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Review

# The Health Impact of mHealth Interventions in India: Systematic Review and Meta-Analysis

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## Abstract

**Background:** Considerable use of mobile health (mHealth) interventions has been seen, and these interventions have beneficial effects on health and health service delivery processes, especially in resource-limited settings. Various functionalities of mobile phones offer a range of opportunities for mHealth interventions.

**Objective:** This review aims to assess the health impact of mHealth interventions in India.

**Methods:** This systematic review and meta-analysis was conducted in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. Studies conducted in India, and published between April 1, 2011, and March 31, 2021, were considered. A literature search was conducted using a combination of MeSH (Medical Subject Headings) terms in different databases to identify peer-reviewed publications. Thirteen out of 1350 articles were included for the final review. Risk of bias was assessed using the Risk of Bias 2 tool for RCTs and Risk Of Bias In Non-randomised Studies - of Interventions tool (for nonrandomized trials), and a meta-analysis was performed using RevMan for 3 comparable studies on maternal, neonatal, and child health.

**Results:** The meta-analysis showed improved usage of maternal and child health services including iron-folic acid supplementation (odds ratio [OR] 14.30, 95% CI 6.65-30.75), administration of both doses of the tetanus toxoid (OR 2.47, 95% CI 0.22-27.37), and attending 4 or more antenatal check-ups (OR 1.82, 95% CI 0.65-5.09). Meta-analysis for studies concerning economic evaluation and chronic diseases could not be performed due to heterogeneity. However, a positive economic impact was observed from a societal perspective (ReMiND [reducing maternal and newborn deaths] and ImTeCHO [Innovative Mobile Technology for Community Health Operation] interventions), and chronic disease interventions showed a positive impact on clinical outcomes, patient and provider satisfaction, app usage, and improvement in health behaviors.

**Conclusions:** This review provides a comprehensive overview of mHealth technology in all health sectors in India, analyzing both health and health care usage indicators for interventions focused on maternal and child health and chronic diseases.

**Trial Registration:** PROSPERO 2021 CRD42021235315; <https://tinyurl.com/yh4tp2j7>

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**KEYWORDS**

mobile applications; mobile apps; cost-benefit analysis; telemedicine; technology; India; patient satisfaction; pregnancy

## Introduction

The use of mobile computing and communication technologies in health care and public health are seen as a rapidly expanding area within eHealth. The World Health Organization's Global Observatory for eHealth defined mobile health (mHealth) as "medical and public health practice supported by mobile devices, like mobile phones, patient monitoring devices, personal digital assistants, and other wireless devices" [1]. Devices used in mHealth interventions include laptops, tablets, mobile phones, smartphones, palmtops, notebooks, and netbooks.

Features of mobile technology, including mobility, instantaneous access, and direct communication, permit faster transfer of health information, which aid in medical and public health practices. mHealth services range from simple apps to complex technologies including voice messaging, SMS text messaging, multimedia message service, Bluetooth technology, and others, which could transform the worldwide delivery of health services, especially in low- and middle-income countries [1].

Various functionalities such as SMS text messaging, voice messaging, mobile internet browsing, Voice over Internet Protocol services (eg, Skype), instant messaging services, photographic capabilities, and a wide variety of device-based applications available through mobile technology offer a range of opportunities for mHealth interventions, such as text message and interactive voice response campaigns and content to mobile phone-based imaging (which have potential diagnostic capabilities) [2,3]. This technology has a broad extent and accessibility, which can be efficiently leveraged for health care delivery in areas where access is a major constraint [4].

mHealth is increasingly being used for medical services and public health practice for patient communication, monitoring, and education [5,6]. The interventions have also shown to reduce the burden of diseases linked with poverty and an improvement in the accessibility of the health services in terms of clinical diagnosis, treatment adherence, and chronic disease management [1,7-9]. There is considerable interest in mHealth interventions with an enormous potential for beneficial effects on health and health service delivery processes, especially in resource-limited settings such as India [10].

This paper provides a review of evidence regarding the health impacts of mHealth interventions in India. The purpose of this review is to assess health impact in terms of measurable changes in mortality, morbidity, disability-adjusted life years (DALYs), and improved disease detection rates.

## Methods

### Study Design

This systematic review and meta-analysis was conducted in accordance with the PRISMA (Preferred Reporting Items for Systematic Review and Meta-Analyses) guidelines [11]. Randomized controlled trials (RCTs), non-RCTs (including

cluster RCTs and quasi-experimental studies), and prospective parallel cohort studies conducted in India were included. Studies published between April 1, 2011, and March 31, 2021, were considered, and the search was initiated on September 10, 2020, until March 10, 2021. Studies reported in the English language and conducted in India, which addressed the impact of mobile technology, using SMS text messaging or cellular telephone interventions for any disease (eg, diabetes, hypertension, cardiovascular disease, chronic respiratory disease, and cancer) and maternal and child health, and measured outcomes including morbidity, mortality, hospitalization rates, behavioral or lifestyle changes, the process of care improvements, clinical outcomes, patient and provider satisfaction, compliance, and cost-effectiveness, were included in the review.

### Literature Search

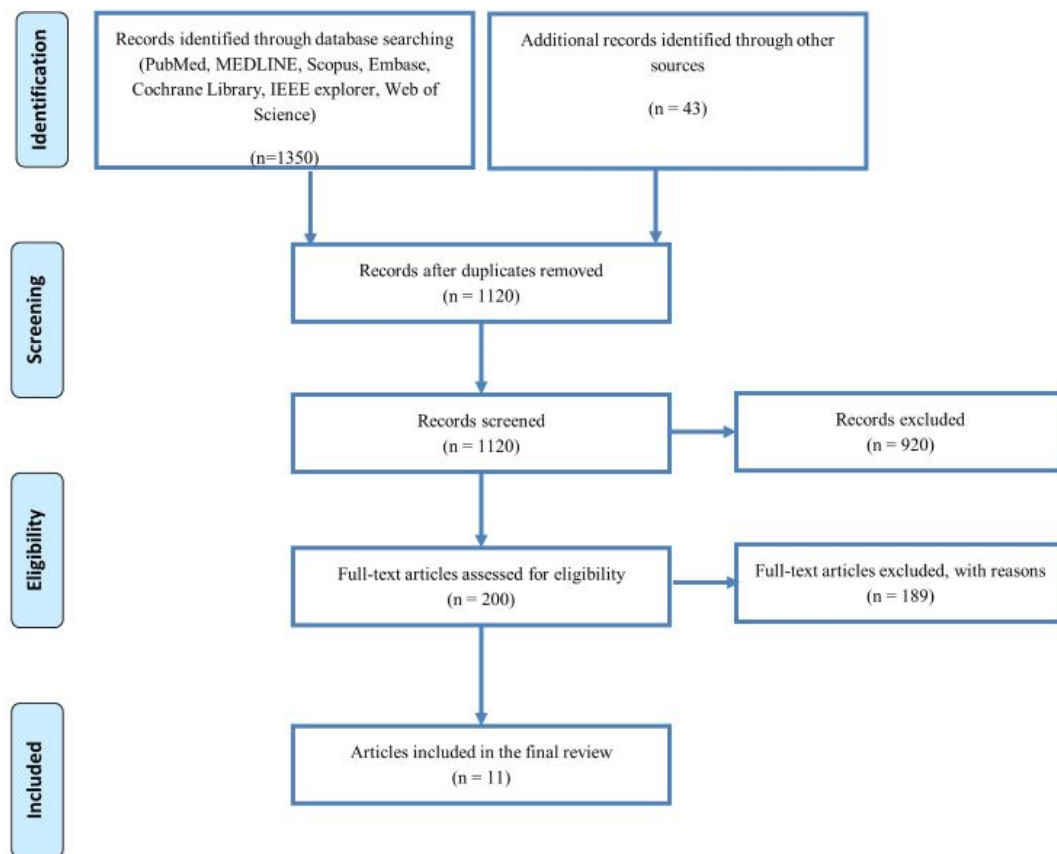
A literature search was conducted using a combination of text and Medical Subject Headings (MeSH) keywords in major databases, including PubMed, MEDLINE, Scopus, Cochrane Library, Web of Science, and Google scholar, to identify peer-reviewed publications. The MeSH keywords included the following: *Text Messaging, Health Literacy, Mobile Applications, Smartphone, Cell phone, Health Impact Assessment, Developing Countries, Multimedia, Cell Phone, Telemedicine, Medication Adherence, India, Hypertension, Primary Health Care, Risk Reduction Behavior, healthcare cost, Health Information Management, and Information Systems*. The search field was limited to the title or abstract (or both), and the type of publication was limited to original articles or full-length research articles. We excluded cross-sectional studies, letters, case reports, study protocols, reviews, opinions, gray literature, and non-peer-reviewed publications. The reference lists of articles were also examined to identify other potentially relevant articles. The protocol for this systematic review and meta-analysis has been registered in PROSPERO 2021 (CRD42021235315).

### Study Selection and Characteristics

Two researchers (VJ and DO) independently screened the titles and abstracts to identify potentially eligible studies, and further assessment was performed by 2 authors (NKJ and YKJ). Only full-text articles published between 2011 and 2021, written in the English language, were included. The authors excluded duplicates and studies conducted outside India.

Initial searches identified 1393 titles. After removing duplicates, 1120 articles were included for initial screening. Of these, 920 articles were excluded after screening by title and abstract, leaving 200 articles, which were considered in more detail. A further 187 papers were subsequently excluded for not meeting the relevant criteria. Thirteen of the eligible studies were intervention studies, comprising 3 RCTs; 5 quasi-RCTs; 1 cluster RCT; 1 prospective, parallel-group cohort study; and 1 quantitative, single-arm, pretest, posttest interventional study (Figure 1).

**Figure 1.** PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram for database searches of studies on mobile health interventions conducted in India in 2011-2020.



## Data Extraction

The extracted data included the names of the authors, year of publication, study design, study location, sampling, and main results. All these details were captured and recorded in an Excel (Microsoft Corp) spreadsheet. The information reported in or calculated from the included studies was used for analysis. Corresponding authors of the articles were not contacted for unpublished or additional information. Disagreements related

to the inclusion of an article were resolved through consensus among the authors.

## Quality Assessment and Assessment of Risk of Bias

Risk of bias of each study was assessed using the Risk of Bias 2 tool for RCTs and Risk Of Bias In Non-randomised Studies - of Interventions for non-RCTs [12,13]. Risk-of-bias grading for the different components of each study is shown in Table 1. Four of the intervention studies were graded as being at low risk of bias, 6 as moderate, and 1 as high.

**Table 1.** Characteristics and results of studies investigating the effectiveness of mobile health (mHealth) interventions in India during 2011-2020.

Study (year; location) [overall risk of bias]	Study population	Intervention and control	Results	Study outcome
Prinja et al [14] (2017; Uttar Pradesh, India) [low]	<ul style="list-style-type: none"> <li>Population: data obtained from the 2011 AHS<sup>a</sup> and 2015 CEAHH<sup>b</sup> survey among women or mothers with 1-year-old children</li> <li>Preintervention: 1508 ASHAs<sup>c</sup> (intervention: n=99; control: n=99); postintervention: 1028 (intervention: n=534; control: n=534)</li> </ul>	<ul style="list-style-type: none"> <li>Intervention: pregnant women and mothers using an mHealth app; control: women and mothers not using mHealth applications</li> </ul>	<ul style="list-style-type: none"> <li>Increase in the coverage IFA<sup>d</sup> supplementation (12.58%; 95% CI 0.086-0.27)</li> <li>Self-reporting of illnesses or complication during pregnancy (13.11%) and after delivery (19.6%)</li> <li>The coverage of <math>\geq 3</math> ANC<sup>e</sup> visits (10.3%; 95% CI 0.039-0.98)</li> <li>Coverage of <math>\geq 2</math> tetanus toxoids (4.28%; 95% CI 0.055-0.68)</li> <li>Institutional delivery (95% CI 0.044-0.59)</li> <li>Full immunization (95% CI 0.20-1.032)</li> <li>No change in the quality of ANC care</li> </ul>	<ul style="list-style-type: none"> <li>Significant improvement in IFA supplementation, identification, and self-reporting of illnesses during pregnancy and after delivery</li> </ul>
Modi et al [15] (Gujarat, India) [low]	<ul style="list-style-type: none"> <li>Population: rural tribal communities of Gujarat, India (neonates and mothers); population: 22 PHC<sup>f</sup> clusters (intervention: n=11; control: n=11)</li> </ul>	<ul style="list-style-type: none"> <li>Intervention (with an mHealth package): 11 PHCs and 280 ASHAs; population: 234,134</li> <li>Control (without an mHealth package): 11 PHCs and 281 ASHAs; population: 242,809</li> </ul>	<ul style="list-style-type: none"> <li>ANC of <math>\geq 4</math>: intervention (n=622, 79.2%); 89.5, 95% CI 86.6-91.3); control (88.7, 95% CI 86.6-90.6)</li> <li>TT<sup>g</sup> during the last pregnancy: intervention (n=771, 98.2%; 98.2, 95% CI 97.4-98.9); control (n=694, 98.3%; 96.8, 95% CI 96-97.6)</li> <li>Delivered at an institution or hospital: intervention (n=580, 73.9%; 83.2, 95% CI 80.4-85.9); control (n=600, 85.0%; 84.9, 95% CI 82.1-87.6)</li> <li>ASHAs present during delivery: intervention (n=267, 34.0%); control (n=267, 37.8%)</li> <li>MACCI<sup>h</sup>: intervention (31%); control (31%)</li> <li>ASHA visit at home at least twice in the first week of delivery: intervention (n=149, 19.0%; 32.4, 95% CI 29.7-35.1); control (n=99, 14.0%; 22.9, 95% CI 20.2-25.6)</li> <li>Low Birth Weight (<math>\leq 2</math> kg) at the time of birth: intervention (3.5, 95% CI 2.3-4.7); control (6.6; 95% CI 5.4-7.8)</li> <li>Practice breastfeeding at 6 months: intervention (n=151, 19.2%; 57.4, 95% CI 54.1-60.8); control (n=95, 13.5%; 45.1, 95% CI 41.8-48.4)</li> </ul>	<ul style="list-style-type: none"> <li>ImTeCHO<sup>i</sup> mobile apps and web-based applications, ASHAs, and PHC staff improved the coverage and quality of MNCH<sup>j</sup> services in difficult-to-reach areas</li> <li>Improvement in coverage home visits by ASHAs during the antenatal period, postnatal period, early initiation of breastfeeding, and exclusive breastfeeding</li> </ul>

