention through introduction of HPV-testing: evaluation of the implementation process of the Jujuy Demonstration Project in Argentina. *Ecancermedicalscience*, *15*, 1199. https://doi.org/10.3332/ecancer.2021.1199

Arrossi, S., Ramos, S., Paolino, M., & Sankaranarayanan, R. (2008). Social inequality in Pap smear coverage: identifying under-users of cervical cancer screening in Argentina. *Reproductive Health Matters*, *16*(32), 50–58. https://doi.org/10.1016/S0968-8080(08)32410-0

Arrossi, S., Thouyaret, L., Herrero, R., Campanera, A., Magdaleno, A., Cuberli, M., Barletta, P., Laudi, R., & Orellana, L. (2015). Effect of self-collection of HPV DNA offered by community health workers at home visits on uptake of screening for cervical cancer (the EMA study): a population-based cluster-randomised trial. *The Lancet Global Health*, *3*(2), e85–e94. https://doi.org/https://doi.org/10.1016/S2214-109X(14)70354-7

Auret, L., & Aldrich, C. (2012). Interpretation of nonlinear relationships between process variables by use of random forests. *Minerals Engineering*, *35*, 27–42. https://doi.org/10.1016/j.mineng.2012.05.008

Aygun, O., & Bó, I. (2017). College Admission with Multidimensional Privileges: The Brazilian Affirmative Action Case. *SSRN Electronic Journal*, *13*(3), 1–28. https://doi.org/10.2139/ssrn.3071751

Bach, S., Binder, A., Montavon, G., Klauschen, F., Müller, K. R., & Samek, W. (2015). On pixel-wise explanations for non-linear classifier decisions by layer-wise relevance propagation. *PLoS ONE*, *10*(7), 1–46. https://doi.org/10.1371/journal.pone.0130140

Ballantyne, M., Liscumb, L., Brandon, E., Jaffar, J., Macdonald, A., & Beaune, L. (2019). Mothers’

Perceived Barriers to and Recommendations for Health Care Appointment Keeping for Children Who Have Cerebral Palsy. *Global Qualitative Nursing Research*, *6*. https://doi.org/10.1177/2333393619868979

Bante, S. A., Getie, S. A., Getu, A. A., Mulatu, K., & Fenta, S. L. (2019). Uptake of pre-cervical cancer screening and associated factors among reproductive age women in Debre Markos town, Northwest Ethiopia, 2017. *BMC Public Health*, *19*(1), 1–9. https://doi.org/10.1186/s12889-019-7398-5

Barjis, J., Kolfschoten, G., & Maritz, J. (2013). A sustainable and affordable support system for rural healthcare delivery. *Decision Support Systems*, *56*(1), 223–233. https://doi.org/10.1016/j.dss.2013.06.005

Barredo Arrieta, A., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*, *58*, 82–115. https://doi.org/https://doi.org/10.1016/j.inffus.2019.12.012

Barrera, D., Brailsford, S., Bravo, C., & Smith, H. K. (2020). *No-show*. https://github.com/DBarreraFerro/No-show

Barrera Ferro, D., Bayer, S., Brailsford, S., & Smith, H. (2022). Improving intervention design to promote cervical cancer screening among hard-to-reach women: assessing beliefs and predicting individual attendance probabilities in Bogotá, Colombia. *BMC Women's Health*, *22*(1), 212. https://doi.org/10.1186/s12905-022-01800-3

Barrera Ferro, D., Brailsford, S., Bravo, C., & Smith, H. (2020). Improving healthcare access management by predicting patient no-show behaviour. *Decision Support Systems*, 113398. https://doi.org/https://doi.org/10.1016/j.dss.2020.113398

Barrow, D., & Kourentzes, N. (2018). The impact of special days in call arrivals forecasting: A neural network approach to modelling special days. *European Journal of Operational Research*, *264*(3), 967–977. https://doi.org/10.1016/j.ejor.2016.07.015

Baskerville, R., Baiyere, A., Gregor, S., Hevner, A., & Rossi, M. (2018). Design science research contributions: Finding a balance between artifact and theory. *Journal of the Association for Information Systems*, *19*(5), 358–376. https://doi.org/10.17705/1jais.00495

Beaurain, G., & Masclet, D. (2016). Does affirmative action reduce gender discrimination and enhance efficiency? New experimental evidence. *European Economic Review*, *90*, 350–362. https://doi.org/10.1016/j.euroecorev.2016.04.009

Benchimol, E. I., Smeeth, L., Guttmann, A., Harron, K., Moher, D., Peteresen, I., Sørensen, H. T., von Elm, E., & Langan, S. M. (2015). The REporting of studies Conducted using Observational Routinely-collected health Data (RECORD) Statement. *PLoS Medicine*, *12*(10), 1–22. https://doi.org/10.1371/journal.pmed.1001885

Bermedo-Carrasco, S., Peña-Sánchez, J. N., Lepnurm, R., Szafron, M., & Waldner, C. (2015). Inequities in cervical cancer screening among Colombian women: A multilevel analysis of a nationwide survey. *Cancer Epidemiology*, *39*(2), 229–236. https://doi.org/10.1016/j.canep.2015.01.011

Bermedo-Carrasco, S., & Waldner, C. L. (2016). The role of socio-demographic factors in premature cervical cancer mortality in Colombia. *BMC Public Health*, *16*(1), 981. https://doi.org/10.1186/s12889-016-3645-1

Bhochhibhoya, S., Dobbs, P. D., & Maness, S. B. (2021). Interventions using mHealth strategies to improve screening rates of cervical cancer: A scoping review. *Preventive Medicine*, *143*, 106387. https://doi.org/10.1016/j.ypmed.2020.106387

Binka, C., Nyarko, S. H., Awusabo-Asare, K., & Doku, D. T. (2019). Barriers to the Uptake of Cervical Cancer Screening and Treatment among Rural Women in Ghana. *BioMed Research International*, *2019*, 6320938. https://doi.org/10.1155/2019/6320938

Black, E., Hyslop, F., & Richmond, R. (2019). Barriers and facilitators to uptake of cervical cancer screening among women in Uganda: A systematic review. *BMC Women's Health*, *19*(1), 1–12. https://doi.org/10.1186/s12905-019-0809-z

Bollinger, L. M., Nire, K. G., Rhodes, M. M., Chisolm, D. J., & O'Brien, S. H. (2011). Caregivers' perspectives on barriers to transcranial Doppler screening in children with sickle-cell disease. *Pediatric Blood & Cancer*, *56*(1), 99–102. https://doi.org/10.1002/pbc.22780

Borrull-Guardeño, J., Sebastiá-Laguarda, C., Donat-Colomer, F., & Sánchez-Martínez, V. (2021). Women's knowledge and attitudes towards cervical cancer prevention: A qualitative study in the Spanish context. *Journal of Clinical Nursing*, *30*(9–10), 1383–1393. https://doi.org/10.1111/jocn.15687

Bradley, E. H., Curry, L. A., & Devers, K. J. (2007). Qualitative Data Analysis for Health Services Research: Developing Taxonomy, Themes, and Theory. *Health Services Research*, *42*(4), 1758–1772. https://doi.org/10.1111/j.1475-6773.2006.00684.x

Brailsford, S., Harper, P., & Sykes, J. (2012). Incorporating human behaviour in simulation models of screening for breast cancer. *European Journal of Operational Research*, *219*(3), 491–507. https://doi.org/10.1016/j.ejor.2011.10.041

Brandt, T., Wubneh, S. B., Handebo, S., Debalkie, G., Ayanaw, Y., Alemu, K., Jede, F., von Knebel Doeberitz, M., & Bussmann, H. (2019). Genital self-sampling for HPV-based cervical cancer screening: a qualitative study of preferences and barriers in rural Ethiopia. *BMC Public Health*, *19*(1), 1026. https://doi.org/10.1186/s12889-019-7354-4

Breiman, L. (2001). Random forests. *Machine Learning*, 5–32. https://doi.org/10.1023/A:1010933404324

Breiman, L. (2002). *Manual on setting up, using and understanding Random Forests V3*. Statistics Deparment University of Californua Berkeley, CA.

Brennan, A., Chick, S. E., & Davies, R. (2006). A taxonomy of model structures for economic evaluation of health technologies. *Health Economics*, *15*(12), 1295–1310. https://doi.org/10.1002/hec.1148

Brewster, S., Bartholomew, J., Holt, R. I. G., & Price, H. (2020). Non-attendance at diabetes outpatient appointments: a systematic review. *Diabetic Medicine*, *37*(9), 1427–1442. https://doi.org/10.1111/dme.14241

Briggs, A., Sculpher, M., Dawson, J., Fitzpatrick, R., Murray, D., & Malchau, H. (2004). The use of probabilistic decision models in technology assessment. *Applied Health Economics and Health Policy*, *3*(2), 79–89. https://doi.org/10.2165/00148365-200403020-00004

Britton, T., & Robinson, N. (2016). Pitfalls and Pearls of Wisdom in 18F-FDG PET Imaging of Tumors. *Journal of Nuclear Medicine Technology*, *44*(2), 59–64. https://doi.org/10.2967/jnmt.115.170803

Broeders, M., & Elfström, K. M. (2020). Importance of International Networking and Comparative Research in Screening to Meet the Global Challenge of Cancer Control. *JCO Global Oncology*, *6*, 180–181. https://doi.org/10.1200/JGO.19.00388

Brouwers, M. C., De Vito, C., Bahirathan, L., Carol, A., Carroll, J. C., Cotterchio, M., Dobbins, M., Lent, B., Levitt, C., Lewis, N., McGregor, S. E., Paszat, L., Rand, C., & Wathen, N. (2011). What implementation interventions increase cancer screening rates? a systematic review. *Implementation Science*, *6*(1), 111. https://doi.org/10.1186/1748-5908-6-111

Brown, R. F., Muller, T. R., & Olsen, A. (2019). Australian women's cervical cancer screening attendance as a function of screening barriers and facilitators. *Social Science and Medicine*, *220*(November 2018), 396–402. https://doi.org/10.1016/j.socscimed.2018.11.038

Busingye, P., Nakimuli, A., Nabunya, E., & Mutyaba, T. (2012). Acceptability of cervical cancer screening via visual inspection with acetic acid or Lugol's iodine at Mulago Hospital, Uganda. *International Journal of Gynaecology and Obstetrics: The Official Organ of the International Federation of Gynaecology and Obstetrics*, *119*(3), 262–265. https://doi.org/10.1016/j.ijgo.2012.06.015

Cameron, E., Heath, G., Redwood, S., Greenfield, S., Cummins, C., Kelly, D., & Pattison, H. (2014). Health care professionals' views of paediatric outpatient non-attendance: Implications for general practice. *Family Practice*, *31*(1), 111–117. https://doi.org/10.1093/fampra/cmt063

Campbell, D. J. T., O'Neill, B. G., Gibson, K., & Thurston, W. E. (2015). Primary healthcare needs and barriers to care among Calgary's homeless populations. *BMC Family Practice*, *16*(1), 1–10. https://doi.org/10.1186/s12875-015-0361-3

Canfell, K., Kim, J. J., Brisson, M., Keane, A., Simms, K. T., Caruana, M., Burger, E. A., Martin, D., Nguyen, D. T. N., Bénard, É., Sy, S., Regan, C., Drolet, M., Gingras, G., Laprise, J.-F., Torode, J., Smith, M. A., Fidarova, E., Trapani, D., … Hutubessy, R. (2020). Mortality impact of achieving WHO cervical cancer elimination targets: a comparative modelling analysis in 78 low-income and lower-middle-income countries. *The Lancet*, *395*(10224), 591–603. https://doi.org/10.1016/S0140-6736(20)30157-4

Carr, K. C., & Sellors, J. W. (2004). Cervical cancer screening in low resource settings using visual inspection with acetic acid. *Journal of Midwifery & Women's Health*, *49*(4), 329–337. https://doi.org/https://doi.org/10.1016/j.jmwh.2004.02.015

Cashman, S. B., Savageau, J. A., Lemay, C. A., & Ferguson, W. (2007). Patient Health Status and Appointment Keeping in an Urban Community Health Center. *Journal of Health Care for the Poor and Underserved*, *15*(3), 474–488. https://doi.org/10.1353/hpu.2004.0037

Caton, S., & Haas, C. (2020). *Fairness in Machine Learning: A Survey*. 1–33. http://arxiv.org/abs/2010.04053

Cavallaro, F. L., Duclos, D., Cresswell, J. A., Faye, S., Macleod, D., Faye, A., & Lynch, C. A. (2018). Understanding "missed appointments" for pills and injectables: A mixed methods study in Senegal. *BMJ Global Health*, *3*(6). https://doi.org/10.1136/bmjgh-2018-000975

Cendales, R., Wiesner, C., Murillo, R. H., Piñeros, M., Tovar, S., & Mejía, J. C. (2010). La calidad de las citologías para tamización de cáncer de cuello uterino en cuatro departamentos de Colombia: un estudio de concordancia. *Biomédica*, *30*(1), 107. https://doi.org/10.7705/biomedica.v30i1.158

Chamberlin, S., Mphande, M., Phiri, K., Kalande, P., & Dovel, K. (2021). How HIV Clients Find Their Way Back to the ART Clinic: A Qualitative Study of Disengagement and Re-engagement with HIV Care in Malawi. *AIDS and Behavior*, *0123456789*. https://doi.org/10.1007/s10461-021-03427-1

Champion, V. (1985). Use of the health belief model in determining frequency of breast self-examination. *Research in Nursing & Health*, *8*(4), 373–379. https://doi.org/10.1002/nur.4770080410

Champion, Victoria, & Skinner, C. S. (2008). The health belief model. *Health Behavior and Health Education: Theory, Research, and Practice*, *4*, 45–65.