Study (year; location) [overall risk of bias]	Study population	Intervention and control	Results	Study outcome
Murthy et al [16] (Mumbai, India) [moderate]	<ul style="list-style-type: none"> <li>2016 pregnant women, aged 18 years or older: intervention (n=500); control (n=1516); analyzed (intervention: n=1038; control: n=379); time 1 (intervention: n=1516; control: n=500); time 2 (intervention: n=1113; control: n=402); time 3 (intervention: n=1038; control: n=379)</li> </ul>	<ul style="list-style-type: none"> <li>Intervention group received mMitra voice messages twice per week throughout their pregnancy and until their infant turned 1 year of age</li> <li>Control group received no mMitra voice message</li> </ul>	<ul style="list-style-type: none"> <li>Infant care practices that the intervention group performed better: infant feeding at 6 months of age (OR<sup>k</sup> 1.4, 95% CI 1.08-1.82; <i>P</i>=.009), fully immunizing the infant (OR 1.531, 95% CI 1.141-2.055; <i>P</i>=.005)</li> <li>Control group performed better on practices: increase in baby weight within 3 months (<i>P</i>=.03; OR 0.77, 95% CI 0.6-0.98)</li> <li>In infant care knowledge: increase in baby solid food by 6 months in the intervention group (OR 1.89, 95% CI 1.371-2.605; <i>P</i>&lt;.01); the ideal birth weight is &gt;2.5 kg (OR 2.279, 95% CI 1.617-3.213; <i>P</i>&lt;.01)</li> </ul>	<ul style="list-style-type: none"> <li>mMitra voice-based mHealth intervention to demonstrate a positive impact on infant birth weight—a health outcome of public health importance</li> </ul>
Ilozumba et al [17] (2018; Jharkhand, India) [low]	<ul style="list-style-type: none"> <li>Population: women between the ages of 18 and 45 years who had delivered a baby in the past 1 year (N=2200; intervention: n=733; control: n=739)</li> </ul>	<p>The study has 3 groups, all of which received standard care government programs that included the recruitment and support of ASHAs:</p> <ul style="list-style-type: none"> <li>An intervention group that received MfM<sup>l</sup> in addition to an NGO's<sup>m</sup> existing interventions</li> <li>A quasi-control group that received NGO programs</li> <li>A standard care group that only received standard care government programs</li> </ul>	<ul style="list-style-type: none"> <li>The odds of having a higher score on maternal health knowledge significantly increased when comparing intervention and control groups</li> <li>Women in the MfM group were more likely to attend 4 or more ANC visits than those in the standard care group (OR 1.36, 95% CI 1.30-1.42) and the NGO group (OR 1.23, 95% CI 1.17-1.29)</li> <li>The odds of a women in the MfM group were significantly higher than the odds of women in the standard care group (OR 1.34, 95% CI 1.28-1.41) and the NGO group (OR 1.19, 95% CI 1.13-1.25)</li> <li>Higher maternal health knowledge -MfM versus standard care (intervention: OR 1.19, 95% CI 1.13-1.25; control [reference] OR 1.00)</li> <li>Attended 4 or more ANC visits (intervention: OR 1.38, 95% CI 1.32-1.44; control [reference] OR 1.00)</li> <li>Delivered at a health facility (intervention OR 1.35, 95% CI 1.29-1.42)</li> </ul>	<ul style="list-style-type: none"> <li>This study showed that women in the intervention group reported higher levels of maternal health knowledge than those in the NGO intervention or those who received standard care</li> <li>The primary outcomes of interest were maternal health knowledge, ANC attendance, and delivery in a health facility</li> </ul>
Prinja et al [18] (2018; Uttar Pradesh, India) [low]		<ul style="list-style-type: none"> <li>Intervention: pregnant women and mothers using an mHealth app; control: women and mothers not using mHealth applications</li> </ul>	<ul style="list-style-type: none"> <li>ReMiND<sup>n</sup> resulted in a cost saving of US \$90 per DALY<sup>o</sup> averted US \$2569 per death averted. From the health system perspective, ReMiND incurred an incremental cost of 12,993 (US \$205) per DALY averted and 371,577 (US \$5865) per death averted</li> </ul>	<ul style="list-style-type: none"> <li>mHealth intervention as part of the ReMiND program is cost-saving from a societal perspective</li> </ul>



Study (year; location) [overall risk of bias]	Study population	Intervention and control	Results	Study outcome
	<ul style="list-style-type: none"> <li>Population: data obtained from the 2011 AHS and 2015 CEAAH survey among women or mothers with 1-year-old children</li> <li>Preintervention: 1508 ASHAs (intervention: n=99; control: n=99); postintervention: 1028 (intervention: n=534; control: n=534)</li> </ul>			
Modi et al [19] (2020; Gujarat, India) [low]	<ul style="list-style-type: none"> <li>Population: rural tribal communities of Gujarat, India (neonates and mothers; population: N=22 PHC clusters: intervention: n=11; control: n=11)</li> </ul>	<ul style="list-style-type: none"> <li>Intervention (with an mHealth package): 11 PHCs and 280 ASHAs; population: n=234,134</li> <li>Control (without an mHealth package): 11 PHCs and 281 ASHAs; population: n=242,809)</li> </ul>	<ul style="list-style-type: none"> <li>ImTeCHO is a cost-effective intervention at an incremental cost of US \$74 per life years saved or US \$5057 per death averted</li> <li>Total births in the study area (n=3014)</li> <li>Cost per live birth (US \$54)</li> <li>Cost per 1000 live births (US \$54,360)</li> <li>Infant deaths averted per 1000 live births (n=11)</li> <li>Life years saved (life expectancy=68.35 years; n=735)</li> <li>Cost per infant deaths averted (US \$5057)</li> <li>Cost per life years saved due to infant deaths averted (US \$74)</li> <li>IMR<sup>P</sup> as intention-to-treat in the study area (cost per ASHA (US \$578.95))</li> </ul>	<ul style="list-style-type: none"> <li>mHealth intervention as part of the ImTeCHO program is cost-effective and should be considered for replication</li> </ul>
Pfammatter et al [20] (2015; India) [moderate]	<ul style="list-style-type: none"> <li>Population: adults aged 18 years and older (N=1925; intervention: n=611; control: n=632)</li> </ul>	<ul style="list-style-type: none"> <li>Intervention: 1 million Nokia subscribers who opted into mDiabetes for 6 months</li> <li>Control: non-Nokia phone subscribers</li> </ul>	<ul style="list-style-type: none"> <li>Intervention group: 24.71% of them improved their fruit and vegetable intake and reduced their fat intake; 128 (20.95%) improved their preventive behavior</li> <li>Control group: 36.55% decline in the number of participants' healthy behaviors; 73 (11.55%) improved their preventive behavior</li> </ul>	<ul style="list-style-type: none"> <li>A text messaging intervention was feasible and showed initial evidence of effectiveness in improving diabetes-related health behaviors</li> </ul>
Kleinman et al [21] (2017; India) [low]	<ul style="list-style-type: none"> <li>Population: aged 18-65 years with type 2 diabetes 6 months from baseline (N=90; intervention: n=44; control: n=46)</li> </ul>	<ul style="list-style-type: none"> <li>Intervention: participants received the mHealth app and a mobile phone data stipend for 6 months</li> <li>Control: manage their diabetes as usual</li> </ul>		<ul style="list-style-type: none"> <li>Significantly more participants in the intervention group than in the control group</li> </ul>



Study (year; location) [overall risk of bias]	Study population	Intervention and control	Results	Study outcome
Prabhakaran et al [22] (2019; India) [moderate]	<ul style="list-style-type: none"> <li>Population: rural population (CHCs<sup>4</sup>), ≥30 years of age, confirmed diagnosis of hypertension or diabetes mellitus</li> <li>Population: 40 clusters; intervention: n=20 (mWellcare) 20 clusters; 1842 participants enrolled (N=2140); control: 20 CHCs (allocated to EUC<sup>r</sup>) and 20 clusters; 1856 participants enrolled (N=2130)</li> </ul>	<ul style="list-style-type: none"> <li>Effectiveness of the mWellcare app for 5 chronic conditions (hypertension, diabetes mellitus, current tobacco and alcohol use, and depression) vs usual care (intervention group: [mWellcare arm]: EUC NCD<sup>s</sup> nurses with the mWellcare system; control group: EUC NCD nurses Without the mWellcare system)</li> </ul>	<ul style="list-style-type: none"> <li>Primary outcome: intervention mean 1.1-1.5; control mean 0.8-1.6 (<math>P=.02</math>)</li> <li>Secondary outcomes: intervention mean 32.6-66.4; control mean 23.5-70.0 (<math>P=.55</math>)</li> <li>BMI change: intervention mean 0.1-1.0; control mean 0.1-1.1 (<math>P=.53</math>)—patient-reported values improved from baseline to 6 months (intervention: n=16, 39.0%; control: n=5, 12.8%; <math>P=.03</math>)</li> <li>Medication adherence (intervention: 39.0%; control: 12.8%; <math>P=.03</math>)</li> <li>Increased frequency of blood glucose self-testing (intervention: 39.0%; control: 10.3%; <math>P=.01</math>)</li> </ul>	<ul style="list-style-type: none"> <li>Incremental benefit of mWellcare over enhanced usual care in chronic conditions</li> <li>The trial did not find any significant difference in the primary outcomes, that is, reduction in SBP or HbA1c, and Secondary outcomes, that is, fasting blood glucose, total cholesterol, predicted 10-year risk of CVD, BMI, depression, and tobacco and alcohol use between the 2 arms</li> </ul>

Study (year; location) [overall risk of bias]	Study population	Intervention and control	Results	Study outcome
			<ul style="list-style-type: none"> <li>• Primary outcomes:               <ul style="list-style-type: none"> <li>• Change in SBP<sup>t</sup>: control: mean -12.7 mm Hg; intervention: mean -13.7 mm Hg (effect size -0.3, adjusted 95% CI -3.9 to 3.3; <i>P</i>=.87)</li> <li>• Change in HbA1c<sup>u</sup>: control: mean -0.58%; intervention: -0.48% (effect size 0.08, adjusted 95% CI -0.27 to 0.44; <i>P</i>=.66)</li> </ul> </li> <li>• Secondary outcomes:               <ul style="list-style-type: none"> <li>• Change in fasting blood glucose: control: mean -22.7 mg/dL; intervention: -15.0 mg/dL (effect size 8.4, adjusted 95% CI -9.6 to 26.5; <i>P</i>=.37)</li> <li>• Change in total cholesterol: control: mean 2.0 mg/dL; intervention: mean 0.1 mg/dL (effect size -2.5, adjusted 95% CI -7.1 to 2.0; <i>P</i>=.29)</li> <li>• Change in CVD<sup>v</sup> risk score: control: mean 0.6%; intervention: 2.4% (effect size -0.4, adjusted 95% CI -2.3 to 1.5; <i>P</i>=.66)</li> <li>• Change in BMI: control: mean 0.08 kg/m<sup>2</sup>; intervention: 0.16 kg/m<sup>2</sup> (effect size -0.05, adjusted 95% CI -0.47 to 0.37; <i>P</i>=.82)</li> <li>• Change in tobacco use: control: mean -7.0%; intervention: mean -0.6% (effect size -0.8, adjusted 95% CI -5.7 to 4.2; <i>P</i>=.76)</li> <li>• Change in alcohol use: control: mean -3.8%; intervention: mean -2.4% (effect size 0.7, adjusted 95% CI -3.7 to 5.1; <i>P</i>=.74)</li> <li>• Change in alcohol use score: control: mean 10.0; intervention: 9.4 (effect size -0.6, adjusted 95% CI -3.2 to 2.1; <i>P</i>=.68)</li> <li>• Change in depression score: control: mean 12.4; intervention: mean 10.9 (effect size -1.6, adjusted 95% CI -4.4 to 1.2; <i>P</i>=.28)</li> </ul> </li> </ul>	

Study (year; location) [overall risk of bias]	Study population	Intervention and control	Results	Study outcome
Garner et al [23] (2020; India) [moderate]	<ul style="list-style-type: none"> <li>Population: urban slum and rural slum dwellers (n=346)</li> <li>Pretest (n=87): those who earned an 8 or above on the pretest paired t test</li> <li>Posttest (n=259): those who earned a 7 or below on the pretest</li> </ul>	<ul style="list-style-type: none"> <li>Intervention through an mHealth app to improve hypertension health literacy</li> </ul>	<ul style="list-style-type: none"> <li>Study aim 1: to assess the effectiveness of an mHealth app to improve hypertension health literacy among participants in India</li> <li>Study aim 2: to estimate relationships between participant hypertension health literacy and sociodemographic variables</li> <li>Pretest: participants who performed moderately well on the pretest also had improved posttest scores (significant mean difference between pretest and posttest scores 2.49; <math>P &lt; .001</math> [paired t test])</li> </ul>	<ul style="list-style-type: none"> <li>The mHealth app provides an effective and valuable culturally tailored educational resource for nurses and other health to improve hypertension health literacy among populations in India</li> </ul>
Gautham et al [24] (2015; Tamil Nadu, India) [high]	<ul style="list-style-type: none"> <li>Population: rural health providers (n=16) and patients (n=126; experimental: n=65; control: n=61)</li> </ul>	<ul style="list-style-type: none"> <li>Intervention group: given applications on their mobile phones</li> <li>Control group: no application given; only the phone and a set of paper guidelines to use in the field</li> </ul>	<ul style="list-style-type: none"> <li>Control group scored significantly higher than the experimental group (control group: mean 13.68; experimental group: 9.51; <math>P &lt; .05</math>) in the posttraining evaluation.</li> <li>Control: mean pretraining score 8.58 out of 19 (SD 2.03); experimental: mean pretraining score 7.01 out of 19 (SD 1.85; <math>P = .19</math>)</li> <li>Control: mean posttraining score 13.68 out of 19 (SD 2.17); experimental: mean posttraining score 9.51 out of 19 (SD 2.48; <math>P &lt; .05</math>)</li> </ul>	<ul style="list-style-type: none"> <li>This study supports the implication that mM-RIGs<sup>w</sup> comprise a feasible and effective solution for standardizing and enhancing the quality of care delivered by millions of frontline rural health providers with varying levels of training and literacy</li> </ul>
Praveen et al [25] (2014; Andhra Pradesh, India) [moderate]	<ul style="list-style-type: none"> <li>Population: ASHAs, NPHWs<sup>x</sup>, and PHC physicians. 227 adults screened by ASHAs, 65 adults screened by PHC physicians</li> </ul>	<ul style="list-style-type: none"> <li>The CDSS<sup>y</sup> was field-tested in 11 villages and 3 PHCs. CVD risk factor profile for participants screened by ASHAs (n=227) and doctors (n=65)</li> </ul>	<ul style="list-style-type: none"> <li>The CDSS recommend referral to a doctor to 128 of 227 adults and did not recommend referral to 99 of 227 adults.</li> <li>High CVD risk was noted in 88 of 128 (69%) adults, and in another 40 of 99 (31%) adults.</li> <li>Blood pressure lowering medication given to 29 of 65 (45%) adults and not to 36 of 65 (55%) adults.</li> <li>The other assessment of behavior change (COM-B<sup>z</sup> model) revealed 3 themes: (1) potential to transform prevailing health care models, (2) task-shifting of CVD screening to the ASHA was the central driver of change, and (3) system-level barriers such as access to doctors and medicines are still present</li> </ul>	<ul style="list-style-type: none"> <li>A tablet-based CDSS implemented within primary health care systems has the potential to help improve CVD outcomes in India</li> </ul>
Jadhav et al [26] (2016; Maharashtra, India) [moderate]				<ul style="list-style-type: none"> <li>Reinforcement of oral health education through SMS text messages is effective media to improve oral health</li> </ul>

Study (year; location) [overall risk of bias]	Study population	Intervention and control	Results	Study outcome
	<ul style="list-style-type: none"> <li>Population: adults aged 18-20 years having a personal mobile phone with SMS text messaging capability (N=400; control: n=200; intervention: n=200)</li> </ul>	<ul style="list-style-type: none"> <li>Intervention group: the message was reinforced through SMS text messages from mobile phones</li> <li>Control: no oral health-related SMS text messages or any kind of health education was given to the participants</li> </ul>	<ul style="list-style-type: none"> <li>Gender-wise distribution of participants: 137 male and 63 female participants in the intervention group and 149 male and 51 female participants in the control group (<math>P&gt;.05</math>)</li> <li>Mean OHI<sup>aa</sup> score at different intervals between the intervention and control groups showed no significant difference at baseline (<math>P=.28</math>) and after the first month (<math>P=.58</math>); however, it was significantly lower in the intervention group after the second, third, and sixth months (<math>P&lt;.01</math>)</li> <li>Mean GI<sup>ab</sup> scores at different intervals between the intervention and control groups were significantly no different at baseline (<math>P=.39</math>) and after the first month (<math>P=.85</math>); however, it was significantly lower in the intervention group after the second, third, and sixth months (<math>P&lt;.01</math>)</li> </ul>	

<sup>a</sup>AHS: Annual Health Survey.

<sup>b</sup>CEAHH: cost-effectiveness analysis household.

<sup>c</sup>ASHA: accredited social health activist.

<sup>d</sup>IFA: iron-folic acid.

<sup>e</sup>ANC: antenatal care.

<sup>f</sup>PHC: primary health center.

<sup>g</sup>TT: Tetanus toxoid.

<sup>h</sup>MACCI: modified accredited social health activist-centric composite coverage index.

<sup>i</sup>ImTeCHO: Innovative Mobile Technology for Community Health Operation.

<sup>j</sup>MNCH: maternal, neonatal, and child health.

<sup>k</sup>OR: odds ratio.

<sup>l</sup>MfM: Mobile for Mothers.

<sup>m</sup>NGO: nongovernmental organization.

<sup>n</sup>ReMiND: reducing maternal and newborn deaths.

<sup>o</sup>DALY: disability-adjusted life year.

<sup>p</sup>IMR: infant mortality rate.

<sup>q</sup>CHC: community health center.

<sup>r</sup>EUC: enhanced usual care.

<sup>s</sup>NCD: noncommunicable disease.

<sup>t</sup>SBP: systolic blood pressure.

<sup>u</sup>HbA<sub>1c</sub>: hemoglobin A<sub>1c</sub>.

<sup>v</sup>CVD: cardiovascular disease.

<sup>w</sup>mMRIG: media-rich interactive guideline.

<sup>x</sup>NPHW: nonphysician health care worker.

<sup>y</sup>CDSS: clinical decision support system.

<sup>z</sup>COM-B: capability, opportunity, and motivation.

<sup>aa</sup>OHI: Oral Hygiene Index.

<sup>ab</sup>GI: Gingival Index.

## Meta-Analysis

There was substantial heterogeneity among studies in their mHealth interventions and outcomes, except for studies on maternal, neonatal, and child health. Consequently, we performed a random-effects meta-analysis using the Mantel-Haenszel method in RevMan [27] for 3 comparable studies, which had all used cell phones rather than routine prenatal care as the intervention and had assessed increases in the number of antenatal check-ups, tetanus toxoids administered to pregnant women, institutional deliveries, and iron-folic acid to assess the effect of health care usage. However, as the relevant intervention for the purpose of this review, we exclusively compared the cell phone group to the usual care group in the meta-analysis. However, given the small number of studies, we did not undertake possible sensitivity analyses.

## Results

### Types of Outcomes Examined

Four studies examined the indicators of maternal, neonatal, and child health [14-17]—these reported the number of antenatal check-ups [14,15,17]; birth weight [15]; institutional delivery [14-17]; knowledge of the danger signs of pregnancy [14,15]; indicators of infant feeding and breastfeeding [14]; usage of antenatal, intrapartum, and postnatal care [14,15,17]; indicators of self-efficacy [15,17]; uptake of immunization [14,15]; and maternal health knowledge [17]. We found two studies evaluating the cost-effectiveness of mHealth programs [18,19]. Other outcomes included improvement in diabetes risk behaviors and increased awareness about the causes and complications of diabetes [20], improvement in medication adherence and the frequency of blood glucose testing [21], change in systolic blood pressure and hemoglobin A<sub>1c</sub> levels [22], quality of care delivered by primary health workers [23-25], and oral health education [26]. The results are organized below in accordance with the types of outcomes examined in each study.

### Effects on Maternal, Neonatal, and Child Health

A pre-post quasi-experimental study used an mHealth application in the Kaushambi district in Uttar Pradesh, India, to increase the quality of counseling by community health volunteers, resulting in improved uptake of maternal, neonatal, and child health services. A significant increase in coverage iron-folic acid supplementation and identification and self-reporting of illnesses or complications during pregnancy and after delivery were seen in the intervention area, but there was no change in the quality of antenatal care (ANC) care [14]. Similarly, an mHealth application was used in an open cluster RCT conducted in 22 primary health centers in 6 tribal blocks of Bharuch and Narmada districts in Gujrat, India, to assess the increase in the coverage of maternal, neonatal, and child health services and that of at least 2 home visits by accredited social health activists within the first week of birth. There were significant improvements in coverage home visits by accredited social health activists during the antenatal and postnatal period, early initiation of breastfeeding, and exclusive breastfeeding [15].

A pseudo-RCT conducted in Mumbai (Maharashtra, India) by Murthy et al [16], assessed the impact of age- and stage-based mobile phone voice messaging for pregnant women on reduction in low birth weight and child malnutrition and improvement in women's infant care knowledge and practices. They observed that the intervention group performed well in infant care practice indicators: administering supplementary feeding to the infant at 6 months of age (odds ratio [OR] 1.4, 95% CI 1.08-1.82;  $P=.009$ ) and fully immunizing the infant (OR 1.531, 95% CI 1.141-2.055;  $P=.005$ ). Moreover, women in the intervention group had increased knowledge of giving infants solid food by 6 months of age and of the fact that the ideal birth weight is  $>2.5$  kg [16]. A study from Jharkhand used a mobile app to support home visits by community health workers; Ilozumba et al [17] found that women receiving the mHealth intervention were more likely to attend 4 or more ANC visits and had significantly higher odds of delivering a baby at a health center than those receiving standard care and those receiving other interventions from a nongovernmental organization. Moreover, the usage of ANC services and delivery at a health center were associated with the education level of the spouse [17].

### Cost-Effectiveness

Prinja et al [18] assessed the cost-effectiveness of the ReMiND (reducing maternal and newborn deaths) program in Uttar Pradesh, India; both the societal and health care perspectives were taken into account. Overall, the ReMiND program was considered a cost-saving intervention from the societal perspective. It resulted in a cost saving of US \$90 per DALY averted US \$2569 per death averted. From the health system perspective, the ReMiND program incurred an incremental cost of 12,993 (US \$205) per DALY averted and 371,577 (US \$5865) per death averted [18]. A study conducted in Gujrat, India, found the ImTeCHO (Innovative Mobile Technology for Community Health Operation) intervention to be cost-effective at an incremental cost of US \$74 per life-years saved or US \$5057 per death averted [19].

### Effect on Chronic Conditions

Study conducted by Pfammatter et al [20] to examine the effect of mDiabetes—a text messaging program to improve diabetes risk behaviors—on fruit, vegetable, and fat intake and exercise among Nokia phone users in India. A greater improvement in the health behavior composite score over 6 months was observed among participants who received the text messages than among those who did not receive text messages [20]. An RCT conducted by Kleinman et al [21] at 3 sites in India assessed the impact of an mHealth diabetes platform on clinical outcomes, patient-reported outcomes, patient and provider satisfaction, and app usage. There was decrease of 1.5% in mean hemoglobin A<sub>1c</sub> levels in the intervention group and 0.8% in the usual care group, an improvement in self-reported medication adherence from baseline, and an increase in blood glucose testing in the intervention group from baseline compared to that in the control group (39.0% vs 10.3%, respectively;  $P=.01$ ) [21]. Prabhakaran et al [22] conducted a cluster-RCT using the mWellcare system for integrated management of 5 chronic conditions (hypertension, diabetes mellitus, current tobacco and alcohol use, and depression). No evidence of

difference in systolic blood pressure and hemoglobin A<sub>1c</sub> levels was observed between the intervention and control groups [22].

**Other Effects**

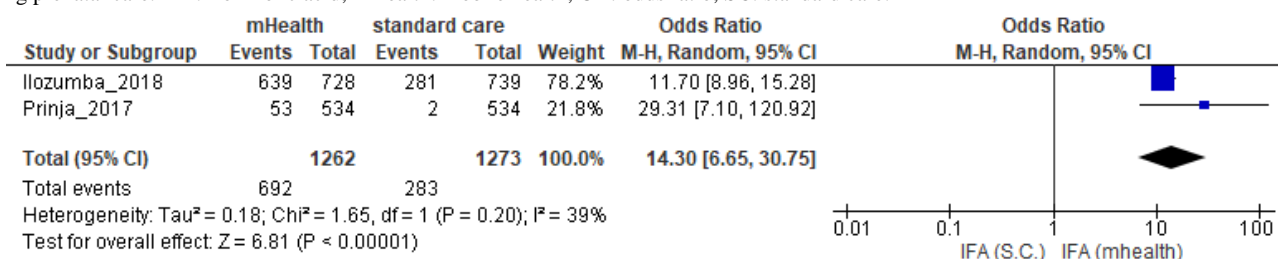
Garner et al [23] determined the effectiveness of an mHealth application to improve hypertension health literacy among vulnerable populations in India. A significant improvement in the understanding of hypertension through the innovative animated application was observed [23]. In the RCT conducted in rural areas of Tamil Nadu, India, Gautham et al [24] observed that mobile app-based procedural guidance for rural frontline health care providers had significant potential for attaining consistently standardized quality of care with patients' acceptance. Praveen et al [25] showed that implementation of a mobile clinical decision support system for cardiovascular disease management by public nonphysician health care workers and physicians in a rural Indian setting increased the number of referrals to the physician and had potential to help improve

cardiovascular disease outcomes, but system-level barriers have an impact on limiting the access to medical care. Jadhav et al [26] assessed the effectiveness of the reinforcement of oral health education SMS text messages and reported that mean Oral Hygiene Index and Gingival Index scores in the intervention group were significantly lower than those in the control group ( $P < .01$ ).

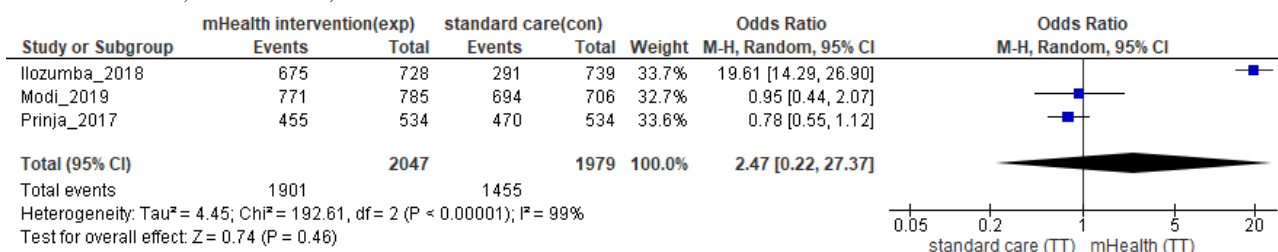
**Effect on Health Care Usage**

Among pregnant women, those using mHealth interventions were more likely to take a complete dose of iron-folic acid supplements (OR 14.30, 95% CI 6.65-30.75; Figure 2), both doses of the tetanus toxoid (OR 2.47, 95% CI 0.22-27.37; Figure 3), and to attended 4 or more antenatal care check-ups (OR 1.82, 95% CI 0.65-5.09; Figure 4) than those who received routine prenatal care. No strong evidence of differences regarding institutional deliveries (OR 1.14, 95% CI 0.26-4.95) were found.