Chan, D. N. S., & So, W. K. W. (2020). The impact of community-based multimedia intervention on the new and repeated cervical cancer screening participation among South Asian women. *Public Health*, *178*, 1–4. https://doi.org/https://doi.org/10.1016/j.puhe.2019.08.015

Chaudhuri, N., & Bose, I. (2020). Exploring the role of deep neural networks for post-disaster decision support. *Decision Support Systems*, *130*, 113234. https://doi.org/https://doi.org/10.1016/j.dss.2019.113234

Chavkin, W. (1997). Topics for our times: affirmative action and women's health. *American Journal of Public Health*, *87*(5), 732–734. https://doi.org/10.2105/ajph.87.5.732

Choi, Y., Oketch, S. Y., Adewumi, K., Bukusi, E., & Huchko, M. J. (2020). A Qualitative Exploration of Women's Experiences with a Community Health Volunteer-Led Cervical Cancer Educational Module in Migori County, Kenya. *Journal of Cancer Education*, *35*(1), 36–43. https://doi.org/10.1007/s13187-018-1437-2

Christie-de Jong, F., & Reilly, S. (2020). Barriers and facilitators to pap-testing among female overseas Filipino workers: a qualitative exploration. *International Journal of Human Rights in Healthcare*, *13*(3), 275–288. https://doi.org/10.1108/IJHRH-01-2020-0006

Christie-Johnston, C.-A., O'Loughlin, R., & Hiscock, H. (2020). 'Getting to clinic study': A mixed methods study of families who fail to attend hospital outpatient clinics. *Journal of Paediatrics and Child Health*, *56*(4), 506–511.

https://doi.org/https://doi.org/10.1111/jpc.14672

Chuang, E., Pourat, N., Chen, X., Lee, C., Zhou, W., Daniel, M., Hoang, H., & Sripipatana, A. (2019). Organizational factors associated with disparities in cervical and colorectal cancer screening rates in community health centers. *Journal of Health Care for the Poor and Underserved*, *30*(1), 161–181. https://doi.org/10.1353/hpu.2019.0014

Cibulka, N. J., Fischer, H. W., & Fischer, A. J. (2012). Improving communication with low-income women using today's technology. *Online Journal of Issues in Nursing*, *17*(2), 9.

Conforti, C., Hirmer, S., Morgan, D., Basaldella, M., & Ben Or, Y. (2020). *Natural Language Processing for Achieving Sustainable Development: the Case of Neural Labelling to Enhance Community Profiling*. *2030*, 8427–8444. https://doi.org/10.18653/v1/2020.emnlp-main.677

Copeland, S., Muir, J., & Turner, A. (2017). Understanding Indigenous patient attendance: A qualitative study. *Australian Journal of Rural Health*, *25*(5), 268–274. https://doi.org/10.1111/ajr.12348

Crosby, F. J., Iyer, A., & Sincharoen, S. (2006). Understanding affirmative action. *Annual Review of Psychology*, *57*, 585–611. https://doi.org/10.1146/annurev.psych.57.102904.190029

Curmi, C., Peters, K., & Salamonson, Y. (2016). Barriers to cervical cancer screening experienced by lesbian women: a qualitative study. *Journal of Clinical Nursing*, *25*(23–24), 3643–3651. https://doi.org/10.1111/jocn.12947

Currie, C. S. M., Fowler, J. W., Kotiadis, K., Monks, T., Onggo, B. S., Robertson, D. A., & Tako, A. A. (2020). How simulation modelling can help reduce the impact of COVID-19. *Journal of Simulation*, *14*(2), 83–97. https://doi.org/10.1080/17477778.2020.1751570

Daggy, J., Willis, D., Turkcan, A., Chakraborty, S., Lawley, M., DeLaurentis, P.-C., Thayer, D., Suelzer, C., & Sands, L. (2010). Using no-show modeling to improve clinic performance. *Health Informatics Journal*, *16*(4), 246–259. https://doi.org/10.1177/1460458210380521

Dahl, M., Lindholt, J., Søgaard, R., Frost, L., Andersen, L. S., & Lorentzen, V. (2018). An interview-based study of nonattendance at screening for cardiovascular diseases and diabetes in older women: Nonattendees' perspectives. *Journal of Clinical Nursing*, *27*(5–6), 939–948. https://doi.org/10.1111/jocn.14018

Dancey, D., Bandar, Z., & McLean, D. (2007). Logistic Model Tree Extraction From Artificial Neural Networks. *IEEE Transactions on Systems, Man and Cybernetics - Part B: Cybernetics*, *37*(4), 73–91. https://doi.org/10.1007/978-3-7908-1771-3_3

Dantas, L. F., Fleck, J. L., Cyrino, F. L., & Hamacher, S. (2018). No-shows in appointment scheduling – a systematic literature review. *Health Policy*, *122*(4), 412–421. https://doi.org/10.1016/j.healthpol.2018.02.002

Dantas, L. F., Hamacher, S., Cyrino Oliveira, F. L., Barbosa, S. D. J., & Viegas, F. (2019). Predicting Patient No-show Behavior: a Study in a Bariatric Clinic. *Obesity Surgery*, *29*(1), 40–47. https://doi.org/10.1007/s11695-018-3480-9

Daryani, S., Shojaeezadeh, D., Batebi, A., Charati, J. Y., & Naghibi, A. (2016). The effect of education based on a health belief model in women's practice with regard to the Pap smear test. *Journal of Cancer Policy*, *8*, 51–56. https://doi.org/10.1016/j.jcpo.2015.11.001

Day, T. E., Ravi, N., Xian, H., & Brugh, A. (2013). An Agent-Based Modeling Template for a Cohort of Veterans with Diabetic Retinopathy. *PloS One*, *8*(6), e66812. https://doi.org/10.1371/journal.pone.0066812

Daye, D., Carrodeguas, E., Glover, M., Guerrier, C. E., Harvey, H. B., & Flores, E. J. (2018). Impact of Delayed Time to Advanced Imaging on Missed Appointments Across Different Demographic and Socioeconomic Factors. *Journal of the American College of Radiology*, *15*(5), 713–720. https://doi.org/10.1016/j.jacr.2018.01.023

De Cuevas, R. M. A., Saini, P., Roberts, D., Beaver, K., Chandrashekar, M., Jain, A., Kotas, E., Tahir, N., Ahmed, S., & Brown, S. L. (2018). A systematic review of barriers and enablers to South Asian women's attendance for asymptomatic screening of breast and cervical cancers in emigrant countries. *BMJ Open*, *8*(7), 1–17. https://doi.org/10.1136/bmjopen-2017-020892

Demirtas, B., & Acikgoz, I. (2013). Promoting attendance at cervical cancer screening: Understanding the relationship with Turkish womens' health beliefs. *Asian Pacific Journal of Cancer Prevention*, *14*(1), 333–340. https://doi.org/10.7314/APJCP.2013.14.1.333

Denberg, T. D., Melhado, T. V., Coombes, J. M., Beaty, B. L., Berman, K., Byers, T. E., Marcus, A. C., Steiner, J. F., & Ahnen, D. J. (2005). Predictors of nonadherence to screening colonoscopy. *Journal of General Internal Medicine*, *20*(11), 989–995. https://doi.org/10.1111/j.1525-1497.2005.00164.x

Denny, L., de Sanjose, S., Mutebi, M., Anderson, B. O., Kim, J., Jeronimo, J., Herrero, R., Yeates, K., Ginsburg, O., & Sankaranarayanan, R. (2017). Interventions to close the divide for women with breast and cervical cancer between low-income and middle-income countries and high-income countries. *The Lancet*, *389*(10071), 861–870. https://doi.org/10.1016/S0140-6736(16)31795-0

Departamento Nacional de Planeacion. (n.d.). *SISBEN III*. Retrieved October 5, 2021, from https://anda.dnp.gov.co/index.php/catalog/94/study-description

Dilgul, M., McNamee, P., Orfanos, S., Carr, C. E., & Priebe, S. (2018). Why do psychiatric patients attend or not attend treatment groups in the community: A qualitative study. *PLoS ONE*, *13*(12), 1–16. https://doi.org/10.1371/journal.pone.0208448

Ding, X., Barth, P., Newman, M., Mather, C., Goldstein, B. A., Poon, E. G., & Gellad, Z. F. (2018). Designing risk prediction models for ambulatory no-shows across different specialties and clinics. *Journal of the American Medical Informatics Association*, *25*(8), 924–930. https://doi.org/10.1093/jamia/ocy002

Do, D. H., & Siegler, J. E. (2018). Diagnoses and other predictors of patient absenteeism in an outpatient neurology clinic. *Neurology: Clinical Practice*, *8*(4), 318–326. https://doi.org/10.1212/CPJ.0000000000000488

Dreiseitl, S., & Ohno-Machado, L. (2002). Logistic regression and artificial neural network classification models: A methodology review. *Journal of Biomedical Informatics*, *35*(5–6), 352–359. https://doi.org/10.1016/S1532-0464(03)00034-0

DuMontier, C., Rindfleisch, K., Pruszynski, J., & Frey, J. J. 3rd. (2013). A multi-method intervention to reduce no-shows in an urban residency clinic. *Family Medicine*, *45*(9), 634–641.