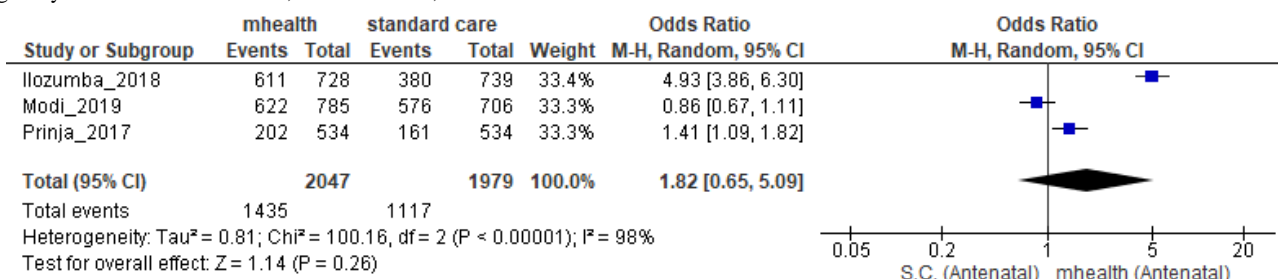
**Figure 2.** Meta-analysis of the effect of mobile health interventions versus standard care on the intake of complete doses of iron-folic acid supplements during prenatal care. IFA: iron-folic acid; mHealth: mobile health; OR: odds ratio; SC: standard care.



**Figure 3.** Meta-analysis of the effect of mobile health interventions versus standard care on taking 2 doses of the tetanus toxoid during pregnancy. mHealth: mobile health; OR: odds ratio; TT: tetanus toxoid.



**Figure 4.** Meta-analysis of the effect of mobile health interventions versus standard care on 3 or more antenatal care check-ups conducted during pregnancy. mHealth: mobile health; OR: odds ratio; SC: standard care.



**Discussion**

**Principal Findings**

mHealth is an implicit, promising tool for addressing several health care system limitations in transitional countries, such as a limited health care workforce, scarce resources, high burden

of disease, rapid population growth, and challenges of extending health care to underserved populations. We identified 13 studies showing the impact of mobile technology-based interventions designed to improve health care service delivery processes in the Indian setting. Most studies were at moderate and low risk of bias. Heterogeneity among studies did not allow the calculation of a pooled estimate for all the parameters. However,



a meta-analysis of 3 studies arbitrated to be sufficiently homogenous showed that mHealth interventions used for maternal and child health improved the usage of prenatal services including the intake of a complete dose of iron-folic acid supplements, taking both doses of the tetanus toxoid, and attending 4 or more antenatal care check-ups. No strong evidence of differences regarding institutional deliveries were found. A similar review conducted by Lee et al [28] for low- to middle-income countries showed that mHealth technologies are rapidly being used to promote health care use, improve the quality of pre- and postnatal care, and collect data on pregnancy and child health.

In our systematic review, we could not use economic evaluation-tailored reporting standards (such as the CHEERS [Consolidated Health Economic Evaluation Reporting Standards] checklist [29]) for full economic evaluation due to the lack of sufficient economic evaluation studies, as indicated by Iribarren et al [30], who described the evidence related to economic evaluations of mHealth interventions in low- to middle-income countries and in the evaluation of 2 mHealth interventions in India: ReMiND [18] and ImTeCHO [19]. These studies included a comparison of the effectiveness of a health-related outcome and reported economic data. Both the studies showed a positive economic impact considering the societal perspective.

All the studies included in this review provide evidence that the interventions conducted for the chronic diseases had an impact on clinical outcomes, patient and provider satisfaction, app usage, and improvement in health behavior (except for the study conducted by Prabhakaran et al [22]). Similar findings were described in the review conducted by Beratarrechea et al [31] for chronic diseases in transitional countries, which addressed more than 1 outcome and reported a positive impact on chronic disease outcomes.

### Limitations and Conclusion

This paper reviews the comprehensive use of mHealth technologies in all sectors of health care in India. We used a thorough, extensive, and highly sensitive literature search technique in this systematic review, which analyses both health and health care usage indicators, encompassing the entire scope of relevant mHealth technologies including those focusing on maternal and child health and chronic diseases. All comparative reviews have been conducted for low- to middle-income countries and mainly focused on the either chronic disease or maternal and child health [28,30-38].

However, due to a small number of studies for a single set of interventions, a meta-analysis for all the impact indicators was not conducted. Additional work is needed to improve and test this with a larger set of interventions, and to determine how to best integrate it with different conceptual frameworks that have been published.

### Conflicts of Interest

None declared.

### Multimedia Appendix 1

PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) checklist.

[DOCX File , 32 KB - [ojphi\\_v15i1e50927\\_app1.docx](#) ]

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## Abbreviations

**ANC:** antenatal care

**CHEERS:** Consolidated Health Economic Evaluation Reporting Standards

**DALY:** disability-adjusted life year

**ImTeCHO:** Innovative Mobile Technology for Community Health Operation

**MeSH:** Medical Subject Headings

**mHealth:** mobile health

**OR:** odds ratio

**PRISMA:** Preferred Reporting Items for Systematic Reviews and Meta-Analyses

**RCT:** randomized controlled trial

**ReMiND:** reducing maternal and newborn deaths

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**Editorial**

# Completion of the Transfer of the Online Journal of Public Health Informatics (OJPHI) to JMIR Publications

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## Abstract

Founded in 2009, the *Online Journal of Public Health Informatics* (OJPHI) strives to provide an unparalleled experience as the platform of choice to advance public and population health informatics. As a premier peer-reviewed journal in this field, OJPHI's mission is to serve as an advocate for the discipline through the dissemination of public health informatics research results and best practices among practitioners, researchers, policymakers, and educators. However, in the current environment, running an independent open access journal has not been without challenges. Judging from the low geographic spread of our current stakeholders, the overreliance on a small volunteer management staff, the limited scope of topics published by the journal, and the long article turnaround time, it is obvious that OJPHI requires a change in direction in order to fully achieve its mission. Fortunately, our new publisher JMIR Publications is the leading brand in this field, with a portfolio of top peer-reviewed journals covering innovation, technology, digital medicine and health services research in the internet age. Under the leadership of JMIR Publications, OJPHI plans to expand its scope to include new topics such as precision public health informatics, the use of artificial intelligence and machine learning in public health research and practice, and infodemiology in public health informatics.

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**KEYWORDS**

public health informatics; data science; precision public health; artificial intelligence; health promotion; disease prevention

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## Introduction

The *Online Journal of Public Health Informatics* (OJPHI) has been delivering the latest developments in the emerging field of public health informatics since 2009. The journal was originally created to fill a gap in the public health informatics publishing and training landscape. I started to recognize the need for such a journal as a result of my own involvement in advancing training and education in public health informatics. In 2002, I had the privilege to cofound and serve as director of the graduate program in Public Health Informatics at the University of Illinois Chicago (UIC) School of Public Health, the very first program of its kind in the United States.

The immeasurable value of transforming raw data into information and knowledge for effective and efficient decision-making by using information and communication technologies (ICTs) was evident during the COVID-19 pandemic. Although public health is an information-intensive

field, it lags behind other health-related fields in the utilization of ICTs for the delivery of services and resource management. The emergence of public health informatics as a professional specialty is part of a larger development of informatics in health-related fields, including medicine, nursing, pharmacy, and dentistry. The interest in informatics as a specialty within these fields reflects the significance of data collection, analysis, and transformation into information and knowledge in the health care sector. Several journals have been launched in response to the growing need for informaticians in these health care disciplines, and many of the JMIR Publications journals, not least one of their flagship journals *JMIR Public Health and Surveillance*, also publish research at the intersection of public health and technology.

Unfortunately, the COVID-19 pandemic and the subsequent increased interest and research output in our discipline also demonstrated the limitations of a self-published, open access journal relying largely on volunteer efforts. Not only is it

becoming increasingly challenging to find peer reviewers, but it is also increasingly difficult to operate in a rapidly changing and complex scholarly publications landscape while running on a shoestring budget. With a broader shift toward open access, libraries now often direct their publications budget toward transformative (hopefully transitional!) agreements that support costs to publish in former subscription journals of large publishing corporations and phasing out institutional open access funds, leaving little or no support for independent journals.

Considering all these factors, it is now time to put the future of OJPHI into professional hands, by choosing a mission-driven publisher that has its roots in academia. JMIR Publications, a medium-sized but rapidly growing publisher with its mission-driven academic leadership and focus on innovation in health and medicine, is the ideal fit as a new home and publisher of OJPHI. With access to the experienced professional staff of JMIR Publications, OJPHI will attract stakeholders from a wide variety of disciplines and geographic areas, achieve a shorter turnaround time, and upgrade the quality of the journal. The new publisher also has the capacity to make deals with institutional partners to put the journal on a more financially stable basis.

Like other journals in the JMIR Publications portfolio, OJPHI seeks to promote interdisciplinary collaboration and welcomes contributions by researchers and practitioners from a wide range of fields, including public health, computer science, data science, health informatics, and related disciplines. As such, it is complementary to the over 34 other titles in the JMIR Publications portfolio, and authors will have the opportunity to transfer their submissions between journals without the need for a new peer review (portable peer reviews).

OJPHI invites submissions of original research articles, reviews, and perspectives or viewpoints that cover a broad range of topics related to public health informatics, including the following:

- Use of health ICTs and data science to improve public health
- Development and implementation of electronic health records and other health information systems by public health agencies
- Framework, evaluation, and use of health information exchange technologies among public health agencies, hospitals, laboratories, and clinics
- Use of data analytics (including artificial intelligence [AI], machine learning, geographic information system, visualization, and data mining technologies) in public health research and practice
- Use of social media in public and population health informatics applications for health promotion and disease prevention

- Evaluation of mobile health technology and digital platforms in public health practice
- Integration of social determinants of health within public health practice using ICTs
- Ethical, legal, and social implications of public health informatics
- Precision public health informatics
- Analysis and utilization of big data for health promotion and health equity
- Development and evaluation of contact tracing technologies for public health practice and policy
- Infodemiology in public health informatics (complementing similar sections in the *Journal of Medical Internet Research*, *JMIR Public Health and Surveillance*, and the recently launched journal *JMIR Infodemiology*)

The manuscript management system and journal homepage has been migrated to the JMIR Publications platform (under its new URL [ojphi.jmir.org](http://ojphi.jmir.org)) and submissions are now open as of July 2023. Articles under consideration on the current platform are in the process of being migrated, and the review process for the articles in the pipeline will commence thereafter. For new articles, authors are encouraged to indicate their preferences by selecting from the list the topics under which they want their articles to be reviewed. This will aid search engine optimization and make it easier to automate the process of allocating the articles to specific reviewers. Authors of manuscripts submitted to other JMIR Publications journals are also encouraged to consider OJPHI as a destination for manuscript transfer.

In addition, we are refreshing our editorial board, and I invite interested researchers who are passionate about advancing the field of public health informatics to contact us. I am personally excited about the future of the field and that of the journal, which I consider in excellent hands with JMIR Publications. I thank our stakeholders, including authors and peer reviewers, for their continued patience and support as we are making this transition.

Joining JMIR Publications, an established and top-notch publisher, positions OJPHI within a wider ecosystem of open access biomedical and health informatics journals. We now have the facilities needed to reach out to a diverse group of authors and readers from universities, public health agencies, and policy makers in developed countries and the Global South. JMIR Publications provides us with the platform to improve the quality of the journal, article turnaround time, and become the public and population health informatics journal of choice among our stakeholders.

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## Conflicts of Interest

EM is the editor-in-chief of the *Online Journal of Public Health Informatics* (OJPHI) and receives a nominal honorarium.

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**Abbreviations**

**AI:** artificial intelligence

**ICT:** information and communication technology

**OJPHI:** Online Journal of Public Health Informatics

**UIC:** University of Illinois Chicago

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Original Paper

# Intersection of Perceived COVID-19 Risk, Preparedness, and Preventive Health Behaviors: Latent Class Segmentation Analysis

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## Abstract

**Background:** COVID-19 risk perception is a factor that influences the pandemic spread. Understanding the potential behavioral responses to COVID-19, including preparedness and adoption of preventive measures, can inform interventions to curtail its spread.

**Objective:** We assessed self-perceived and latent class analysis (LCA)-based risks of COVID-19 and their associations with preparedness, misconception, information gap, and preventive practices among residents of a densely populated city in Nigeria.

**Methods:** We used data from a cross-sectional survey conducted among residents (N=140) of Onitsha, Nigeria, in March 2020, before the government-mandated lockdown. Using an iterative expectation-maximization algorithm, we applied LCA to systematically segment participants into the most likely distinct risk clusters. Furthermore, we used bivariate and multivariable logistic regression models to determine the associations among knowledge, attitude, preventive practice, perceived preparedness, misconception, COVID-19 information gap, and self-perceived and LCA-based COVID-19 risks.

**Results:** Most participants (85/140, 60.7%) had good knowledge and did not perceive themselves as at risk of contracting COVID-19. Three-quarters of the participants (102/137, 74.6%;  $P < .001$ ) experienced COVID-19-related information gaps, while 62.9% (88/140;  $P = .04$ ) of the participants had some misconceptions about the disease. Conversely, most participants (93/140, 66.4%;  $P < .001$ ) indicated that they were prepared for the COVID-19 pandemic. The majority of the participants (94/138, 68.1%;  $P < .001$ ) self-perceived that they were not at risk of contracting COVID-19 compared to 31.9% (44/138) who professed to be at risk of contracting COVID-19. Using the LCA, we identified 3 distinct risk clusters ( $P < .001$ ), namely, prudent or low-risk takers, skeptics or high-risk takers, and carefree or very high-risk takers with prevalence rates (probabilities of cluster membership that represent the prevalence rate [ $\gamma_c$ ]) of 47.5% (95% CI 40%-55%), 16.2% (95% CI 11.4%-20.9%), and 36.4% (95% CI 28.8%-43.9%), respectively. We recorded a significantly negative agreement between self-perceived risk and LCA-based segmentation of COVID-19 risk ( $\kappa = -0.218$ , SD 0.067;  $P = .01$ ). Knowledge, attitude, and perceived need for COVID-19 information were significant predictors of COVID-19 preventive practices among the Onitsha city residents.

**Conclusions:** The clustering patterns highlight the impact of modifiable risk behaviors on COVID-19 preventive practices, which can provide strong empirical support for health prevention policies. Consequently, clusters with individuals at high risk of contracting COVID-19 would benefit from multicomponent interventions delivered in diverse settings to improve the population-based response to the pandemic.

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**KEYWORDS**

COVID-19; latent class analysis; risk perception; preparedness; preventive health behaviors; Nigeria

**Introduction**

Since the declaration of COVID-19 as a public health emergency of international concern by the World Health Organization on January 30, 2020, the global case counts have reached 644 million, with more than 6.6 million deaths [1]. Despite recommended guidelines such as mask wearing, physical distancing, isolation, and good personal hygiene (handwashing) to prevent COVID-19 spread [2], some individuals tend to flout these guidelines, including government restrictions and rules. Government measures to contain the COVID-19 pandemic can only be effective with widespread compliance by the general public [3]. The fact that individuals in these challenging times act so differently indicates that the risk perception relating to this novel virus strongly differs between different places and individuals [4]. This situation, coupled with the pervasiveness of misinformation about the virus [5-9], is raising significant concerns, especially in Africa, where the fragile health systems put additional pressure on preparedness and effective pandemic response efforts. Consequently, COVID-19 risk perception may be a strong modifier of the evolution of the epidemic [4]. This means that access to and type of information received and political and economic situations may influence how people perceive the risk of COVID-19 and how they act on it, including their patterns of adhering to preventive actions [10].

In an early COVID-19 modeling study, Nigeria was identified as having a high coronavirus importation risk and high vulnerability, with moderate capacity to contain the outbreak [11]. The city of Onitsha in Nigeria is a highly populated town and home to the largest market in West Africa [12,13]. This city is known for the daily influx of people and frequent international, regional, and local interactions through commerce, which can facilitate the spread of COVID-19 within and outside the city. Previous studies in Onitsha have assessed COVID-19-related knowledge, attitude, and practice (KAP) [14]; public opinions regarding government response to the pandemic [3]; impact of COVID-19 misconceptions on the control efforts [15]; COVID-19-related information sources; and gaps [16]. However, it is unclear how the residents of Onitsha perceived the risk of COVID-19 and whether their initial risk perceptions informed their preparedness and decisions to adopt recommended protective measures. Risk perceptions tend to guide individuals' judgments and evaluations of threats and can limit public compliance with and response to information from public health authorities [4,10,17,18].

Cori et al [4] espouse the need to apply established theories of risk perception research to COVID-19 and use this knowledge to improve health risk communication, build trust, and contribute to collaborating governance. People who perceive greater risks are believed to be more motivated to implement protective behaviors [10,17,18]. Although the global consequences of COVID-19 are hard to predict, an assessment of the initial population-level response to the disease in Onitsha regarding risk perception, preparedness, and preventive health behaviors could provide helpful information for interventions and improve

current and future public health response. Understanding the risk perceptions of community residents is critical for planning, risk communication, and intervention.

In light of the foregoing situation, this study aims to (1) assess the association of self-perceived risk of COVID-19, preparedness, and preventive practices among residents of Onitsha, (2) apply latent class analysis (LCA) to systematically segment the heterogeneous sample population into the most likely distinct risk clusters by using selected measures, and (3) examine the predictive factors for COVID-19 preventive practices among Onitsha city residents. An understanding and application of the interplay of these factors in the real world could influence behavior change, improve risk management decision-making, and inform a more targeted and effective COVID-19 intervention strategy to prevent and control the disease spread in the city.

**Methods****Data Source, Study Design, and Participants**

We conducted a secondary analysis of cross-sectional data obtained from a KAP survey in Onitsha, Anambra, Nigeria, in March 2020 (period of the pandemic before the government-mandated lockdown on March 29, 2020) [14]. A convenience sampling method was used to recruit 140 study participants from different representative locations within the city of Onitsha that includes commercial markets and housing units. The city of Onitsha is the largest commercial city in south-eastern Nigeria and has a population of nearly 8.1 million residents with a population density of 4100 per square kilometer [19]. This survey was conducted through in-person interviews of consenting adults aged 18 years and older living and working in Onitsha. A more detailed description of the survey instrument used, data collection procedures, and the study area can be found in the study by Iloanusi et al [14].

**Analytical Measures**

The analytical measures used in this study were obtained from baseline data collection [14]. The data set captured KAP data as quantitative and categorical measures coded dichotomously as poor or good [14]. The quantitative part represented the KAP indices. COVID-19 misconceptions were assessed based on the study of Iloanusi et al [14] and categorized as none, low, and high [15]. Participants were asked to indicate what they considered to be their risk perception for COVID-19 by using a 5-point Likert scale (ranging from not at risk to extremely at risk). This was classified into 3 categories (not at risk at all, somewhat or likely at risk, likely or extremely likely at risk) and, subsequently, reclassified as 2 categories (not at risk vs at risk). To assess the participant's perceived level of preparedness, they were asked how prepared they were for the impending COVID-19 outbreak, with the response options being "undecided or not prepared at all," "somewhat prepared for COVID-19," and "prepared for COVID-19." This was later classified into 2 categories for subsequent analysis, with the

last 2 options grouped as one and referred to as “prepared for COVID-19.” To assess information gaps, participants were asked if they needed COVID-19 information and coded dichotomously as Yes or No [14,17]. The demographic characteristics of the sample population used in this study have been described in detail previously by Iloanusi et al [14].

### Statistical Analysis

Using the chi-square test, we conducted univariable analyses of measures of interest, namely, risk perception for COVID-19 outbreaks, KAP, participants’ level of preparedness, misconceptions, and the COVID-19 information gap. To examine the relationships between KAP indices by self-perceived COVID-19 risk, preparedness, and information (gap), we conducted a linear regression analysis with a density contour overlay to show the potential patterns (clusters) within the measures. The bivariate fit models produced equations that described the relationships between the measures.

LCA was used to fit a latent class model to determine the most likely cluster or latent class for each observable measure by using an iterative expectation-maximization algorithm [20,21]. LCA was considered appropriate for understanding and exploring the meaning behind the participants’ risk perception. Using LCA allowed for estimating the population characteristics derived from the sample data, adjusting the measurement error, and determining the number of classes [22]. The LCA produced the latent class prevalence ( $\gamma_c$ ) and the conditional probabilities ( $p$ ) for each cluster and response category. Estimates of the effect size and likelihood ratio logworth obtained from a contingency table analysis of expected counts for cluster membership by levels or categories of a Y column were used to quantify differences within the response scales. The final LCA model fitness was determined using negative log-likelihood ( $-\log$ -likelihood), Bayesian information criterion, and Akaike information criterion to compare clusters with the smallest values of each, indicating the best fit. In addition, we considered entropy values, latent class probabilities, and interpretability of the model class identified in selecting the final model [21,23]. Based on these characteristics, definitions for each latent class were created. We identified 3 distinct risk clusters named as “prudent or low-risk takers,” “skeptics or high-risk takers,” and “carefree or very high-risk takers.” To enhance the ease of interpretation and clearer application to practice, the risk clusters were recoded dichotomously as “not at risk (0)” for prudent or low-risk takers and “at risk (1)” for both skeptics or high-risk takers and carefree or very high-risk takers. Furthermore, we determined the independent association between self-perceived COVID-19 risk and LCA-assessed COVID-19 risk and the study population characteristics by using a chi-square test or Fisher exact test (cell number  $<5$ ), when applicable.

To identify factors associated with the adoption of COVID-19 preventive practice, we conducted multivariable logistic regression analyses to estimate the unadjusted odds ratios and adjusted odds ratios (aORs) along with 95% CIs and the corresponding  $P$  values for each factor. We applied the mosaic plot data visualization with the associated chi-square test to display the intersection between self-perceived COVID-19 risk, LCA-based risk subgroup, and preventive practices by perceived preparedness. All statistical tests performed were 2-tailed, with a probability value of .05 used as the minimum threshold for declaring statistical significance. Data management, statistical analyses, and visualizations were conducted using SAS JMP Statistical Discovery Software (version 16.2; SAS Institute). This study was reported following the STROBE (Strengthening The Reporting of Observational Studies in Epidemiology) statement [24] and aligns with the minimum specific reporting requirements in the cross-sectional study checklist [25].

### Ethics Approval

All relevant ethical guidelines, including institutional review board approval and oral informed consent, were provided by all participants and documented during the primary data collection period [14]. Data used for this study were codified and anonymized to protect confidentiality and ensure individual participants’ privacy. The study protocol for this secondary data analysis was reviewed and approved (approval 00002363) by the institutional review board of the University of Houston.

## Results

### Descriptive Analysis of Measures

The descriptive characteristics of the study participants have been presented in detail by Iloanusi et al [14]. The demographic characteristics of this study population is displayed in [Multimedia Appendix 1](#). The univariable analysis of the measures evaluated is shown in [Table 1](#). We noted a significant difference in participants’ COVID-19 knowledge levels, with more than half of them (85/140, 60.7%;  $P=.01$ ) having a high knowledge of the disease. However, the majority (85/140, 60.7%;  $P<.001$ ) did not perceive they were at risk of contracting COVID-19. About 62.9% (88/140;  $P=.047$ ) of the participants had some misconceptions about COVID-19, while only 37.1% (52/140;  $P=.047$ ) had no misconceptions about the disease. As much as 74.6% (102/137;  $P<.001$ ) indicated the need for more COVID-19-related information. However, most participants (93/140, 66.4%;  $P<.001$ ) indicated that they were prepared for the COVID-19 pandemic. Overall, the study participants ( $N=140$ ) were indifferent ( $P>.05$ ) in their attitude and preventive practice levels.

**Table 1.** Univariable analysis of the study measures (N=140).

Characteristic	Values, n (%)	P value
<b>Knowledge</b>		.01 <sup>a</sup>
Low	55 (39.3)	
High	85 (60.7)	
<b>Attitude</b>		.13 <sup>b</sup>
Poor	61 (43.6)	
Good	79 (56.4)	
<b>Preventive practice</b>		.39 <sup>b</sup>
Poor	65 (46.4)	
Good	75 (53.6)	
<b>COVID-19 misconception</b>		.047 <sup>c</sup>
None	52 (37.1)	
Low	55 (39.3)	
High	33 (23.6)	
<b>Perceived need for COVID-19 information</b>		<.001 <sup>d</sup>
No	35 (25.5)	
Yes	102 (74.5)	
<b>Perceived preparedness</b>		<.001 <sup>d</sup>
Not prepared for COVID-19	47 (33.6)	
Prepared for COVID-19	93 (66.4)	

<sup>a</sup>Significant at  $P < .01$ .

<sup>b</sup>Not significant ( $P > .05$ ).

<sup>c</sup>Significant at  $P < .05$ .

<sup>d</sup>Significant at  $P < .001$ .

## Relationships Between KAP Indices

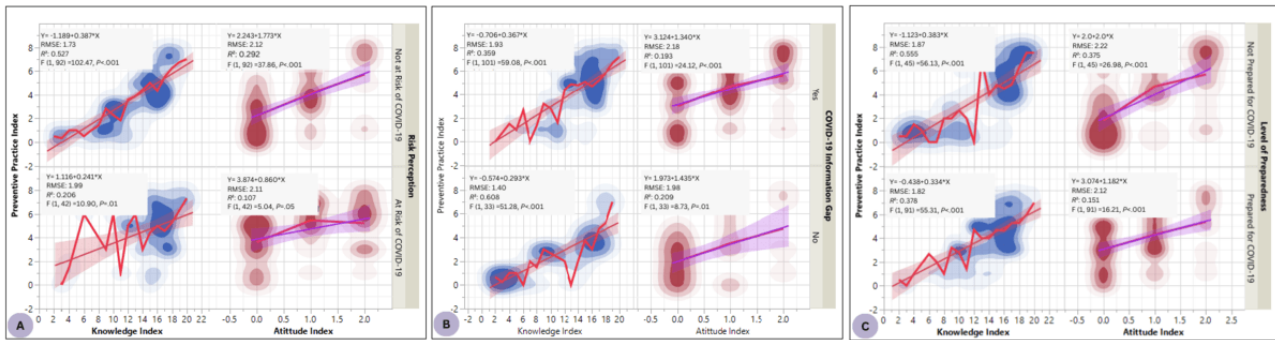
The relationships among KAP indices by COVID-19 risk perception are shown in [Figure 1A](#). A linear relationship was observed across the measures among individuals who perceived that they were at risk or not at risk of COVID-19. The contours show the regions of data density relative to the indices. Among the at-risk group, increased COVID-19 knowledge index and attitude index scores resulted in an increased level of preventive practice implementation ( $R^2=0.206$  for knowledge index;  $P < .001$  vs  $R^2=0.107$  for attitude index;  $P=.05$ ). In contrast, knowledge index and attitude index significantly ( $P < .001$ ) predicted as much as 52.7% and 29.2% of the preventive practice levels implemented by study participants who perceived they were not at risk of contracting COVID-19.

[Figure 1B](#) depicts the relationships among KAP indices by perceived COVID-19 information gap with the bands indicating the concentration of participants relative to their scores. Within participants who perceived that they had gaps in COVID-19-related information, increased knowledge index and attitude index resulted in a significant linear increase in their adoption of recommended preventive practices, as indicated by the preventive practice indices ( $R^2=0.359$  vs  $R^2=0.193$ ,

respectively). However, participants who did not perceive any gap in COVID-19 information had higher predictive associations among KAP indices. For instance, a positive increase in knowledge index and attitude index resulted in a corresponding increase in preventive practice indices and coefficients of determination of 60.8% (knowledge index,  $P < .001$ ) and 20.9% (attitude index,  $P < .01$ ).

The relationships among KAP indices by perceived preparedness with the contours indicating the density of participants relative to their index values are shown in [Figure 1C](#). Within participants who perceived that they were prepared for the COVID-19 pandemic, increased knowledge index and attitude index brought about a significant ( $P < .001$ ) linear increase in their adoption of recommended preventive practices, as reflected in the preventive practice index values ( $R^2=0.378$  vs  $R^2=0.151$ , respectively). However, participants who perceived themselves unprepared for the COVID-19 pandemic recorded comparatively higher predictive values. For instance, a positive increase in knowledge index and attitude index resulted in a corresponding increase in preventive practice index and coefficients of determination of 55.5% (knowledge index,  $P < .001$ ) and 37.5% (attitude index,  $P < .001$ ).

**Figure 1.** (A) Relationships among knowledge, attitude, and preventive practice indices by self-perceived COVID-19 risk. (B) Relationships among knowledge, attitude, and preventive practice indices by perceived COVID-19 information gap. (C) Relationships among knowledge, attitude, and preventive practice indices by perceived COVID-19 pandemic preparedness.