Dunn, R. A., & Tan, A. K. G. (2010). Cervical cancer screening in Malaysia: Are targeted interventions necessary? *Social Science and Medicine*, *71*(6), 1089–1093. https://doi.org/10.1016/j.socscimed.2010.06.016

Dwork, C., Hardt, M., Pitassi, T., Reingold, O., & Zemel, R. (2012). Fairness through awareness. *ITCS 2012 - Innovations in Theoretical Computer Science Conference*, 214–226. https://doi.org/10.1145/2090236.2090255

Eades, C., & Alexander, H. (2019). A mixed-methods exploration of non-attendance at diabetes appointments using peer researchers. *Health Expectations*, *22*(6), 1260–1271. https://doi.org/10.1111/hex.12959

Ellis, D. A., Luther, K., & Jenkins, R. (2018). Missed medical appointments during shifts to and from daylight saving time. *Chronobiology International*, *35*(4), 584–588. https://doi.org/10.1080/07420528.2017.1417313

Ellis, D. A., McQueenie, R., McConnachie, A., Wilson, P., & Williamson, A. E. (2017). Demographic and practice factors predicting repeated non-attendance in primary care: a national retrospective cohort analysis. *The Lancet Public Health*, *2*(12), e551–e559. https://doi.org/10.1016/S2468-2667(17)30217-7

Ellison, G., & Pathak, P. A. (2021). The Efficiency of Race-Neutral Alternatives to Race-Based Affirmative Action: Evidence from Chicago's Exam Schools†. *American Economic Review*, *111*(3), 943–975. https://doi.org/10.1257/AER.20161290

Eng, J. (2003). Sample size estimation: How many individuals should be studied? *Radiology*, *227*(2), 309–313. https://doi.org/10.1148/radiol.2272012051

Fägerstad, A., Lundgren, J., Arnrup, K., & Carlson, E. (2019). Barriers and facilitators for adolescent girls to take on adult responsibility for dental care–a qualitative study. *International Journal of Qualitative Studies on Health and Well-Being*, *14*(1). https://doi.org/10.1080/17482631.2019.1678971

Feitsma, W. N., Popping, R., & Jansen, D. E. M. C. (2012). No-show at a forensic psychiatric outpatient clinic: Risk factors and reasons. *International Journal of Offender Therapy and Comparative Criminology*, *56*(1), 96–112. https://doi.org/10.1177/0306624X10389435

Féris, M. A. A., Zwikael, O., & Gregor, S. (2017). QPLAN: Decision support for evaluating planning quality in software development projects. *Decision Support Systems*, *96*, 92–102. https://doi.org/10.1016/j.dss.2017.02.008

Fetters, M. D., Curry, L. A., & Creswell, J. W. (2013). Achieving integration in mixed methods designs-principles and practices. *Health Services Research*, *48*(6 Pt 2), 2134–2156. https://doi.org/10.1111/1475-6773.12117

Feuerriegel, S., Dolata, M., & Schwabe, G. (2020). Fair AI: Challenges and Opportunities. *Business and Information Systems Engineering*, *62*(4), 379–384. https://doi.org/10.1007/s12599-020-00650-3

Figueredo, G. P., Siebers, P.-O., Owen, M. R., Reps, J., & Aickelin, U. (2014). Comparing Stochastic Differential Equations and Agent-Based Modelling and Simulation for Early-Stage Cancer. *PLOS ONE*, *9*(4), e95150. https://doi.org/10.1371/journal.pone.0095150

Filade, T. E., Dareng, E. O., Olawande, T., Fagbohun, T. A., Adebayo, A. O., & Adebamowo, C. A. (2017). Attitude to Human Papillomavirus Deoxyribonucleic Acid-Based Cervical Cancer Screening in Antenatal Care in Nigeria: A Qualitative Study. *Frontiers in Public Health*, *5*(September), 1–10. https://doi.org/10.3389/fpubh.2017.00226

Finn, R. T., Lloyd, B., Patel, Y. A., Allen, J. T., Cornejo, J., Davis, A., McIntosh, T., Ferguson, S., Sims, K., Sudaj, S., Taheri, J., Provenzale, D., & Gellad, Z. F. (2019). Decreasing Endoscopy No-Shows Using a Lean Improvement Framework. *Clinical Gastroenterology and Hepatology*. https://doi.org/10.1016/j.cgh.2019.02.002

Flores, Y. N., Bishai, D. M., Lőrincz, A., Shah, K. V., Lazcano-Ponce, E., Hernández, M., Granados-García, V., Pérez, R., & Salmerón, J. (2011). HPV testing for cervical cancer screening appears more cost-effective than Papanicolau cytology in Mexico. *Cancer Causes and Control*, *22*(2), 261–272. https://doi.org/10.1007/s10552-010-9694-3

Fong, R., & Vedaldi, A. (2019). *Explanations for Attributing Deep Neural Network Predictions BT - Explainable AI: Interpreting, Explaining and Visualizing Deep Learning* (W. Samek, G. Montavon, A. Vedaldi, L. K. Hansen, & K.-R. Müller (eds.); pp. 149–167). Springer International Publishing. https://doi.org/10.1007/978-3-030-28954-6_8

Francis, S. A., Leser, K. A., Esmont, E. E., & Griffith, F. M. (2013). An analysis of key stakeholders' attitudes and beliefs about barriers and facilitating factors in the development of a cervical cancer prevention program in South Africa. *African Journal of Reproductive Health*, *17*(1), 158–168.

Fredrickson, J., Mannino, M., Alqahtani, O., & Banaei-Kashani, F. (2019). Using similarity measures for medical event sequences to predict mortality in trauma patients. *Decision Support Systems*, *116*, 35–47. https://doi.org/https://doi.org/10.1016/j.dss.2018.10.008

Freed, C. R., Hansberry, S. T., & Arrieta, M. I. (2013). Structural and hidden barriers to a local primary health care infrastructure: Autonomy, decisions about primary health care, and the centrality and significance of power. *Research in the Sociology of Health Care*, *31*(2013), 57–81. https://doi.org/10.1108/S0275-4959(2013)0000031006

French, L. R., Turner, K. M., Sharp, D. J., Morley, H., Goldsworthy, L., & Hamilton-Shield, J. (2017). Characteristics of children who do not attend their hospital appointments, and GPs' response: a mixed methods study in primary and secondary care. *British Journal of General Practice*, *67*(660), e483–e489. https://doi.org/10.3399/bjgp17x691373

Frost, L., Jenkins, L. S., & Emmink, B. (2017). Improving access to health care in a rural regional hospital in South Africa: Why do patients miss their appointments? *African Journal of Primary Health Care and Family Medicine*, *9*(1), 1–5. https://doi.org/10.4102/phcfm.v9i1.1255

Gajardo, M., & Urrutia, M. T. (2017). Creencias sobre el cancer cervicouterino y Papanicolaou y su relación con la adherencia al tamizaje. *Revista Chilena de Obstetricia y Ginecología*, *82*(6), 706–712. https://doi.org/10.4067/s0717-75262017000600706

Gale, N. K., Heath, G., Cameron, E., Rashid, S., & Redwood, S. (2013). Using the framework method for the analysis of qualitative data in multi-disciplinary health research. *BMC Medical Research Methodology*, *13*(1), 117. https://doi.org/10.1186/1471-2288-13-117

Garcia-Subirats, I., Vargas, I., Mogollón-Pérez, A. S., De Paepe, P., da Silva, M. R. F., Unger, J. P., Borrell, C., & Vázquez, M. L. (2014). Inequities in access to health care in different health systems: a study in municipalities of central Colombia and north-eastern Brazil. *International Journal for Equity in Health*, *13*(1), 10. https://doi.org/10.1186/1475-9276-13-10

Gashu, K. D., Gelaye, K. A., & Tilahun, B. (2021). Adherence to TB treatment remains low during continuation phase among adult patients in Northwest Ethiopia. *BMC Infectious Diseases*, *21*(1), 1–10. https://doi.org/10.1186/s12879-021-06428-6

Gatumo, M., Gacheri, S., Sayed, A. R., & Scheibe, A. (2018). Women's knowledge and attitudes related to cervical cancer and cervical cancer screening in Isiolo and Tharaka Nithi counties, Kenya: A cross-sectional study. *BMC Cancer*, *18*(1), 1–9. https://doi.org/10.1186/s12885-018-4642-9

Gellasch, P. (2019). The Developmental Screening Behaviors, Skills, Facilitators, and Constraints of Family Nurse Practitioners in Primary Care: A Qualitative Descriptive Study. *Journal of Pediatric Health Care*, *33*(4), 466–477. https://doi.org/10.1016/j.pedhc.2019.01.004

Gemeda, E. Y., Kare, B. B., Negera, D. G., Bona, L. G., Derese, B. D., Akale, N. B., Kebede, K. M., Koboto, D. D., & Tekle, A. G. (2020). Prevalence and Predictor of Cervical Cancer Screening Service Uptake Among Women Aged 25 Years and Above in Sidama Zone, Southern Ethiopia, Using Health Belief Model. *Cancer Control*, *27*(1), 1–8. https://doi.org/10.1177/1073274820954460

Getachew, S., Getachew, E., Gizaw, M., Ayele, W., Addissie, A., & Kantelhardt, E. J. (2019). Cervical cancer screening knowledge and barriers among women in Addis Ababa, Ethiopia. *PLoS ONE*, *14*(5), 1–13. https://doi.org/10.1371/journal.pone.0216522

Giunta, D., Briavore, A., Baun, A., & Luna, D. (2013). Factors associated with nonattendance at clinical medicine scheduled outpatient appointments in a university general hospital. *Patient Preference and Adherence*, *7*(November), 1163–1170. https://doi.org/10.2147/PPA.S51841

Goffman, R. M., Milicevic, A. S., Rodriguez, K. L., Myaskovsky, L., Harris, S. L., Tjader, Y. C., May, J. H., Vargas, D. L., & Monte, R. J. (2017). Modeling Patient No-Show History and Predicting

Future Outpatient Appointment Behavior in the Veterans Health Administration. *Military Medicine*, *182*(5), e1708–e1714. https://doi.org/10.7205/milmed-d-16-00345

Gombe, M. M., Cakouros, B. E., Ncube, G., Zwangobani, N., Mareke, P., Mkwamba, A., Prescott, M. R., Bhatasara, T., Murwira, M., Mangwiro, A. Z., & Prust, M. L. (2020). Key barriers and enablers associated with uptake and continuation of oral pre-exposure prophylaxis (PrEP) in the public sector in Zimbabwe: Qualitative perspectives of general population clients at high risk for HIV. *PLoS ONE*, *15*(1), 1–18. https://doi.org/10.1371/journal.pone.0227632

Gregor, S., Chandra Kruse, L., & Seidel, S. (n.d.). The anatomy of a design principle. In *Journal of the Association for Information Systems*.

Gregor, S., & Hevner, A. R. (2013). Positioning and Presenting Design Science Research for Maximum Impact. *MIS Q.*, *37*(2), 337–356. https://doi.org/10.25300/MISQ/2013/37.2.01

Greibe Andersen, J., Shrestha, A. D., Gyawali, B., Neupane, D., & Kallestrup, P. (2020). Barriers and facilitators to cervical cancer screening uptake among women in Nepal–a qualitative study. *Women and Health*, *60*(9), 963–974. https://doi.org/10.1080/03630242.2020.1781742

Gromisch, E. S., Turner, A. P., Leipertz, S. L., Beauvais, J., & Haselkorn, J. K. (2020). Who is not coming to clinic? A predictive model of excessive missed appointments in persons with multiple sclerosis. *Multiple Sclerosis and Related Disorders*, *38*, 101513. https://doi.org/https://doi.org/10.1016/j.msard.2019.101513

Gu, C., Chan, C. W. H., Chow, K. M., Yang, S., Luo, Y., Cheng, H., & Wang, H. (2018). Understanding the cervical screening behaviour of Chinese women: The role of health care system and health professions. *Applied Nursing Research*, *39*(September 2016), 58–64. https://doi.org/10.1016/j.apnr.2017.09.009

Guetterman, T. C., Sakakibara, R. V, Plano Clark, V. L., Luborsky, M., Murray, S. M., Castro, F. G., Creswell, J. W., Deutsch, C., & Gallo, J. J. (2019). Mixed methods grant applications in the health sciences: An analysis of reviewer comments. *PLOS ONE*, *14*(11), e0225308. https://doi.org/10.1371/journal.pone.0225308

Guidotti, R., Monreale, A., & Ruggieri, S. (2018). A Survey of Methods for Explaining Black Box Models. *ACM Computing Surveys*, *51*(5). https://doi.org/=https://doi.org/10.1145/3236009

Gultekin, M., Ramirez, P. T., Broutet, N., & Hutubessy, R. (2020). World Health Organization call for action to eliminate cervical cancer globally. *International Journal of Gynecological Cancer*, *30*(4), 426–427. https://doi.org/10.1136/ijgc-2020-001285

Guo, C., & Berkhahn, F. (2016). *Entity Embeddings of Categorical Variables*. *1*, 1–9. http://arxiv.org/abs/1604.06737

Guvenc, G., Akyuz, A., & Açikel, C. H. (2011). Health Belief Model Scale for Cervical Cancer and Pap Smear Test: Psychometric testing. *Journal of Advanced Nursing*, *67*(2), 428–437. https://doi.org/10.1111/j.1365-2648.2010.05450.x

Hadi, M., Lawey, A., El-Gorashi, T., & Elmirghani, J. (2019). Using Machine Learning and Big Data Analytics to Prioritize Outpatients in HetNets. *INFOCOM 2019 - IEEE Conference on Computer Communications Workshops, INFOCOM WKSHPS 2019*, 726–731. https://doi.org/10.1109/INFCOMW.2019.8845225

Haimes, Y., Lasdon, L., & Wismer, D. (1971). On a Bicriterion Formulation of the Problems of Integrated System Identification and System Optimization. *IEEE Transactions on Systems, Man, and Cybernetics*, *SMC-1*(3), 296–297. https://doi.org/10.1109/TSMC.1971.4308298