**LCA Model**

The LCA model parameter estimates with the conditional probabilities ( $\rho$ ) for each cluster and response category are presented in Table 2. Following the study population heterogeneity concerning a set of manifest variables, we used LCA to identify 3 significantly ( $P < .001$ ) distinct most likely clusters or latent classes (homogeneous subgroups or segments) of individuals. Those were named after their unique characteristics as prudent or low-risk takers ( $\gamma = 47.5\%$ ), skeptics or high-risk takers ( $\gamma = 16.2\%$ ), and carefree or very high-risk takers ( $\gamma = 36.4\%$ ). The key characteristics of the prudent or low-risk takers include high COVID-19 knowledge ( $\rho = 95.2\%$ ), good attitude ( $\rho = 85.4\%$ ), self-perception of not being at risk of COVID-19 ( $\rho = 58.9\%$ ), perceived preparedness for COVID-19 pandemic ( $\rho = 62\%$ ), experienced information gap ( $\rho = 81.5\%$ ),

no misconceptions ( $\rho = 66.5\%$ ), and good preventive practices ( $\rho = 87.5\%$ ). Among individuals characterized as skeptics or high-risk takers, 59.9% of them had high knowledge of COVID-19, a poor attitude ( $\rho = 66.6\%$ ), claimed not to be at risk of COVID-19 ( $\rho = 54.9\%$ ), perceived themselves as being prepared for the disease ( $\rho = 87\%$ ), had very serious information gaps ( $\rho = 98.5\%$ ), many misconceptions ( $\rho = 97.9\%$ ), and surprisingly, practiced good prevention strategies against COVID-19 ( $\rho = 82.5\%$ ). However, carefree or very high-risk takers had low knowledge ( $\rho = 81.3\%$ ), poor attitude ( $\rho = 72.7\%$ ), self-perception of not being at risk of COVID-19 ( $\rho = 84.5\%$ ), perceived preparedness for COVID-19 pandemic ( $\rho = 60\%$ ), experienced information gap ( $\rho = 53.5\%$ ), had moderate misconceptions ( $\rho = 68.1\%$ ), and implemented poor preventive practices ( $\rho = 99.4\%$ ).

**Table 2.** Parameter estimates from latent class segmentation analysis.<sup>a</sup>

Parameter, category	n	Probability ( $\rho$ ) of latent class membership (%)			Effect size	LRL <sup>b</sup>
		Prudent or low-risk takers	Skeptics or high-risk takers	Carefree or very high-risk takers		
Overall ( $\gamma_c$ )	140	47.5	16.2	36.4	— <sup>c</sup>	—
<b>Prevention practice</b>					0.83 <sup>d</sup>	24.80
Poor	65	12.5	17.5	99.4		
Good	75	87.5	82.5	0.6		
<b>Knowledge</b>					0.71 <sup>d</sup>	17.16
Low	55	4.8	40.1	81.3		
High	85	95.2	59.9	18.7		
<b>Attitude</b>					0.57 <sup>e</sup>	10.20
Poor	61	14.6	66.6	72.7		
Good	79	85.4	33.4	27.3		
<b>Risk perception</b>					0.28 <sup>f</sup>	2.39
Not at risk of COVID-19	94	58.9	54.9	84.5		
At risk of COVID-19	44	41.1	45.1	15.5		
<b>Perceived preparedness</b>					0.20 <sup>f</sup>	1.36
Not prepared for COVID-19	47	38	13	40		
Prepared for COVID-19	91	62	87	60		
<b>COVID-19 information gap</b>					0.38 <sup>f</sup>	4.81
Yes	101	81.5	98.5	53.5		
No	35	18.5	1.5	46.5		
<b>Misconception</b>					0.48 <sup>e</sup>	8.15
No	52	66.5	2.1	31.9		
Yes	88	33.5	97.9	68.1		

<sup>a</sup>The overall probabilities of cluster membership ( $\gamma_c$ ) and the conditional probabilities ( $\rho$ ) for each cluster are shown for each response category. Model fit statistics best fit estimates: negative log-likelihood=563.04; Bayesian information criterion=1239.07; and Akaike information criterion=1172.08.

<sup>b</sup>LRL: likelihood ratio logworth. A logworth value above 2 corresponds to significance at the .01 significance level ( $P < .01$ ).

<sup>c</sup>Not applicable.

<sup>d</sup>Large effect size.

<sup>e</sup>Medium effect size.

<sup>f</sup>Small effect size.

### Associations Between Self-Perceived and LCA-Based Segmentation of COVID-19 Risks and Selected Measures

Table 3 shows the associations among KAP, misconception, perceived information needs, preparedness, COVID-19 risk perception, and LCA COVID-19 risk assessment. Most participants (94/138, 68.1%;  $P < .001$ ) self-perceived that they were not at risk of COVID-19 compared to 31.9% (44/138;  $P < .001$ ) who professed to be at risk of contracting COVID-19.

Based on the LCA assessment, we recorded no statistical difference ( $P > .05$ ) between the 2 groups (67/136, 49.3% vs 69/136, 50.7%). However, with the LCA classification, we recorded statistically significant variations ( $P = .05$ ) across all measures considered, except perceived preparedness compared to self-perceived risk assessment, where knowledge ( $P = .01$ ) and preventive practice ( $P = .03$ ) were the only significant sources of variations. Based on the participant's characteristics, the LCA generally tends to classify more participants as at risk of contracting COVID-19 than the self-perceived assessment. For



instance, the proportion of participants who self-perceived themselves as being at risk were 5, 3, 3.8, and 3 times more than those who had poor COVID-19 knowledge, attitude, preventive practice, and high misconception, respectively, based on the LCA-based assessment of their COVID-19 risk status.

**Table 3.** Associations between self-perceived and latent class analysis-based segmentation of COVID-19 risk and selected measures.

Measure	Self-perceived COVID-19 risk (n=138)			Latent class analysis-based COVID-19 risk assessment (n=136)		
	Not at risk, n (%)	At risk, n (%)	P value	Not at risk, n (%)	At risk, n (%)	P value
Overall	94 (68.1)	44 (31.9)	<.001 <sup>a</sup>	67 (49.3)	69 (50.7)	.86 <sup>b</sup>
<b>Knowledge</b>			.01 <sup>c</sup>			<.001 <sup>a</sup>
Low	43 (31.2)	10 (7.3)		2 (1.5)	50 (36.8)	
High	51 (37)	34 (24.6)		65 (47.8)	19 (13.9)	
<b>Attitude</b>			.68 <sup>b</sup>			<.001 <sup>a</sup>
Poor	42 (30.4)	18 (13)		7 (5.2)	53 (38.9)	
Good	52 (37.7)	26 (18.8)		60 (44.1)	16 (11.8)	
<b>Preventive practice</b>			.03 <sup>d</sup>			<.001 <sup>a</sup>
Poor	49 (35.5)	14 (10.1)		9 (6.6)	52 (38.2)	
Good	45 (32.6)	30 (21.7)		58 (42.7)	17 (12.5)	
<b>COVID-19 misconception</b>			.96 <sup>b</sup>			<.001 <sup>a</sup>
None	34 (24.6)	17 (12.3)		37 (27.2)	13 (9.6)	
Low	37 (26.8)	17 (12.3)		27 (19.8)	26 (19.1)	
High	23 (16.7)	10 (7.3)		3 (2.2)	30 (22.1)	
<b>Perceived need for COVID-19 information</b>			.33 <sup>b</sup>			.045 <sup>d</sup>
No	26 (19.1)	9 (6.6)		54 (40)	46 (34.1)	
Yes	66 (48.5)	35 (25.7)		12 (8.9)	23 (17)	
<b>Perceived preparedness</b>			.44 <sup>b</sup>			.59 <sup>b</sup>
Not prepared for COVID-19	34 (24.6)	13 (9.4)		25 (18.4)	22 (16.2)	
Prepared for COVID-19	60 (43.5)	31 (22.5)		42 (30.8)	47 (34.6)	

<sup>a</sup>Significant at  $P < .001$ .

<sup>b</sup>Not significant ( $P > .05$ ).

<sup>c</sup>Significant at  $P < .01$ .

<sup>d</sup>Significant at  $P < .05$ .

### Multivariable Logistic Regression Model

The multivariable logistic regression model showing the unadjusted and aORs of the measures and COVID-19 preventive practice is presented in Table 4. Of all the measures included in our model, knowledge, attitude, and perceived need for COVID-19 information were the participants' only significant predictors of COVID-19 preventive practices (entropy  $R^2 = 0.3352$ ). Participants who had high COVID-19 knowledge

and good attitude toward the management of COVID-19 were 11 (aOR 11.22, 95% CI 4.34-28.97;  $P < .001$ ) and 3 (aOR 2.93, 95% CI 1.14-7.55;  $P = .03$ ) times more likely to have good COVID-19 preventative practices, respectively. Surprisingly, participants who needed more COVID-19 information were about 4 times more likely (aOR 3.92, 95% CI 1.36-11.30;  $P < .01$ ) to have good COVID-19 preventive practices compared to those who experienced no information gap.

**Table 4.** Multivariable logistic regression model of COVID-19 preventive practice.<sup>a</sup>

Measures	Unadjusted		Adjusted	
	Odds ratio (95% CI)	<i>P</i> value	Odds ratio (95% CI)	<i>P</i> value
<b>Knowledge</b>		<.001 <sup>b</sup>		<.001 <sup>b</sup>
Low (reference)	1		1	
High	14.63 (6.26-34.18)		11.22 (4.34-28.97)	
<b>Attitude</b>		<.001 <sup>b</sup>		.03 <sup>c</sup>
Poor (reference)	1		1	
Good	4.70 (2.29-9.63)		2.93 (1.14-7.55)	
<b>Risk perception for COVID-19</b>		.03 <sup>c</sup>		.41 <sup>d</sup>
Not at risk at all (reference)	1		1	
At risk	2.33 (1.10-4.95)		1.51 (0.57-3.99)	
<b>COVID-19 misconception</b>		.14 <sup>d</sup>		.99 <sup>d</sup>
Low (reference)	1		1	
High	0.60 (0.85-3.27)		0.99 (0.37-2.65)	
<b>Perceived need for COVID-19 information</b>		.01 <sup>b</sup>		.01 <sup>e</sup>
No (reference)	1		1	
Yes	4.21 (1.82-9.71)		3.92 (1.36-11.30)	
<b>Perceived preparedness</b>		.67 <sup>d</sup>		.85 <sup>d</sup>
Not prepared for COVID-19 (reference)	1		1	
Prepared for COVID-19	1.16 (0.58-2.35)		1.10 (0.41-2.92)	

<sup>a</sup>Model statistics: McFadden's pseudo R-square ( $R^2$  [U])=0.34; Akaike information criterion=139.25; Bayesian information criterion=158.76. Normal approximation used for ratio confidence limits effects. Tests and confidence intervals of odds ratios are Wald test-based.

<sup>b</sup>Significant at  $P < .001$ .

<sup>c</sup>Significant at  $P < .05$ .

<sup>d</sup>Not significant ( $P > .05$ ).

<sup>e</sup>Significant at  $P < .01$ .

### Intersection of Perceived COVID-19 Risk, Latent Class Risk Subgroup, Preparedness, and Preventive Practice

The mosaic plot in [Figure 2](#) displays the associations between self-perceived COVID-19 risk, LCA-based risk subgroup, and preventive practices by perceived preparedness. Among participants who perceived themselves as not at risk of COVID-19 but were prepared, 71% (5/7) were characterized as prudent low-risk takers and adopted good preventive strategies ( $P < .001$ ). Similarly, most of the participants who perceived themselves as somewhat likely or likely or extremely likely at risk of contracting COVID-19 and were prepared for the pandemic ended up as prudent low-risk takers (5/7, 71%;

$P = .05$  vs 12/16, 75%;  $P = .01$ , respectively) and implemented good preventive measures. However, most participants, including those who were prepared and not prepared for the COVID-19 pandemic, practiced the recommended preventive measures poorly (60%-100%) and were classified as carefree or very high-risk takers based on the LCA model. Only 29% (2/7;  $P = .05$ ) and 25% (4/16;  $P = .01$ ) of the participants who implemented good preventive practices were skeptics or high-risk takers and self-perceived themselves as likely at risk and extremely likely at risk of contracting COVID-19 ([Figure 2](#)). Overall, we recorded a significant negative agreement between self-perceived and LCA-based segmentation of the risk groups ( $\kappa = -0.2182$ , SD 0.0665;  $P = .01$ ).



**Figure 2.** Mosaic plot of the associations between self-perceived COVID-19 risk and latent class analysis–based risk assessment of most likely cluster membership by perceived preparedness.



## Discussion

### Principal Findings

During the initial days of the COVID-19 pandemic, the Nigerian government, like many other governments, implemented a series of preventive practices that included public lockdown, handwashing, use of hand sanitizer, wearing of face masks, and social distancing in public places, to curtail the spread of COVID-19. Although these interventions are effective, they require voluntary behavior change and compliance by citizens, who found this challenging to achieve and monitor. Our study investigates the role of behavioral determinants on self-perceived and LCA-based COVID-19 risks and the adoption of COVID-19 preventive practices. Our findings revealed that adopting good COVID-19 preventive practices among residents of Onitsha was generally driven by increased knowledge and improved attitude toward COVID-19 infection moderated by their risk perception status, information gaps, and level of preparedness. Several COVID-19–related studies have previously established the relationships between COVID-19 knowledge, attitude, and prevention practices [14,26,27]. Individuals who believed they were at low risk of developing COVID-19 were more likely to engage in unhealthy or risky behaviors [28].

Using the LCA, we identified 3 distinct risk clusters ( $P < .001$ ), namely, prudent or low-risk takers, skeptics or high-risk takers, and carefree or very high-risk takers, with prevalence rates of 47.5%, 16.2%, and 36.4%, respectively. Individuals who were high-risk to very high–risk takers tended to have many misconceptions, experienced COVID-19 information gaps, self-perceived themselves as not being at risk of contracting COVID-19, and therefore adopted poor preventive practices. A previous study has highlighted the existence of fundamental misconceptions that hindered compliance with prevention practices among Onitsha residents [15]. Similarly, COVID-19 information gaps and low diffusion due to government delays

in initiating awareness campaigns using accessible and efficient channels of information have been associated with poor COVID-19 preventive practices [16,29,30].