Harvey, H. B., Liu, C., Ai, J., Jaworsky, C., Guerrier, C. E., Flores, E., & Pianykh, O. (2017). Predicting No-Shows in Radiology Using Regression Modeling of Data Available in the Electronic Medical Record. *Journal of the American College of Radiology*, *14*(10), 1303–1309. https://doi.org/10.1016/j.jacr.2017.05.007

Hasahya, O. T., Berggren, V., Sematimba, D., Nabirye, R. C., & Kumakech, E. (2016). Beliefs, perceptions and health-seeking behaviours in relation to cervical cancer: A qualitative study among women in Uganda following completion of an HPV vaccination campaign. *Global Health Action*, *9*(1), 1–9. https://doi.org/10.3402/gha.v9.29336

Heaman, M. I., Sword, W., Elliott, L., Moffatt, M., Helewa, M. E., Morris, H., Gregory, P., Tjaden, L., & Cook, C. (2015). Barriers and facilitators related to use of prenatal care by inner-city women: Perceptions of health care providers. *BMC Pregnancy and Childbirth*, *15*(1), 1–13. https://doi.org/10.1186/s12884-015-0431-5

Hernández Vargas, J. A., Ramírez Barbosa, P. X., Gil Quijano, A. M., Valbuena, A. M., Acuña, L., & González, J. A. (2020). Patterns of breast, prostate and cervical cancer incidence and mortality in Colombia: an administrative registry data analysis. *BMC Cancer*, *20*(1), 1097. https://doi.org/10.1186/s12885-020-07611-9

Hernández Vargas, J. A., Ramírez Barbosa, P. X., Valbuena-Garcia, A. M., Acuña, L., & González-Diaz, J. A. (2021). Factors associated with delays in time to treatment initiation in Colombian women with cervical cancer: A cross-sectional analysis. *Gynecologic Oncology Reports*, *35*. https://doi.org/10.1016/j.gore.2021.100697

Hinman, A. R., & Orenstein, W. A. (2021). Elimination of cervical cancer: Lessons learned from polio and earlier eradication programs. *Preventive Medicine*, *144*(November 2020), 106325. https://doi.org/10.1016/j.ypmed.2020.106325

Hussain-Gambles, M., Neal, R. D., Dempsey, O., Lawlor, D. A., & Hodgson, J. (2004). Missed appointments in primary care: Questionnaire and focus group study of health professionals. *British Journal of General Practice*, *54*(499), 108–113.

Iivari, J., Rotvit Perlt Hansen, M., & Haj-Bolouri, A. (2020). A proposal for minimum reusability evaluation of design principles. *European Journal of Information Systems*, 1–18. https://doi.org/10.1080/0960085X.2020.1793697

Ilevbare, O. E., Adegoke, A. A., & Adelowo, C. M. (2020). Drivers of cervical cancer screening uptake in Ibadan, Nigeria. *Heliyon*, *6*(3), e03505. https://doi.org/10.1016/j.heliyon.2020.e03505

International Agency for Research on Cancer. (2021a). *GLOBOCAN 2020: Cervix uteri Fact sheet*. https://gco.iarc.fr/today/data/factsheets/cancers/23-Cervix-uteri-fact-sheet.pdf

International Agency for Research on Cancer. (2021b). *GLOBOCAN 2020: Colombia Fact sheet*. https://gco.iarc.fr/today/data/factsheets/populations/170-colombia-fact-sheets.pdf

Jefferson, L., Atkin, K., Sheridan, R., Oliver, S., Macleod, U., Hall, G., Forbes, S., Green, T., Allgar, V., & Knapp, P. (2019). Non-attendance at urgent referral appointments for suspected cancer: a qualitative study to gain understanding from patients and GPs. *British Journal of General Practice*, *69*(689), e850 LP-e859. https://doi.org/10.3399/bjgp19X706625

Jones, C. J., Smith, H., & Llewellyn, C. (2014). Evaluating the effectiveness of health belief model interventions in improving adherence: a systematic review. *Health Psychology Review*, *8*(3), 253–269. https://doi.org/10.1080/17437199.2013.802623

Kangmennaang, J., Onyango, E. O., Luginaah, I., & Elliott, S. J. (2018). The next Sub Saharan African epidemic? A case study of the determinants of cervical cancer knowledge and screening in Kenya. *Social Science and Medicine*, *197*(December 2017), 203–212. https://doi.org/10.1016/j.socscimed.2017.12.013

Kheirkhah, P., Feng, Q., Travis, L. M., Tavakoli-Tabasi, S., & Sharafkhaneh, A. (2016). Prevalence, predictors and economic consequences of no-shows. *BMC Health Services Research*, *16*(1), 13. https://doi.org/10.1186/s12913-015-1243-z

Klatte, I. S., Harding, S., & Roulstone, S. (2019). Speech and language therapists' views on parents' engagement in Parent–Child Interaction Therapy (PCIT). *International Journal of Language and Communication Disorders*, *54*(4), 553–564. https://doi.org/10.1111/1460-6984.12459

Kocaöz, S., Özçelik, H., Talas, M. S., Akkaya, F., Özkul, F., Kurtuluş, A., & Ünlü, F. (2018). The Effect of Education on the Early Diagnosis of Breast and Cervix Cancer on the Women's Attitudes and Behaviors Regarding Participating in Screening Programs. *Journal of Cancer Education*, *33*(4), 821–832. https://doi.org/10.1007/s13187-017-1193-8

Kue, J., Szalacha, L. A., Happ, M. B., & Menon, U. (2020). Perceptions of cervical cancer and screening behavior among cambodian and Lao Women in the United States: An exploratory, mixed-methods study. *Journal of Health Care for the Poor and Underserved*, *31*(2), 889–908. https://doi.org/10.1353/hpu.2020.0067

Lacy, N. L., Paulman, A., Reuter, M. D., & Lovejoy, B. (2004). Why we don't come: Patient perceptions on no-shows. *Annals of Family Medicine*, *2*(6), 541–545. https://doi.org/10.1370/afm.123

Lam, Y., Westergaard, R., Kirk, G., Ahmadi, A., Genz, A., Keruly, J., Hutton, H., & Surkan, P. J. (2016). Provider-level and other health systems factors influencing engagement in HIV care: A qualitative study of a vulnerable population. *PLoS ONE*, *11*(7), 1–14. https://doi.org/10.1371/journal.pone.0158759

Laranjeira, C. A. (2013). Portuguese women's knowledge and health beliefs about cervical cancer and its screening. *Social Work in Public Health*, *28*(2), 150–157. https://doi.org/10.1080/19371918.2011.592042

Lau, J., Lim, T.-Z., Wong, G. J., & Tan, K.-K. (2020). The health belief model and colorectal cancer screening in the general population: A systematic review. *Preventive Medicine Reports*, *20*.

Lee, H., Mtengezo, J. T., Kim, D., Makin, M. S., Kang, Y., Malata, A., & Fitzpatrick, J. (2019). Exploring Complicity of Cervical Cancer Screening in Malawi: The Interplay of Behavioral, Cultural, and Societal Influences. *Asia-Pacific Journal of Oncology Nursing*, *7*(1), 18–27. https://doi.org/10.4103/apjon.apjon_48_19

Lee, Y. S., Kim, T. H., & Kim, J. (2018). Association between missed appointment and related factors of patients with cancer in a tertiary hospital. *International Journal of Health Planning and Management*, *33*(3), e873–e882. https://doi.org/10.1002/hpm.2551

Leijdesdorff, S., Klaassen, R., Wairata, D.-J., Rosema, S., van Amelsvoort, T., & Popma, A. (2021). Barriers and facilitators on the pathway to mental health care among 12-25 year olds.

International Journal of Qualitative Studies on Health and Well-Being, *16*(1), 1963110. https://doi.org/10.1080/17482631.2021.1963110

Lewis, A. K., Harding, K. E., Snowdon, D. A., & Taylor, N. F. (2018). Reducing wait time from referral to first visit for community outpatient services may contribute to better health outcomes: A systematic review. *BMC Health Services Research*, *18*(1), 1–14. https://doi.org/10.1186/s12913-018-3669-6

Li, Q., Liu, Q., Chen, X., Tan, X., Zhang, M., Tuo, J., Xiang, Q., Yu, Q., & Zhu, Z. (2020). Protection motivation theory in predicting cervical cancer screening participation: A longitudinal study in rural Chinese women. *Psycho-Oncology*, *29*(3), 564–571. https://doi.org/https://doi.org/10.1002/pon.5307

Li, Y., Lawley, M. A., Siscovick, D. S., Zhang, D., & Pagán, J. A. (2016). Agent-Based Modeling of Chronic Diseases: A Narrative Review and Future Research Directions. *Preventing Chronic Disease*, *13*, E69. https://doi.org/10.5888/pcd13.150561

Liebermann, E. J., VanDevanter, N., Hammer, M. J., & Fu, M. R. (2018). Social and Cultural Barriers to Women's Participation in Pap Smear Screening Programs in Low- and Middle-Income Latin American and Caribbean Countries: An Integrative Review. *Journal of Transcultural Nursing*, *29*(6), 591–602. https://doi.org/10.1177/1043659618755424

Liebermann, E. J., VanDevanter, N., Shirazian, T., Frías Gúzman, N., Niles, M., Healton, C., & Ompad, D. (2020). Barriers to Cervical Cancer Screening and Treatment in the Dominican Republic: Perspectives of Focus Group Participants in the Santo Domingo Area. *Journal of Transcultural Nursing*, *31*(2), 121–127. https://doi.org/10.1177/1043659619846247

Llovet, D., Serenity, M., Conn, L. G., Bravo, C. A., McCurdy, B. R., Dubé, C., Baxter, N. N., Paszat, L., Rabeneck, L., Peters, A., & Tinmouth, J. (2018). Reasons For Lack of Follow-up Colonoscopy Among Persons With A Positive Fecal Occult Blood Test Result: A Qualitative Study. *American Journal of Gastroenterology*, *113*(August), 1872–1880. https://doi.org/10.1038/s41395-018-0381-4

Logan, L., & McIlfatrick, S. (2011). Exploring women's knowledge, experiences and perceptions of cervical cancer screening in an area of social deprivation. *European Journal of Cancer Care*, *20*(6), 720–727. https://doi.org/10.1111/j.1365-2354.2011.01254.x

Lou, S., Frumer, M., Olesen, S., Nielsen, A. H., & Væggemose, U. (2016). Danish patients are positive towards fees for nonattendance in public hospitals. A qualitative study. *Danish Medical Journal*, *63*(7), 7–10.

Lu, J. C. ., Dorfman, A. L., Ghadimi Mahani, M., Lowery, R., Yu, S., & Agarwal, P. P. (2017). Predictors of missed appointments in patients referred for congenital or pediatric cardiac magnetic resonance. *Pediatric Radiology*, *47*(8), 911–916. https://doi.org/10.1007/s00247-017-3851-8

Lyon, R., & Reeves, P. J. (2006). An investigation into why patients do not attend for out-patient radiology appointments. *Radiography*, *12*(4), 283–290. https://doi.org/10.1016/j.radi.2005.09.003

Mabotja, M. C., Levin, J., & Kawonga, M. (2021). Beliefs and perceptions regarding cervical cancer and screening associated with Pap smear uptake in Johannesburg: A crosssectional study. *PLoS ONE*, *16*(2 February), 1–13. https://doi.org/10.1371/journal.pone.0246574

Machado, A. T., Azeredo, M., Werneck, F., & Lucas, S. D. (2011). *Who did not appear ? First dental visit absences in secondary care in a major Brazilian city : a cross-sectional study Quem não compareceu ? Ausências às primeiras consultas odontológicas na atenção secundária em um município brasileiro de grande porte :* . 289–298. https://doi.org/10.1590/1413-81232014201.01012014

Magadzire, B. P., Mathole, T., & Ward, K. (2017). Reasons for missed appointments linked to a public-sector intervention targeting patients with stable chronic conditions in South Africa: Results from in-depth interviews and a retrospective review of medical records. *BMC Family Practice*, *18*(1), 1–10. https://doi.org/10.1186/s12875-017-0655-8

Mahajan, A., Harish, S. P., & Urpelainen, J. (2020). The behavioral impact of basic energy access: A randomized controlled trial with solar lanterns in rural India. *Energy for Sustainable Development*, *57*, 214–225. https://doi.org/10.1016/j.esd.2020.04.005

Maharjan, M., Thapa, N., Panthi, D., Maharjan, N., Petrini, M. A., & Jiong, Y. (2020). Health beliefs and practices regarding cervical cancer screening among women in Nepal: A descriptive cross-sectional study. *Nursing and Health Sciences*, *22*(4), 1084–1093. https://doi.org/10.1111/nhs.12775

Makurirofa, L., Mangwiro, P., James, V., Milanzi, A., Mavu, J., Nyamuranga, M., & Kamtauni, S. (2019). Women's knowledge, attitudes and practices (KAP) relating to breast and cervical cancers in rural Zimbabwe: A cross sectional study in Mudzi District, Mashonaland East Province. *BMC Public Health*, *19*(1), 1–9. https://doi.org/10.1186/s12889-018-6333-5

Maldonado, S., Miranda, J., Olaya, D., Vásquez, J., & Verbeke, W. (2021). Redefining profit metrics for boosting student retention in higher education. *Decision Support Systems*, *143*, 113493.

https://doi.org/https://doi.org/10.1016/j.dss.2021.113493

Malhotra, C., Bilger, M., Liu, J., & Finkelstein, E. (2016). Barriers to Breast and Cervical Cancer Screening in Singapore: a Mixed Methods Analysis. *Asian Pacific Journal of Cancer Prevention : APJCP*, *17*(8), 3887–3895.

Mander, G. T. W., Reynolds, L., Cook, A., & Kwan, M. M. (2018). Factors associated with appointment non-attendance at a medical imaging department in regional Australia: a retrospective cohort analysis. *Journal of Medical Radiation Sciences*, *65*(3), 192–199. https://doi.org/10.1002/jmrs.284

Marshall, D. A., Burgos-Liz, L., Ijzerman, M. J., Crown, W., Padula, W. V., Wong, P. K., Pasupathy, K. S., Higashi, M. K., & Osgood, N. D. (2015). Selecting a dynamic simulation modeling method for health care delivery research - Part 2: Report of the ISPOR dynamic simulation modeling emerging good practices task force. *Value in Health*, *18*(2), 147–160. https://doi.org/10.1016/j.jval.2015.01.006

Marshall, D. A., Burgos-Liz, L., Ijzerman, M. J., Osgood, N. D., Padula, W. V., Higashi, M. K., Wong, P. K., Pasupathy, K. S., & Crown, W. (2015). Applying dynamic simulation modeling methods in health care delivery research - The SIMULATE checklist: Report of the ISPOR simulation modeling emerging good practices task force. *Value in Health*, *18*(1), 5–16. https://doi.org/10.1016/j.jval.2014.12.001

Marshall, D., Quinn, C., Child, S., Shenton, D., Pooler, J., Forber, S., & Byng, R. (2016). What IAPT services can learn from those who do not attend. *Journal of Mental Health*, *25*(5), 410–415. https://doi.org/10.3109/09638237.2015.1101057

Martin, C., Perfect, T., & Mantle, G. (2005). Non-attendance in primary care: The views of patients and practices on its causes, impact and solutions. *Family Practice*, *22*(6), 638–643. https://doi.org/10.1093/fampra/cmi076

Maseko, T. N., Huang, H. C., & Lin, K. C. (2019). Cervical cancer screening behavior of African women: The Rosenstock health belief model assessment. *Health Care for Women International*, *0*(0), 1–16. https://doi.org/10.1080/07399332.2019.1677665

Matenge, T. G., & Mash, B. (2018). Barriers to accessing cervical cancer screening among HIV positive women in Kgatleng district, Botswana: A qualitative study. *PLoS ONE*, *13*(10), 1–13. https://doi.org/10.1371/journal.pone.0205425

Mbada, C. E., Nonvignon, J., Ajayi, O., Pt, B. M. R., Dada, O. O., Awotidebe, T. O., Johnson, O. E., Olarinde, A., & Aat, B. S. (2013). Impact of missed appointments for out- patient physiotherapy on cost , efficiency , and patients ' recovery. *Hong Kong Physiotherapy Journal*, *31*(1), 30–35. https://doi.org/10.1016/j.hkpj.2012.12.001

McComb, S., Sands, L., Zhang, L., Tian, Z., Lawley, M., Frazier, S., & Turkcan, A. (2017). Cancelled Primary Care Appointments: A Prospective Cohort Study of Diabetic Patients. *Journal of Medical Systems*, *41*(4). https://doi.org/10.1007/s10916-017-0700-0

McQueenie, R., Ellis, D. A., McConnachie, A., Wilson, P., & Williamson, A. E. (2019). Morbidity, mortality and missed appointments in healthcare: A national retrospective data linkage study. *BMC Medicine*, *17*(1), 1–9. https://doi.org/10.1186/s12916-018-1234-0

Mehraban, S. S. Z., Namdar, A., & Naghizadeh, M. M. (2018). Assessment of preventive behavior for cervical cancer with the health belief model. *Asian Pacific Journal of Cancer Prevention*, *19*(8), 2155–2163. https://doi.org/10.22034/APJCP.2018.19.8.2155

Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2021). A survey on bias and fairness in machine learning. *ACM Computing Surveys (CSUR)*, *54*(6), 1–35.

Michelson, D., & Day, C. (2014). Improving attendance at child and adolescent mental health services for families from socially disadvantaged communities: Evaluation of a pre-intake engagement intervention in the UK. *Administration and Policy in Mental Health and Mental Health Services Research*, *41*(2), 252–261. https://doi.org/10.1007/s10488-012-0462-4

Mikhaeil, J. S., Celo, E., Shanahan, J., Harvey, B., Sipos, B., & Law, M. P. (2019). Attend: A Two-Pronged Trial to Eliminate No Shows in Diagnostic Imaging at a Community-Based Hospital. *Journal of Medical Imaging and Radiation Sciences*, *50*(1), 36–42. https://doi.org/10.1016/j.jmir.2018.10.012

Millhiser, W. P., & Veral, E. A. (2019). A decision support system for real-time scheduling of multiple patient classes in outpatient services. *Health Care Management Science*, *22*, 180–195. https://doi.org/10.1007/s10729-018-9430-1

Minick, S. G., May, S. B., Rivet Amico, K., Cully, J., Davila, J. A., Kallen, M. A., & Giordano, T. P. (2018). Participants' perspectives on improving retention in HIV care after hospitalization: A post-study qualitative investigation of the MAPPS study. *PLoS ONE*, *13*(8), 1–14. https://doi.org/10.1371/journal.pone.0202917

Resolution 603280, (2018) (testimony of Ministerio de Salud y Proteccion Social). https://www.minsalud.gov.co/Normatividad_Nuevo/Resolución No. 3280 de 20183280.pdf

Resolution 276, (2019) (testimony of Ministerio de Salud y Protección Social). http://achc.org.co/wp-content/uploads/2019/02/RES-276-19-Modifica-tiempos-para-implementación-acciones-Ruta-Perinatal.pdf

Mkhonta, S. S., & Shirinde, J. (2021). Registered nurses' perspectives on barriers of cervical cancer screening in swaziland: A qualitative study. *Pan African Medical Journal*, *38*, 1–12. https://doi.org/10.11604/pamj.2021.38.295.22431

Modibbo, F. I., Dareng, E., Bamisaye, P., Jedy-Agba, E., Adewole, A., Oyeneyin, L., Olaniyan, O., & Adebamowo, C. (2016). Qualitative study of barriers to cervical cancer screening among Nigerian women. *BMJ Open*, *6*(1). https://doi.org/10.1136/bmjopen-2015-008533

Mohammadi, I., Wu, H., Turkcan, A., Toscos, T., & Doebbeling, B. N. (2018). Data Analytics and Modeling for Appointment No-show in Community Health Centers. *Journal of Primary Care and Community Health*, *9*. https://doi.org/10.1177/2150132718811692

Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G. (2009). Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *BMJ*, *339*, b2535. https://doi.org/10.1136/bmj.b2535

Morris, M. D., Popper, S. T., Rodwell, T. C., Brodine, S. K., & Brouwer, K. C. (2009). Healthcare barriers of refugees post-resettlement. *Journal of Community Health*, *34*(6), 529–538. https://doi.org/10.1007/s10900-009-9175-3

Moss, J. L., Leach, K., Stoltzfus, K. C., Granzow, M., Reiter, P. L., Onega, T., Klesges, L. M., & Ruffin, M. T. (2021). Multilevel Associations with Cancer Screening Among Women in Rural, Segregated Communities Within the Northeastern USA: a Mixed-Methods Study. *Journal of Cancer Education*, *0123456789*. https://doi.org/10.1007/s13187-021-02069-0

Mugassa, A. M., & Frumence, G. (2020). Factors influencing the uptake of cervical cancer screening services in Tanzania: A health system perspective from national and district levels. *Nursing Open*, *7*(1), 345–354. https://doi.org/10.1002/nop2.395

Munthali, A. C., Ngwira, B. M., & Taulo, F. (2015). Exploring barriers to the delivery of cervical cancer screening and early treatment services in Malawi: Some views from service providers. *Patient Preference and Adherence*, *9*, 501–508. https://doi.org/10.2147/PPA.S69286

Murillo, R., Wiesner, C., Cendales, R., PiÃ\pmeros, M., & Tovar, S. (2011). Comprehensive evaluation of cervical cancer screening programs: the case of Colombia. *Salud Pública México*, *53*, 469–477. http://www.scielo.org.mx/scielo.php?script=sci_arttext&pid=S0036-

36342011000600002&nrm=iso

Murphy, P. J., Marlow, L. A. V., Waller, J., & Vrinten, C. (2018). What is it about a cancer diagnosis that would worry people? A population-based survey of adults in England. *BMC Cancer*, *18*(1), 1–10. https://doi.org/10.1186/s12885-017-3963-4

Musa, J., Achenbach, C. J., O'Dwyer, L. C., Evans, C. T., McHugh, M., Hou, L., Simon, M. A., Murphy, R. L., & Jordan, N. (2017). Effect of cervical cancer education and provider recommendation for screening on screening rates: A systematic review and meta-analysis. *PLOS ONE*, *12*(9), e0183924. https://doi.org/10.1371/journal.pone.0183924

Muthukrishnan, R., & Rohini, R. (2016). LASSO: A feature selection technique in predictive modeling for machine learning. *2016 IEEE International Conference on Advances in Computer Applications (ICACA)*, 18–20. https://doi.org/10.1109/ICACA.2016.7887916

Naz, M. S. G., Simbar, M., Fakari, F. R., & Ghasemi, V. (2018). Effects of model-based interventions on breast cancer screening behavior of women: a systematic review. *Asian Pacific Journal of Cancer Prevention: APJCP*, *19*(8), 2031.