Accurate public risk perceptions are critical to effectively managing COVID-19, especially considering that people’s behavior can fundamentally influence and alter the spread of a pandemic [31–33]. In an attempt to assess “COVID-19 risk as feelings” (self-perceived) and “COVID-19 risk as analysis” (LCA-based assessment), we recorded a significant negative agreement between self-perceived risk and LCA-based segmentation of COVID-19 risk ( $\kappa = -0.218$ ,  $SD 0.067$ ;  $P < .01$ ). Consequently, participants with poor knowledge, attitude, preventive practice, and high misconception who claimed not to be at risk of COVID-19 infection were reported to be 3–5 times more at risk of contracting COVID-19 when assessed using LCA. These measures also had significant effect sizes in determining the probability of latent class membership. Although risk perceptions influence individual protective behaviors [17,34], our findings indicate that an individual’s perception of risk may not necessarily correlate positively with the actual analyzed risk. A pessimistic bias, that is, perceptions of risk that are (much) higher than the actual risk, is more likely for new risks such as COVID-19 that are perceived as uncontrollable [35].

LCA was considered appropriate for understanding and exploring the meaning behind risk perceptions in our study population. Threat appraisal and risk perception are essential determinants of the public’s willingness to cooperate and adopt health-protective behaviors during pandemics, including frequent handwashing, physical distancing, avoiding public places, and wearing face masks [36–38]. These risk perceptions guide individuals’ judgments and evaluations of threats and can limit public compliance with and response to information that authorities communicate [4,10,17,18,39]. LCA has been used to study various issues in vulnerable populations, including

mental health among Black youth [40], young Malawian adults with or at risk for HIV [41], and adolescent perceptions of in-school discrimination [42].

Of all the measures included in our multivariable model, only knowledge, attitude, and perceived need for COVID-19 information were significant predictors of COVID-19 preventive practices among the participants. Previous studies have also documented the associations between the KAP indices in this population [14]. However, it was surprising that participants who experienced the COVID-19 information gap were about 4 times more likely to have good preventative practices against the disease. This suggests that public health messages by the Nigeria Center for Disease Control and other governmental agencies may have been responsible for a positive behavioral change toward risk aversion during the early stage of the COVID-19 pandemic [3,16]. Residents of Onitsha, like many others worldwide, were faced with a new and unfamiliar health threat that could result in deaths, coupled with the fact that information on the disease was initially limited and changed more often with time. Fear of the unknown has been associated with the absence of information and, when encountered in sufficiently predictable and controllable contexts, could facilitate positive responses [43,44]. This may have been the case in our study population.

The intersection of self-perceived COVID-19 risk, LCA most likely risk clusters, perceived preparedness, and preventive practice indicates that most participants who self-perceived themselves as not being at risk of COVID-19 and had poor preventive practices (carefree ones) were noted to be at a very high risk of contracting COVID-19 infection when assessed using LCA. This make-belief may have brought about complacency on the public part, enforced by false or misleading COVID-19 narratives promoted by some groups to discredit legitimate public health measures [45]. The advent of social media and web-based platforms, which provide a fertile medium for disinformation to flourish, has been widely acknowledged as a threat to global efforts toward ending the pandemic [15,16,40]. This situation raises important concerns, especially in Africa, where the fragile health systems put additional pressure on preparedness and effective pandemic response efforts. However, our study noted that all the participants who claimed nonpreparedness but the likelihood of being somewhat at risk of COVID-19 accurately matched the LCA-based assessment classification as prudent or low-risk takers. People who perceive greater risks are believed to be more motivated to implement protective behaviors [10,17,18]. Efforts to improve pandemic preparedness and response to the next pandemic might benefit from greater investment in risk communication and community engagement and in developing strategies to counter misinformation and boost individuals' confidence in public health guidance [15,16,39,44-46]. Since latent class membership helps explain the patterns of individuals' scores on the indicator variables used to derive the classes, the LCA solutions therefore represent typologies that can help researchers and practitioners understand commonalities and differences across individuals, which have implications for both practice and future research [21].

## Strengths and Limitations

This study's findings should be interpreted with caution because of some limitations. This study is a secondary data analysis based on a cross-sectional study conducted during the early onset of the COVID-19 pandemic using a nonprobability convenience sampling method with a small sample size. Therefore, the data may be subject to sampling and potential response biases due to social desirability and unobserved confounding, leading to nonrepresentativeness of the population and possibly overestimating the direction and strength of associations. Similarly, the use of LCA is limited by the fact that individuals are assigned to classes based on the probability of likely cluster membership predicated on the scores of the indicator variables [21]. As a result, the exact number or percentage of class memberships cannot be guaranteed due to some level of misclassifications. Further, the complexity of the classes may inadvertently engage in a naming fallacy, wherein the class name does not accurately reflect the class membership [21]. Therefore, from the foregoing situation, definite causality cannot be inferred, and the generalizability of our findings is limited. The government intervention's role in messaging may also have impacted an individual's risk assessment and response to preventive care practices [3]. Finally, it is essential to note that the availability and uptake of the COVID-19 vaccines more than 2 years after the data used in this study were collected may have decreased self-perceived risk and adherence to COVID-19 preventive measures over time [47].

Despite these limitations, our study's strength lies in applying latent class segmentation analysis to reveal important insights into the relationships between behavioral measures and COVID-19 infection risk. Although self-report may not allow for the assessment of actual behavior due to social desirability, the application of LCA allowed for culturally competent and context-specific risk classification, which may be particularly useful in identifying subgroups of individuals who could benefit from a common intervention based on their shared characteristics [21,23]. Data used for this study were collected during the early phase of the COVID-19 pandemic and, thus, provide rich baseline information that could be used by public health authorities to assess COVID-19 response efforts or for current and future pandemic intervention planning.

## Conclusion

The LCA clustering patterns highlight the impact of modifiable risk behaviors on COVID-19 preventive practices, which can provide strong empirical support that may encourage behavior change, especially during the COVID-19 pandemic or any future outbreak of similar infectious diseases. Consequently, clusters with individuals at high risk of contracting COVID-19 would benefit from multicomponent interventions delivered in diverse settings to improve the population response to the COVID-19 pandemic. This finding may also offer clinicians the opportunity to refer their patients at high risk of contracting the disease to social workers or psychologists for behavioral counseling. In addition, understanding the role of risk perceptions in motivating people to engage in preventive behavior by public health authorities may also help with intervention program planning and designing evidence-based risk communication strategies.

## Data Availability

Data for this study can be made available upon reasonable request from the corresponding author.

## Authors' Contributions

OM contributed to conceptualization, project administration, data curation, methodology, formal analysis, validation, visualization, writing the original draft, reviewing, and editing. SI contributed to conceptualization, project administration, resources, methodology, data curation, validation, reviewing, and editing. IY, N-JRI, SG, and EJE contributed to validation, reviewing, and editing. All authors read and approved the final version of the manuscript submitted for publication.

## Conflicts of Interest

None declared.

## Multimedia Appendix 1

Demographic characteristics of the study population.

[PNG File , 37 KB - [ojphi\\_v15i1e50967\\_app1.png](#) ]

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## Abbreviations

**aOR:** adjusted odds ratio

**KAP:** knowledge, attitude, and practice

**LCA:** latent class analysis

**STROBE:** Strengthening The Reporting of Observational studies in Epidemiology

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Original Paper

# Toxicology Test Results for Public Health Surveillance of the Opioid Epidemic: Retrospective Analysis

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## Abstract

**Background:** Addressing the opioid epidemic requires timely insights into population-level factors, such as trends in prevalence of legal and illegal substances, overdoses, and deaths.

**Objective:** This study aimed to examine whether toxicology test results of living individuals from a variety of sources could be useful in surveilling the opioid epidemic.

**Methods:** A retrospective analysis standardized, merged, and linked toxicology results from 24 laboratories in Marion County, Indiana, United States, from September 1, 2018, to August 31, 2019. The data set consisted of 33,787 Marion County residents and their 746,681 results. We related the data to general Marion County demographics and compared alerts generated by toxicology results to opioid overdose-related emergency department visits. Nineteen domain experts helped prototype analytical visualizations. Main outcome measures included test positivity in the county and by ZIP code; selected demographics of individuals with toxicology results; and correlation of toxicology results with opioid overdose-related emergency department visits.

**Results:** Four percent of Marion County residents had at least 1 toxicology result. Test positivity rates ranged from 3% to 19% across ZIP codes. Males were underrepresented in the data set. Age distribution resembled that of Marion County. Alerts for opioid toxicology results were not correlated with opioid overdose-related emergency department visits.

**Conclusions:** Analyzing toxicology results at scale was impeded by varying data formats, completeness, and representativeness; changes in data feeds; and patient matching difficulties. In this study, toxicology results did not predict spikes in opioid overdoses. Larger, more rigorous and well-controlled studies are needed to assess the utility of toxicology tests in predicting opioid overdose spikes.

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**KEYWORDS**

opioid epidemic; clinical laboratory techniques; public health; epidemiology; toxicology

## Introduction

A key challenge in addressing the opioid epidemic [1,2] is timely insight into population-level factors, such as trends in prevalence of legal and illegal substances, overdoses, and deaths. Many

surveillance systems and approaches at the national, regional, and local levels exist [3-12] but are limited by being (1) focused on late-stage outcomes such as drug-related arrests and overdose deaths [13,14], (2) frequently not available until long after an

event occurs [15,16], (3) drawn from fragmented and siloed data, and (4) not representative [17].

This project explored whether toxicology laboratory results [18,19] from testing in health care and jail settings (in short, “toxicology results”) are potentially useful in surveilling the opioid epidemic. Our work builds on similar efforts to leverage calls to poison control centers for surveillance [5]. These selected toxicology tests may be useful because they occur in a variety of settings where effects of changing opioid use may first become apparent, can be communicated in real time through health information technology standards such as Health Level 7 (HL7) [20] and Logical Observation Identifiers Names and Codes (LOINC) [21,22], can be integrated at an individual level using record linkage [23], and are required in many states' prescription drug monitoring programs and are recommended for monitoring patients on chronic opioid therapy [24,25].

To date, toxicology results have been used primarily for retrospective, one-off analyses [26-29]. The goal of this project was to investigate whether ongoing, timely monitoring of living individuals' toxicology results gathered from several sources might indicate changes in the general population's opioid use. This study addresses the following questions: (1) how can toxicology test data from multiple sources be aggregated and homogenized? (2) What are the characteristics of persons in an aggregated set of toxicology test data in Marion County, Indiana, United States, compared to those of the general population? (3) Can toxicology test data provide direct indicators for trends regarding the opioid epidemic? (4) How might such toxicology test data be integrated into a dashboard for managing the opioid epidemic?

## Methods

### Overview

The health care company managing this project receives many types of laboratory tests from its clients, which are primarily clinical laboratories. The orders for and results of these tests are transmitted to the health care company in near real time using the HL7 protocol. The transmissions typically contain patient demographics, ordering provider and location, specimen information, the ordered tests, and the quantitative or qualitative results. All laboratory test information is transmitted to a data lake where it is refined, enriched, and deidentified.

### Sample Characteristics

The data set for this study included all toxicology results with a patient (or, if not available, an order or accession) address in Marion County (the largest county in Indiana with a population of 954,760 individuals as of 2018; home to Indianapolis—the capital of Indiana) collected between September 1, 2018, and August 31, 2019.

Patient and provider records were refined using several methods, including standardizing variable values and formatting, decomposing composite fields, and retrieving missing information (eg, ZIP codes based on address). We refined organizations through a similar process and categorized them by type, such as addiction treatment centers, criminal justice, forensics, hospital, emergency department, pain management,

and primary care. Patient records were linked through a string similarity function that assigned a master patient identifier if records had a match rate of 95% or greater.

Matching tests across multiple laboratories was one of the most challenging aspects of cleaning and homogenizing the data. We used string matching functions and manual review to assign a LOINC code to each test, which we then mapped to a local drug class hierarchy.

For result records, abnormality was calculated by comparing the result value with the transmitted reference range. Positivity for toxicology tests, based on keywords or numeric values, were determined by profiling client data. Multiple tests for the same patient were considered as separate, with the exception of pairs of screening and confirmatory tests (which occurred rarely and were considered positive if the confirmatory test yielded a positive finding).

We only included records with ZIP codes from Marion County (either the patients' or, if unavailable, the ordering location's records). We retained only the data from hospitals, primary care providers, clinical specialty providers, and jails because emergency department, coroner, forensics, police department, sheriff's offices, state police, and employer testing data were expected to exhibit markedly different result patterns. For instance, in emergency departments and law enforcement, sampling due to suspected alcohol and drug use typically results in high positivity rates. Positivity rates for employment drug testing, on the other hand, are often low since individuals applying for jobs know a drug test is required. Because these patterns were observed in our data, we excluded results from these settings. We included data from jails because positivity rates were fairly consistent with those reported in Marion County.

In total, 24 clients of the health care company had data for at least 1 Marion County patient. The largest contributor provided 64% of the results' volume but only supplied data from January to April 2018. We excluded these data because they mostly comprised employment testing and had, comparatively, a much lower positivity rate. Of the remaining data, 67% of them were obtained from a regional reference laboratory and the core laboratory for several hospitals in Indiana, and the next 15% of them were obtained from a laboratory carrying out testing for law enforcement and forensics (only jail data were included). The remainder of the laboratories were primarily regional toxicology and reference laboratories. In addition to our data refinement and linking infrastructure, we already had built a preliminary dashboard for visualizing the data that served as the basis for this project [30].

### Dashboard Development and Data Analysis

The project was advised by a 9-member external advisory group consisting of 3 academic researchers; 5 public health professionals at the local, state, and international level; and 1 corporate participant. This group met several times with 8 health care company staff members and executive leaders over the course of the project period to provide high-level strategic guidance. A technical working group, consisting of 3 members of the external advisory group and company technical personnel,



prepared and analyzed the data and designed and prototyped the dashboard.