Ng'Ang'A, A., Nyangasi, M., Nkonge, N. G., Gathitu, E., Kibachio, J., Gichangi, P., Wamai, R. G., & Kyobutungi, C. (2018). Predictors of cervical cancer screening among Kenyan women: Results of a nested case-control study in a nationally representative survey. *BMC Public Health*, *18*(Suppl 3). https://doi.org/10.1186/s12889-018-6054-9

Nigussie, T., Admassu, B., & Nigussie, A. (2019). Cervical cancer screening service utilization and associated factors among age-eligible women in Jimma town using health belief model, South West Ethiopia. *BMC Women's Health*, *19*(1), 1–10. https://doi.org/10.1186/s12905-019-0826-y

Nishimura, H., Yeh, P. T., Oguntade, H., Kennedy, C. E., & Narasimhan, M. (2021). HPV self-sampling for cervical cancer screening: a systematic review of values and preferences. *BMJ Global Health*, *6*(5), e003743. https://doi.org/10.1136/bmjgh-2020-003743

Noman, S., Shahar, H. K., Abdul Rahman, H., Ismail, S., Abdulwahid Al-Jaberi, M., & Azzani, M. (2021). The Effectiveness of Educational Interventions on Breast Cancer Screening Uptake, Knowledge, and Beliefs among Women: A Systematic Review. In *International Journal of Environmental Research and Public Health* (Vol. 18, Issue 1). https://doi.org/10.3390/ijerph18010263

Norris, J. B., Kumar, C., Chand, S., Moskowitz, H., Shade, S. A., & Willis, D. R. (2014). An empirical investigation into factors affecting patient cancellations and no-shows at outpatient clinics. *Decision Support Systems*, *57*(1), 428–443. https://doi.org/10.1016/j.dss.2012.10.048

Nuche-Berenguer, B., & Sakellariou, D. (2019). Socioeconomic determinants of cancer screening utilisation in Latin America: A systematic review. *PLoS ONE*, *14*(11), 1–18. https://doi.org/10.1371/journal.pone.0225667

O'Brien, B. C., Harris, I. B., Beckman, T. J., Reed, D. A., & Cook, D. A. (2014). Standards for reporting qualitative research: A synthesis of recommendations. *Academic Medicine*, *89*(9), 1245–1251. https://doi.org/10.1097/ACM.0000000000000388

O'Donovan, J., O'Donovan, C., & Nagraj, S. (2019). The role of community health workers in cervical cancer screening in low-income and middle-income countries: A systematic scoping review of the literature. *BMJ Global Health*, *4*(3), 1–8. https://doi.org/10.1136/bmjgh-2019-001452

Odonkor, C. A., Christiansen, S., Chen, Y., Sathiyakumar, A., Chaudhry, H., Cinquegrana, D., Lange, J., He, C., & Cohen, S. P. (2017). Factors Associated with Missed Appointments at an Academic Pain Treatment Center: A Prospective Year-Long Longitudinal Study. *Anesthesia and Analgesia*, *125*(2), 562–570. https://doi.org/10.1213/ANE.0000000000001794

OECD. (2016). *Colombia still faces challenges to improve health care quality*. http://www.oecd.org/health/colombia-still-faces-challenges-to-improve-health-care-quality.htm

Ofei-Dodoo, S., Kellerman, R., Hartpence, C., Mills, K., & Manlove, E. (2019). Why Patients Miss Scheduled Outpatient Appointments at Urban Academic Residency Clinics. *Kansas Journal of Medicine*, *12*(3), 57–61. https://doi.org/10.17161/kjm.v12i3.11793

Ogunsiji, O., Wilkes, L., Peters, K., & Jackson, D. (2013). Knowledge, attitudes and usage of cancer screening among West African migrant women. *Journal of Clinical Nursing*, *22*(7–8), 1026–1033. https://doi.org/10.1111/jocn.12063

Okada, S., Ohzeki, M., & Taguchi, S. (2019). Efficient partition of integer optimization problems with one-hot encoding. *Scientific Reports*, *9*(1), 1–12. https://doi.org/10.1038/s41598-019-49539-6

Oketch, S. Y., Kwena, Z., Choi, Y., Adewumi, K., Moghadassi, M., Bukusi, E. A., & Huchko, M. J. (2019). Perspectives of women participating in a cervical cancer screening campaign with community-based HPV self-sampling in rural western Kenya: A qualitative study. *BMC*

Women's Health, *19*(1), 1–10. https://doi.org/10.1186/s12905-019-0778-2

Olwanda, E., Shen, J., Kahn, J. G., Bryant-Comstock, K., & Huchko, M. J. (2018). Comparison of patient flow and provider efficiency of two delivery strategies for HPV-based cervical cancer screening in Western Kenya: a time and motion study. *Global Health Action*, *11*(1). https://doi.org/10.1080/16549716.2018.1451455

Oneto, L., & Chiappa, S. (2020). Fairness in machine learning. In *Recent Trends in Learning From Data* (pp. 155–196). Springer, Cham.

Onyenwenyi, A. O. C., & McHunu, G. G. (2018). Barriers to cervical cancer screening uptake among rural women in South West Nigeria: A qualitative study. *South African Journal of Obstetrics and Gynaecology*, *24*(1), 22–26. https://doi.org/10.7196/SAJOG.2018.v24i1.1290

Parente, C. A., Salvatore, D., Gallo, G. M., & Cipollini, F. (2018). Using overbooking to manage no-shows in an Italian healthcare center. *BMC Health Services Research*, *18*(1), 1–12. https://doi.org/10.1186/s12913-018-2979-z

Parker, L. J., Gaugler, J. E., Samus, Q., & Gitlin, L. N. (2019). Adult Day Service Use Decreases Likelihood of a Missed Physician's Appointment Among Dementia Caregivers. *Journal of the American Geriatrics Society*, 1467–1471. https://doi.org/10.1111/jgs.15995

Paz Soldan, V. A., Lee, F. H., Carcamo, C., Holmes, K. K., Garnett, G. P., & Garcia, P. (2008). Who is getting Pap smears in urban Peru? *International Journal of Epidemiology*, *37*(4), 862–869. https://doi.org/10.1093/ije/dyn118

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Bllondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, A., Cournapeau, D., Brucher, M., M, P., & Duchesnay, E. (2011). Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research*, *12*(85), 2825–2830. https://doi.org/10.1145/2786984.2786995

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A design science research methodology for information systems research. *Journal of Management Information Systems*, *24*(3), 45–77. https://doi.org/10.2753/MIS0742-1222240302

Pegon-Machat, E., Tubert-Jeannin, S., Loignon, C., Landry, A., & Bedos, C. (2009). Dentists' experience with low-income patients benefiting from a public insurance program. *European Journal of Oral Sciences*, *117*(4), 398–406. https://doi.org/10.1111/j.1600-0722.2009.00643.x

Pilleron, S., Cabasag, C. J., Ferlay, J., Bray, F., Luciani, S., Almonte, M., & Piñeros, M. (2020).

Cervical cancer burden in Latin America and the Caribbean: Where are we? *International Journal of Cancer*, *n/a*(n/a). https://doi.org/10.1002/ijc.32956

Piñeros, M., Laversanne, M., Barrios, E., Cancela, M. de C., de Vries, E., Pardo, C., & Bray, F. (2022). An updated profile of the cancer burden, patterns and trends in Latin America and the Caribbean. *The Lancet Regional Health – Americas*. https://doi.org/10.1016/j.lana.2022.100294

Policia Nacional de Colombia. (2019). *Crime statistics*. https://www.policia.gov.co/grupo-información-criminalidad/estadistica-delictiva

Poll, R., Allmark, P., & Tod, A. M. (2017). Reasons for missed appointments with a hepatitis C outreach clinic: A qualitative study. *International Journal of Drug Policy*, *39*, 130–137. https://doi.org/10.1016/j.drugpo.2015.12.027

Pope, C., & Mays, N. (2020). The role of Theory in Qualitative Research. In *Quality in Qualitative Research* (pp. 15–26). https://doi.org/10.1002/9781119410867.ch15

Price, R. A., Zapka, J., Edwards, H., & Taplin, S. H. (2010). Organizational factors and the cancer screening process. *Journal of the National Cancer Institute - Monographs*, *40*, 38–57. https://doi.org/10.1093/jncimonographs/lgq008

Quaife, S. L., Waller, J., von Wagner, C., & Vrinten, C. (2018). Cancer worries and uptake of breast, cervical, and colorectal cancer screening: A population-based survey in England. *Journal of Medical Screening*. https://doi.org/10.1177/0969141318796258

Rasul, V. H., Cheraghi, M. A., & Moghdam, Z. B. (2016). Barriers to cervical cancer screening among Iraqi Kurdish women: A qualitative study. *Acta Medica Mediterranea*, *32*(SpecialIssue4), 1249–1256.

Raymond, N. C., Osman, W., O'Brien, J. M., Ali, N., Kia, F., Mohamed, F., Mohamed, A., Goldade, K. B., Pratt, R., & Okuyemi, K. (2014). Culturally informed views on cancer screening: A qualitative research study of the differences between older and younger Somali immigrant women. *BMC Public Health*, *14*(1), 1–8. https://doi.org/10.1186/1471-2458-14-1188

Reis, N., Bebis, H., Kose, S., Sis, A., Engin, R., & Yavan, T. (2012). Knowledge, behavior and beliefs related to cervical cancer and screening among Turkish women. *Asian Pacific Journal of Cancer Prevention*, *13*(4), 1463–1470. https://doi.org/10.7314/APJCP.2012.13.4.1463

Ritchie, D., Van den Broucke, S., & Van Hal, G. (2020). The health belief model and theory of planned behavior applied to mammography screening: A systematic review and meta-analysis. *Public Health Nursing*.

Rivillas, J. C., & Colonia, F. D. (2017). Reducing causes of inequity: policies focused on social determinants of health during generational transitions in Colombia. *Global Health Action*, *10*(1), 1349238. https://doi.org/10.1080/16549716.2017.1349238

Rosenbaum, J. I., Hippe, D. S., Bhargava, P., Gunn, M. L., Mieloszyk, R. J., & Hall, C. S. (2018). Understanding Why Patients No-Show: Observations of 2.9 Million Outpatient Imaging Visits Over 16 Years. *Journal of the American College of Radiology*, *15*(7), 944–950. https://doi.org/10.1016/j.jacr.2018.03.053

Rosenstock, I. M., Strecher, V. J., & Becker, M. H. (1988). Social Learning Theory and the Health Belief Model. *Health Education Quarterly*, *15*(2), 175–183. https://doi.org/10.1177/109019818801500203

Rosentock, I. M. (1960). What research in motivation suggests for public health. *American Journal of Public Health and the Nation's Health*, *50*(3 Pt 1), 295–302. https://doi.org/10.2105/ajph.50.3_pt_1.295

Rossell, N., Challinor, J., Gigengack, R., & Reis, R. (2017). Choosing a miracle: Impoverishment, mistrust, and discordant views in abandonment of treatment of children with cancer in El Salvador. *Psycho-Oncology*, *26*(9), 1324–1329. https://doi.org/10.1002/pon.4302

Rotem, N., Yair, G., & Shustak, E. (2021). Open the gates wider: affirmative action and dropping out. *Higher Education*, *81*(3), 551–566. https://doi.org/10.1007/s10734-020-00556-9

Roux, A. N., Kenfack, B., Ndjalla, A., Sormani, J., Wisniak, A., Tatrai, K., Vassilakos, P., Petignat, P., & Schmidt, N. (2021). Barriers to cervical cancer prevention in rural Cameroon: A qualitative study on healthcare providers' perspective. *BMJ Open*, *11*(6), 1–8. https://doi.org/10.1136/bmjopen-2020-043637

Ruggeri, K., Folke, T., Benzerga, A., Verra, S., Büttner, C., Steinbeck, V., Yee, S., & Chaiyachati, K. (2020). Nudging New York: adaptive models and the limits of behavioral interventions to reduce no-shows and health inequalities. *BMC Health Services Research*, *20*(1), 363. https://doi.org/10.1186/s12913-020-05097-6

Sadler, L., Albrow, R., Shelton, R., Kitchener, H., & Brabin, L. (2013). Development of a pre-notification leaflet to encourage uptake of cervical screening at first invitation: a qualitative study. *Health Education Research*, *28*(5), 793–802. https://doi.org/10.1093/her/cys103

Saleh, M., Caron, J., Hernandez, S., & Boyd, L. (2021). Determinants of Clinic Absenteeism in

Gynecologic Oncology Clinic at a Safety Net Hospital. *Journal of Community Health*, *46*(2), 399–404. https://doi.org/10.1007/s10900-020-00942-5

Samami, E., Seyedi-Andi, S., Bayat, B., Shojaeizadeh, D., & Tori, N. (2021). The effect of educational intervention based on the health belief model on knowledge, attitude, and function of women about Pap smear test at Iranian health centers: A randomized controlled clinical trial. *Journal of Education and Health Promotion*, *10*(1). https://doi.org/10.4103/jehp.jehp_33_20

Samek, W., Binder, A., Montavon, G., Lapuschkin, S., & Müller, K. R. (2017). Evaluating the visualization of what a deep neural network has learned. *IEEE Transactions on Neural Networks and Learning Systems*, *28*(11), 2660–2673. https://doi.org/10.1109/TNNLS.2016.2599820

Samek, W., Wiegand, T., & Müller, K.-R. (2017). *Explainable Artificial Intelligence: Understanding, Visualizing and Interpreting Deep Learning Models*. http://arxiv.org/abs/1708.08296

Sandelowski, M. (2000). Combining Qualitative and Quantitative Sampling, Data Collection, and Analysis Techniques in Mixed-Method Studies. *Research in Nursing & Health*, *23*(3), 246–255. https://doi.org/10.1002/1098-240X(200006)23:3<246::AID-NUR9>3.0.CO;2-H

Schoenberg, N. E., Kruger, T. M., Bardach, S., & Howell, B. M. (2013). Appalachian women's perspectives on breast and cervical cancer screening. *Rural and Remote Health*, *13*(3), 2452.

Schwebel, F. J., & Larimer, M. E. (2018). Using text message reminders in health care services: A narrative literature review. *Internet Interventions*, *13*(June), 82–104. https://doi.org/10.1016/j.invent.2018.06.002

Schwennesen, N., Henriksen, J. E., & Willaing, I. (2016). Patient explanations for non-attendance at type 2 diabetes self-management education: A qualitative study. *Scandinavian Journal of Caring Sciences*, *30*(1), 187–192. https://doi.org/10.1111/scs.12245

Secretaría Distrital de Planeación. (2018). *Caracterizacion Socioconomica: Encuestas SISBEN III*. http://www.sdp.gov.co/sites/default/files/caracterizacion_2018_dic.pdf

Shawi, R. El, Sherif, Y., Al-Mallah, M., & Sakr, S. (2019). Interpretability in HealthCare A Comparative Study of Local Machine Learning Interpretability Techniques. *2019 IEEE 32nd International Symposium on Computer-Based Medical Systems (CBMS)*, 275–280. https://doi.org/10.1109/CBMS.2019.00065

Sheppard, V. B., Huei-yu Wang, J., Eng-Wong, J., Martin, S. H., Hurtado-de-Mendoza, A., & Luta, G.

(2013). Promoting mammography adherence in underserved women: the telephone coaching adherence study. *Contemporary Clinical Trials*, *35*(1), 35–42. https://doi.org/10.1016/j.cct.2013.02.005

Sherbuk, J. E., Tabackman, A., McManus, K. A., Kemp Knick, T., Schexnayder, J., Flickinger, T. E., & Dillingham, R. (2020). A qualitative study of perceived barriers to hepatitis C care among people who did not attend appointments in the non-urban US South. *Harm Reduction Journal*, *17*(1), 64. https://doi.org/10.1186/s12954-020-00409-9

Shi, Z. R., Wang, C., & Fang, F. (2020). *Artificial Intelligence for Social Good: A Survey*. 1–78. http://arxiv.org/abs/2001.01818

Shrestha, M. P., Hu, C., & Taleban, S. (2017). Appointment Wait Time, Primary Care Provider Status, and Patient Demographics are Associated with Nonattendance at Outpatient Gastroenterology Clinic. *Journal of Clinical Gastroenterology*, *51*(5), 433–438. https://doi.org/10.1097/MCG.0000000000000706

Shuja, A., Harris, C., Aldridge, P., Malespin, M., & De Melo, S. W. (2019). Predictors of No-show Rate in the GI Endoscopy Suite at a Safety Net Academic Medical Center. *Journal of Clinical Gastroenterology*, *53*(1), 29–33. https://doi.org/10.1097/MCG.0000000000000928

Simbar, M., Ghazanfarpour, M., & Abdolahian, S. (2020). Effects of training based on the health belief model on Iranian women’s performance about cervical screening: A systematic review and meta-analysis. *Journal of Education and Health Promotion*, *9*, 179. https://doi.org/10.4103/jehp.jehp_684_19

Sinclair, A., & Alexander, H. A. (2012). Using outreach to involve the hard-to-reach in a health check: What difference does it make? *Public Health*, *126*(2), 87–95. https://doi.org/10.1016/j.puhe.2011.11.004

Sivaram, S., Majumdar, G., Perin, D., Nessa, A., Broeders, M., Lynge, E., Saraiya, M., Segnan, N., Sankaranarayanan, R., Rajaraman, P., Trimble, E., Taplin, S., Rath, G. K., & Mehrotra, R. (2018). Population-based cancer screening programmes in low-income and middle-income countries: regional consultation of the International Cancer Screening Network in India. *The Lancet Oncology*, *19*(2), e113–e122. https://doi.org/10.1016/S1470-2045(18)30003-2

Smith-Miller, C. A., Berry, D. C., & Miller, C. T. (2020). The Space Between: Transformative Learning and Type 2 Diabetes Self-Management. *Hispanic Health Care International*, *18*(2), 85–97. https://doi.org/10.1177/1540415319888435

Smith, B. M., Martinez, R. N., Evans, C. T., Saban, K. L., Balbale, S., Proescher, E. J., Stroupe, K., & Hogan, T. P. (2018). Barriers and strategies for coordinating care among veterans with traumatic brain injury: a mixed methods study of VA polytrauma care team members. *Brain Injury*, *32*(6), 755–762. https://doi.org/10.1080/02699052.2018.1444205

Smith, M., & Mercado-Sierra, M. (2021). Health beliefs as a predictor of screening behaviors among college students. *Social Work in Public Health*, *00*(00), 1–14. https://doi.org/10.1080/19371918.2021.1905130

So, W. K. W., Kwong, A. N. L., Chen, J. M. T., Chan, J. C. Y., Law, B. M. H., Sit, J. W. H., & Chan, C. W. H. (2019). A Theory-Based and Culturally Aligned Training Program on Breast and Cervical Cancer Prevention for South Asian Community Health Workers: A Feasibility Study. *Cancer Nursing*, *42*(2). https://journals.lww.com/cancernursingonline/Fulltext/2019/03000/A_Theory_Based_and_Culturally_Aligned_Training.13.aspx

Spadea, T., Bellini, S., Kunst, A., Stirbu, I., & Costa, G. (2010). The impact of interventions to improve attendance in female cancer screening among lower socioeconomic groups: A review. *Preventive Medicine*, *50*(4), 159–164. https://doi.org/https://doi.org/10.1016/j.ypmed.2010.01.007

Spencer, L., Ritchie, J., & O'Connor, W. (2014). Analysis: Principles and Processes. In *Qualitative Research Practice A guide for social science students & researchers* (pp. 269–343).

Srinivas, S., & Ravindran, A. R. (2018). Optimizing outpatient appointment system using machine learning algorithms and scheduling rules: A prescriptive analytics framework. *Expert Systems with Applications*, *102*, 245–261. https://doi.org/10.1016/j.eswa.2018.02.022

Steiner, J. F., Shainline, M. R., Dahlgren, J. Z., Kroll, A., & Xu, S. (2018). Optimizing number and timing of appointment reminders: A randomized trial. *American Journal of Managed Care*, *24*(8), 377–384.

Strutton, R., Du Chemin, A., Stratton, I. M., & Forster, A. S. (2016). System-level and patient-level explanations for non-attendance at diabetic retinopathy screening in Sutton and Merton (London, UK): A qualitative analysis of a service evaluation. *BMJ Open*, *6*(5), 1–6. https://doi.org/10.1136/bmjopen-2015-010952

Sundstrom, B., Smith, E., Delay, C., Luque, J. S., Davila, C., Feder, B., Paddock, V., Poudrier, J., Pierce, J. Y., & Brandt, H. M. (2019). A reproductive justice approach to understanding women's experiences with HPV and cervical cancer prevention. *Social Science and Medicine*, *232*(May), 289–297. https://doi.org/10.1016/j.socscimed.2019.05.010

Sung, H., Ferlay, J., Siegel, R. L., Laversanne, M., Soerjomataram, I., Jemal, A., & Bray, F. (2021). Global Cancer Statistics 2020: GLOBOCAN Estimates of Incidence and Mortality Worldwide for 36 Cancers in 185 Countries. *CA: A Cancer Journal for Clinicians*, *71*(3), 209–249. https://doi.org/https://doi.org/10.3322/caac.21660

Tae, K. H., & Whang, S. E. (2021). Slice Tuner: A Selective Data Acquisition Framework for Accurate and Fair Machine Learning Models. In *Proceedings of the ACM SIGMOD International Conference on Management of Data* (Vol. 1, Issue 1). Association for Computing Machinery. https://doi.org/10.1145/3448016.3452792

Tatari, C. R., Andersen, B., Andersen, B., Brogaard, T., Badre-Esfahani, S. K., Badre-Esfahani, S. K., Badre-Esfahani, S. K., Jaafar, N., & Kirkegaard, P. (2020). Perceptions about cancer and barriers towards cancer screening among ethnic minority women in a deprived area in Denmark - A qualitative study. *BMC Public Health*, *20*(1), 1–10. https://doi.org/10.1186/s12889-020-09037-1

Thomas, L., Crook, J., & Edelman, D. (2017). *Credit Scoring and Its Applications* (2nd ed.). SIAM-Society for Industrial and Applied Mathematics.

Tibshirani, R. (1996). Regression Shrinkage and Selection Via the Lasso. *Journal of the Royal Statistical Society: Series B (Methodological)*, *58*(1), 267–288. https://doi.org/10.1111/j.2517-6161.1996.tb02080.x

Tong, Z., Liu, Y., Ma, H., Zhang, J., Lin, B., Bao, X., Xu, X., Gu, C., Zheng, Y., Liu, L., Fang, W., Deng, S., & Zhao, P. (2020). Development, Validation and Comparison of Artificial Neural Network Models and Logistic Regression Models Predicting Survival of Unresectable Pancreatic Cancer. *Frontiers in Bioengineering and Biotechnology*, *8*(March), 1–11. https://doi.org/10.3389/fbioe.2020.00196

Topuz, K., Uner, H., Oztekin, A., & Yildirim, M. B. (2018). Predicting pediatric clinic no-shows: a decision analytic framework using elastic net and Bayesian belief network. *Annals of Operations Research*, *263*(1–2), 479–499. https://doi.org/10.1007/s10479-017-2489-0

Topuzoğlu, A., Ay, P., Hidiroglu, S., & Gurbuz, Y. (2007). The barriers against childhood immunizations: A qualitative research among socio-economically disadvantaged mothers. *European Journal of Public Health*, *17*(4), 348–352. https://doi.org/10.1093/eurpub/ckl250

Torrado-García, L. M., Martínez-Vega, R. A., & Rincon-Orozco, B. (2020). A novel strategy for cervical cancer prevention using cervical-vaginal self-collected samples shows high acceptability in women living in low-income conditions from bucaramanga, colombia. *International Journal of Women's Health*, *12*, 1197–1204. https://doi.org/10.2147/IJWH.S265130

Touch, J., & Berg, J. P. (2016). Parent perspectives on appointment nonattendance: A descriptive study. *Pediatric Nursing*, *42*(4), 181–188.

Tsai, W. C., Lee, W. C., Chiang, S. C., Chen, Y. C., & Chen, T. J. (2019). Factors of missed appointments at an academic medical center in Taiwan. *Journal of the Chinese Medical Association*, *82*(5), 436–442. https://doi.org/10.1097/JCMA.0000000000000068

Tsang, M., Cheng, D., & Liu, Y. (2017). *Detecting Statistical Interactions from Neural Network Weights*. 1–21. http://arxiv.org/abs/1705.04977

Tseng, F. Y. (2010). Non-attendance in endocrinology and metabolism patients. *Journal of the Formosan Medical Association*, *109*(12), 895–900. https://doi.org/10.1016/S0929-6646(10)60136-2

Tull, F., Borg, K., Knott, C., Beasley, M., Halliday, J., Faulkner, N., Sutton, K., & Bragge, P. (2019). Short Message Service Reminders to Parents for Increasing Adolescent Human Papillomavirus Vaccination Rates in a Secondary School Vaccine Program: A Randomized Control Trial. *Journal of Adolescent Health*. https://doi.org/10.1016/j.jadohealth.2018.12.026

Urrutia S, M. T. (2012). Creencias sobre Papanicolaou y cáncer cérvicouterino en un grupo de mujeres chilenas. *Revista Chilena de Obstetricia y Ginecología*, *77*(1), 3–10. https://doi.org/10.4067/s0717-75262012000100002

Utomo, D. S., Onggo, B. S. S., Eldridge, S., Daud, A. R., & Tejaningsih, S. (2022). Eliciting agents' behaviour using scenario-based questionnaire in agent-based dairy supply chain simulation. *Journal of Simulation*, *16*(1), 58–72. https://doi.org/10.1080/17477778.2020.1753251

Vahabi, M., & Lofters, A. (2016). Muslim immigrant women's views on cervical cancer screening and HPV self-sampling in Ontario, Canada. *BMC Public Health*, *16*(1), 1–13. https://doi.org/10.1186/s12889-016-3564-1

Valdivia, A., Sánchez-Monedero, J., & Casillas, J. (2021). How fair can we go in machine learning? Assessing the boundaries of accuracy and fairness. *International Journal of Intelligent Systems*, *36*(4), 1619–1643. https://doi.org/10.1002/int.22354

Vale, Diama B., Teixeira, J. C., Bragança, J. F., Derchain, S., Sarian, L. O., & Zeferino, L. C. (2021). Elimination of cervical cancer in low- and middle-income countries: Inequality of access and fragile healthcare systems. *International Journal of Gynecology and Obstetrics*, *152*(1), 7–11. https://doi.org/10.1002/ijgo.13458

Vale, Diama Bhadra, Silva, M. T., Discacciati, M. G., Polegatto, I., Teixeira, J. C., & Zeferino, L. C. (2021). Is the HPV-test more cost-effective than cytology in cervical cancer screening? An economic analysis from a middle-income country. *Plos One*, *16*(5), e0251688. https://doi.org/10.1371/journal.pone.0251688

Vandewiele, G., Dehaene, I., Kovács, G., Sterckx, L., Janssens, O., Ongenae, F., De Backere, F., De Turck, F., Roelens, K., Decruyenaere, J., Van Hoecke, S., & Demeester, T. (2020). *Overly Optimistic Prediction Results on Imbalanced Data: Flaws and Benefits of Applying Over-sampling*. http://arxiv.org/abs/2001.06296

Vargas, I., Mogollón-Pérez, A. S., De Paepe, P., Ferreira Da Silva, M. R., Unger, J. P., & Vázquez, M. L. (2016). Barriers to healthcare coordination in market-based and decentralized public health systems: A qualitative study in healthcare networks of Colombia and Brazil. *Health Policy and Planning*, *31*(6), 736–748. https://doi.org/10.1093/heapol/czv126

Vargas, I., Vzquez, M. L., Mogollán-Pérez, A. S., & Unger, J. P. (2010). Barriers of access to care in a managed competition model: Lessons from Colombia. *BMC Health Services Research*, *10*(1), 297. https://doi.org/10.1186/1472-6963-10-297

Vasileiou, K., Barnett, J., Thorpe, S., & Young, T. (2018). Characterising and justifying sample size sufficiency in interview-based studies: systematic analysis of qualitative health research over a 15-year period. *BMC Medical Research Methodology*, *18*(1), 148. https://doi.org/10.1186/s12874-018-0594-7

Vasudevan, L., Stinnett, S., Mizelle, C., Melgar, K., Makarushka, C., Pieters, M., Sanchez, L. E. R., Jeronimo, J., Huchko, M. J., & Proeschold-Bell, R. J. (2020). Barriers to the uptake of cervical cancer services and attitudes towards adopting new interventions in Peru. *Preventive Medicine Reports*, *20*, 101212. https://doi.org/10.1016/j.pmedr.2020.101212

Veloso, M. (2013). An agent-based simulation model for informed shared decision making in multiple sclerosis. *Multiple Sclerosis and Related Disorders*, *2*(4), 377–384. https://doi.org/https://doi.org/10.1016/j.msard.2013.04.001

Verbeke, W., Baesens, B., & Bravo, C. (2017). Profit-Driven Model Evaluation and Implementation. In *Profit-Driven Business Analytics* (pp. 296–354).

https://doi.org/doi:10.1002/9781119443179.ch6

Verma, S., & Rubin, J. (2018). Fairness definitions explained. *Proceedings - International Conference on Software Engineering*, 1–7. https://doi.org/10.1145/3194770.3194776

Victoria, S. A., Racquel E, K., Lucila, S., Melisa, P., Viswanath, K., & Silvina, A. (2020). Knowledge and perceptions regarding triage among human papillomavirus–tested women: A qualitative study of perspectives of low-income women in Argentina. *Women's Health*, *16*. https://doi.org/10.1177/1745506520976011

Vorsters, A., Bosch, F. X., Bosch, F. X., Bonanni, P., Franco, E. L., Baay, M., Simas, C., Waheed, D. E. N., Castro, C., Murillo, R., Trujillo, L., Wiesner, C., & Muñoz, N. (2020). Prevention and control of HPV infection and HPV-related cancers in Colombia- a meeting report. *BMC Proceedings*, *14*(Suppl 9), 1–13. https://doi.org/10.1186/s12919-020-00192-2

Vrinten, C., McGregor, L. M., Heinrich, M., von Wagner, C., Waller, J., Wardle, J., & Black, G. B. (2017). What do people fear about cancer? A systematic review and meta-synthesis of cancer fears in the general population. *Psycho-Oncology*, *26*(8), 1070–1079. https://doi.org/10.1002/pon.4287

Wallace, B. B., & MacEntee, M. I. (2012). Access to dental care for low-income adults: Perceptions of affordability, availability and acceptability. *Journal of Community Health*, *37*(1), 32–39. https://doi.org/10.1007/s10900-011-9412-4

Wallace, D. J., Ray, K. N., Degan, A., Kurland, K., Angus, D. C., & Malinow, A. (2018). Transportation characteristics associated with non-arrivals to paediatric clinic appointments: A retrospective analysis of 51 580 scheduled visits. *BMJ Quality and Safety*, *27*(6), 437–444. https://doi.org/10.1136/bmjqs-2017-007168

Wang, S., Ji, B., Zhao, J., Liu, W., & Xu, T. (2018). Predicting ship fuel consumption based on LASSO regression. *Transportation Research Part D: Transport and Environment*, *65*(October 2017), 817–824. https://doi.org/10.1016/j.trd.2017.09.014

Weaver, K. R., Talley, M., Mullins, M., & Selleck, C. (2019). Evaluating Patient Navigation to Improve First Appointment No-show Rates in Uninsured Patients with Diabetes. *Journal of Community Health Nursing*, *36*(1), 11–18. https://doi.org/10.1080/07370016.2018.1555315

Weng, Q., Jiang, J., Haji, F. M., Nondo, L. H., & Zhou, H. (2020). Women's knowledge of and attitudes toward cervical cancer and cervical cancer screening in Zanzibar, Tanzania: A cross-sectional study. *BMC Cancer*, *20*(1), 1–12. https://doi.org/10.1186/s12885-020-6528-x

Wentzensen, N., Clarke, M. A., & Perkins, R. B. (2021). Impact of COVID-19 on cervical cancer screening: Challenges and opportunities to improving resilience and reduce disparities. *Preventive Medicine*, *151*, 106596. https://doi.org/https://doi.org/10.1016/j.ypmed.2021.106596

Williams-Brennan, L., Gastaldo, D., Cole, D. C., & Paszat, L. (2012). Social determinants of health associated with cervical cancer screening among women living in developing countries: A scoping review. *Archives of Gynecology and Obstetrics*, *286*(6), 1487–1505. https://doi.org/10.1007/s00404-012-2575-0

Wisdom, J. P., Cavaleri, M. A., Onwuegbuzie, A. J., & Green, C. A. (2012). Methodological Reporting in Qualitative, Quantitative, and Mixed Methods Health Services Research Articles. *Health Services Research*, *47*(2), 721–745. https://doi.org/10.1111/j.1475-6773.2011.01344.x

Wolf, E. R., O'neil, J., Pecsok, J., Etz, R. S., Opel, D. J., Wasserman, R., & Krist, A. H. (2020). Caregiver and clinician perspectives on missed well-child visits. *Annals of Family Medicine*, *18*(1), 30–34. https://doi.org/10.1370/afm.2466

Wong, L. P., Wong, Y. L., Low, W. Y., Khoo, E. M., & Shuib, R. (2008). Cervical cancer screening attitudes and beliefs of Malaysian women who have never had a pap smear: A qualitative study. *International Journal of Behavioral Medicine*, *15*(4), 289–292. https://doi.org/10.1080/10705500802365490

Wong, L. P., Wong, Y. L., Low, W. Y., Khoo, E. M., & Shuib, R. (2009). Knowledge and awareness of cervical cancer and screening among Malaysian women who have never had a Pap smear: a qualitative study. *Singapore Medical Journal*, *50*(1), 49–53.

Wong, W., Fos, P. J., & Petry, F. E. (2003). Combining the performance strengths of the logistic regression and neural network models: a medical outcomes approach. *TheScientificWorldJournal*, *3*, 455–476. https://doi.org/10.1100/tsw.2003.35

World Health Organización.WHO. (n.d.). *Cervical cancer*. Retrieved June 18, 2022, from https://www.who.int/health-topics/cervical-cancer#tab=tab_1

World Health Organización.WHO. (2020). *Global strategy to accelerate the elimination of cervical cancer as a public health problem*. https://www.who.int/publications/i/item/9789240014107

World Health Organization. (2019). *Health technology assessment*. Health Technology

Assessment. https://www.who.int/medical_devices/assessment/en/

Wu, Y., Liang, Y., Zhou, Q., Liu, H., Lin, G., Cai, W., Li, Y., & Gu, J. (2019). Effectiveness of a short message service intervention to motivate people with positive results in preliminary colorectal cancer screening to undergo colonoscopy: A randomized controlled trial. *Cancer*, 1–10. https://doi.org/10.1002/cncr.32043

Yan, R., Wang, S., Cao, J., & Sun, D. (2021). Shipping Domain Knowledge Informed Prediction and Optimization in Port State Control. *Transportation Research Part B: Methodological*, *149*, 52–78. https://doi.org/10.1016/j.trb.2021.05.003

Yang, K.-K., & Cayirli, T. (2020). Managing clinic variability with same-day scheduling, intervention for no-shows, and seasonal capacity adjustments. *Journal of the Operational Research Society*, *71*(1), 133–152. https://doi.org/10.1080/01605682.2018.1557023

Yang, M., Xie, J., Zhang, H., Chen, Y., Xie, S., Peng, R., Jia, Y., Chen, Y., & Wang, L. (2020). Qualitative Analyses of the Reasons Why Patients Do Not Attend Scheduled Inpatient Appointments in a Hospital in Guangzhou, China. *Risk Management and Healthcare Policy*, *13*, 2857–2865. https://doi.org/10.2147/RMHP.S280665

Yang, Y., Tresp, V., Wunderle, M., & Fasching, P. A. (2018). Explaining therapy predictions with layer-wise relevance propagation in neural networks. *Proceedings - 2018 IEEE International Conference on Healthcare Informatics, ICHI 2018*, 152–162. https://doi.org/10.1109/ICHI.2018.00025

Ye, T., Johnson, R., Fu, S., Copeny, J., Donnelly, B., Freeman, A., Lima, M., Walsh, J., & Ghani, R. (2019). Using Machine Learning to Help Vulnerable Tenants in New York City. *Proceedings of the 2nd ACM SIGCAS Conference on Computing and Sustainable Societies*, 248–258. https://doi.org/10.1145/3314344.3332484

Zanardelli, I., & Robinson, N. (2019). Factors that influence patients' decisions to discontinue with an acupuncture service—A qualitative study. *European Journal of Integrative Medicine*, *25*(August 2018), 92–99. https://doi.org/10.1016/j.eujim.2018.12.004

Zebina, M., Melot, B., Binachon, B., Ouissa, R., Lamaury, I., & Hoen, B. (2019). Impact of an SMS reminder service on outpatient clinic attendance rates by patients with HIV followed-up at Pointe-à-Pitre University Hospital. *Patient Preference and Adherence*, *Volume 13*, 215–221. https://doi.org/10.2147/ppa.s182186

Zhang, X., Zeng, Q., Cai, W., & Ruan, W. (2021). Trends of cervical cancer at global, regional, and national level: data from the Global Burden of Disease study 2019. *BMC Public Health*, *21*(1), 1–10. https://doi.org/10.1186/s12889-021-10907-5

Zhang, Y., Ornelas, I. J., Do, H. H., Magarati, M., Jackson, J. C., & Taylor, V. M. (2017). Provider Perspectives on Promoting Cervical Cancer Screening Among Refugee Women. *Journal of Community Health*, *42*(3), 583–590. https://doi.org/10.1007/s10900-016-0292-5

Zhang, Z., & Hong, Y. (2017). Development of a novel score for the prediction of hospital mortality in patients with severe sepsis: The use of electronic healthcare records with LASSO regression. *Oncotarget*, *8*(30), 49637–49645. https://doi.org/10.18632/oncotarget.17870

Zullig, L. L., Jazowski, S. A., Wang, T. Y., Hellkamp, A., Wojdyla, D., Thomas, L., Egbuonu-Davis, L., Beal, A., & Bosworth, H. B. (2019). Novel application of approaches to predicting medication adherence using medical claims data. *Health Services Research*, *54*(6), 1255–1262. https://doi.org/10.1111/1475-6773.13200