After data preparation, we summarized toxicology results data descriptively and compared them to data for Marion County where possible. We performed 2-proportion  $z$  tests on each category, excluding unknown counts in totals. In addition, we developed a set of design ideas for a local dashboard to manage the opioid epidemic and evaluated them through a survey of the advisory group and additional company personnel. In the survey, we presented proposed design features and asked one or more questions, such as “What kind of useful information can you glean from the presented visualization?” “What kind of information is missing?” “Is it easy to determine values of interest?” The survey was distributed to 19 invitees (8 advisory group members and 11 company staff).

Last, we evaluated how toxicology results trends related to signals derived from opioid overdose-related emergency department visits. The goal of this analysis was to determine whether simple positivity rates from toxicology results can provide useful signals for trends regarding the opioid epidemic. For instance, intuition would suggest that test positivity rates might rise prior to spikes in overdoses. For the toxicology tests, we used the specimen collection date, and for emergency department encounters, the visit date.

The Marion County Department of Health uses ESSENCE (Electronic Surveillance System for the Early Notification of Community-Based Epidemics) [31] to analyze opioid-related data, such as opioid overdose-related emergency department visits [32], and generate alerts for notable events. To detect spikes in test positivity, or the incidence of opioid overdose-related emergency department visits, we applied the ESSENCE C2 detection method to toxicology results and emergency department opioid overdose data between September 1, 2018, and August 31, 2019. The algorithm uses a moving sample average and sample SD to standardize each observation, with a 2-day lag in the mean and SD calculations [33]. The implemented baseline in ESSENCE is 28 days, compared to the baseline of 7 days. For emergency department data, the opioid outbreak indicator was the daily count of individuals with any overdose, and for laboratory data, the daily positive proportion of opioid toxicology tests. If the result exceeded 3 SDs above the sample mean, an alert was generated.

## Ethics Approval

This project (protocol #1802267756: Development and formative evaluation of the Opioid Epidemic Management Dashboard) was approved as expedited by the Indiana University institutional review board on February 2, 2018.

## Results

### Overview

Table 1 shows a comparison of the major characteristics of the health care company's data set and Marion County demographics. For the study period, 4% of people with a Marion County address had at least 1 test result. The health care company data set's gender distribution (35.9% males and 64.1% females—within the 82.5% of individuals with a known gender) differed significantly from the gender distribution of Marion County's population (48.2% males and 51.8% females). A much larger, national data set of test results had a more similar gender distribution (40.5% males and 59.5% females). In numerous records, data on race and ethnicity were missing and therefore not included. Age distributions (within the 81.9% of individuals with a known age) also showed differences, with individuals aged up to 19 years significantly underrepresented and those aged 20 to 39 years significantly overrepresented in the health care company data set.

Table 2 provides additional detail about toxicology results for the 37 ZIP codes in Marion County. The proportion of residents by ZIP code with at least 1 toxicology test result within the study period ranged from 0.4% to 41.5%. In 28 (76%) ZIP codes, the range was between 0.4% and 3%; in 5 (14%), between 5.1% and 8.4%; and in 4 (11%), between 10.7% and 41.5%. For the 46.2% of records having no patient address, the ZIP code of the ordering location was used, which implies that ZIP codes with large order volumes and low populations showed higher percentages of tested residents. For example, ZIP code 46202, which has the highest percentage at 41.5%, is the location of Marion County Jail II. The next 4 highest percentages are in ZIP codes that include major hospitals. The result positivity rate, defined as the number of positive results divided by the number of nonmissing or nondeterminate results, ranged from 3% to 19%. Visits to the emergency department due to overdose and overdose deaths are provided for context. However, it should be noted that the time periods for the number of residents and overdose deaths are for 2018, only partially overlapping with the September 2018 to August 2019 date range of the laboratory tests.

**Table 1.** Comparison of gender and age characteristics of the health care company's data set (September 1, 2018, to August 31, 2019) to Marion County demographics obtained from US Census Bureau (2018).

	Health care Company (N=33,787), n (%)	Marion County (N=954,670), n (%)	P value (Z test)
<b>Gender</b>			
Male	10,012 (35.9)	460,093 (48.2)	<.01
Female	17,856 (64.1)	494,577 (51.8)	<.01
Unknown	5923 (N/A <sup>a</sup> )	N/A (N/A)	N/A
<b>Age (years)</b>			
0-19	3901 (14.1)	257,636 (27.0)	<.01
20-39	14,268 (51.5)	293,706 (30.8)	<.01
40-59	6046 (21.8)	228,542 (23.9)	<.01
60-79	3088 (11.2)	145,891 (15.3)	<.01
>80	391 (1.4)	28,895 (3)	<.01
unknown	6093 (N/A)	N/A (N/A)	N/A

<sup>a</sup>N/A: not applicable.

**Table 2.** Toxicology results for the 37 ZIP codes in Marion County, Indiana, United States, sorted by the number of residents in descending order from September 1, 2018, to August 31, 2019 (except for the number of residents and overdose deaths from January 1, 2018, to December 31, 2018).

ZIP code	Residents, n	Residents in the data set, n (%)	Residents with positive results, n	Results, n	Positive results, n	Result positivity rate (%)	Overdose-related emergency department visits, n	Overdose deaths, n
46227	56,449	2931 (5.2)	1545	43,211	4508	10.4	264	20
46226	45,998	1183 (2.6)	729	18,119	1842	10.2	208	14
46237	39,803	427 (1.1)	268	7312	934	12.8	128	13
46203	38,313	546 (1.4)	359	7958	1023	12.9	282	20
46254	36,530	934 (2.6)	424	17,121	1238	7.2	66	8
46224	35,177	575 (1.6)	331	9977	1382	13.9	93	<5
46220	33,833	751 (2.2)	439	11,509	1423	12.4	64	<5
46219	33,646	4407 (13.1)	3030	59,509	8048	13.5	269	17
46222	33,061	372 (1.1)	219	4774	534	11.2	153	19
46260	32,779	2768 (8.4)	1690	40,864	4746	11.6	79	<5
46241	30,918	420 (1.4)	288	3488	550	15.8	177	23
46218	30,516	903 (3.0)	587	12,892	1306	10.1	215	16
46201	30,487	863 (2.8)	639	13,216	1817	13.7	361	34
46217	29,558	296 (1.0)	165	4082	363	8.9	103	10
46235	29,507	766 (2.6)	387	11,117	817	7.3	99	5
46229	27,913	1437 (5.1)	1019	21,806	4182	19.2	105	13
46221	27,054	206 (0.8)	105	2988	295	9.9	146	7
46236	26,751	462 (1.7)	242	6522	546	8.4	74	<5
46268	26,411	602 (2.3)	342	8511	726	8.5	64	<5
46205	26,351	553 (2.1)	293	8037	668	8.3	86	11
46234	25,002	158 (0.6)	77	2299	180	7.8	34	7
46239	24,348	311 (1.3)	134	4594	304	6.6	91	5
46214	23,747	275 (1.2)	108	3984	243	6.1	46	<5
46256	23,541	3887 (16.5)	1847	54,212	4155	7.7	55	5
46208	23,312	290 (1.2)	181	4042	394	9.7	77	7
46240	18,817	374 (2.0)	230	4912	478	9.7	40	<5
46250	18,545	490 (2.6)	282	7271	683	9.4	28	5
46202	16,021	6652 (41.5)	5447	263,328	19,823	7.5	139	5
46113	15,037	72 (0.5)	27	1048	66	6.3	22	<5
46228	14,876	182 (1.2)	104	2570	220	8.6	36	<5
46107	12,801	110 (0.9)	49	1721	122	3.0	70	5
46259	11,777	61 (0.5)	25	782	62	7.9	30	<5
46231	11,440	47 (0.4)	24	681	68	10.0	19	<5
46278	7968	98 (1.2)	50	1509	102	6.8	7	<5
46225	6524	489 (7.5)	417	66,361	2014	3.0	65	8
46204	5903	369 (6.3)	291	37,083	1066	2.9	82	<5
46216	1496	160 (10.7)	97	2348	297	12.6	<5	<5
Total	932,210	35,427 (3.8)	22,491	771,758	67,225	8.7	N/A <sup>a</sup>	N/A

<sup>a</sup>N/A: not applicable.

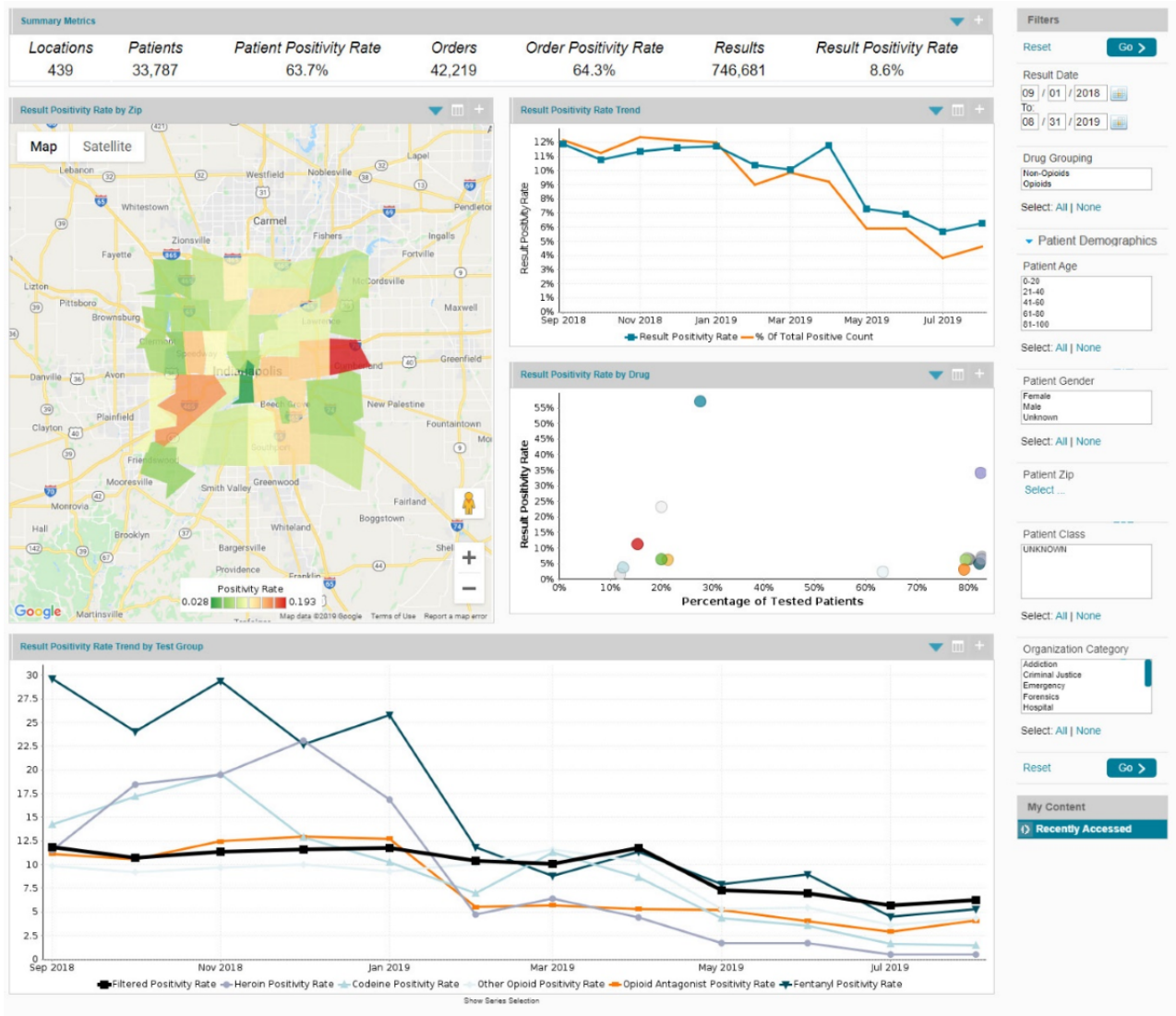
### Dashboard Design and Prototyping

We used the data to explore potential visualizations based on the dashboard we had previously developed [30]. We focused our efforts on designing specific enhancements to the dashboard and identifying potential improvements through a survey. Of the 19 invitees, 10 responded. A description of the main design enhancements and potential improvements follows.

Figure 1 shows the final design of the main dashboard. The Summary Metrics bar near the top summarizes the data in

general with regard to patients, test results, and positivity. The result positivity rate by ZIP heat map provides a geographic overview of Marion County; other graphs display general and drug-specific positivity trends and information. More information can be displayed by hovering over certain areas of the screen. Filters on the right allow the user to subset the data. The following sections provide additional detail and survey results for selected aspects of the design.

Figure 1. Final design of main dashboard displaying summary toxicology results for Marion County, Indiana, United States.



### Summary Metrics Display

The Summary Metrics display in Figure 1 shows the following key numbers:

- Locations: count of distinct physical ordering sites such as a doctor’s office, emergency department, employer, or clinic
- Patients: total number of individual patients with 1 or more test results
- Patient positivity rate: number of patients with at least 1 positive result divided by the number of patients with 1 or more test results

- Orders: total number of unique laboratory orders including 1 or more results
- Order positivity rate: the number of orders with 1 or more positive result divided by the number of orders with 1 or more results
- Results: total number of results (screening and confirmatory tests for the same drug only counted once)
- Result positivity rate: number of positive results divided by the total number of results

Feedback on the Summary Metrics display included the need for clearer labeling of selected metrics, separating toxicology results for licit or illicit substances, and adding contextual data,

such as the total population from which the tests are drawn, naloxone administrations, fatal or nonfatal overdoses, overdose-related emergency medical services runs, prescriptions, and medication-assisted treatment volume.

### Result Positivity Rate by ZIP Code Display

Geographical maps are common in displaying data related to the opioid epidemic [34]. The result positivity rate by ZIP display in [Figure 1](#) shows the map displaying test positivity rates across ZIP codes. Positivity rates range from 0.028 to 0.193. The user can pan and zoom in or out of the map, as well as select data to display using the filters on the right of the dashboard.

Feedback on this design included its usefulness for identifying “hot spots,” and the need to standardize the color range across displays with different minima and maxima of the positivity rate; providing the numerator and denominator for the positivity rate, as well as residents by ZIP code, to judge

representativeness of the data; the ability to “scrub” through the time line; and the ability to correlate with other data, such as overdoses or emergency medical service runs. In addition, map areas did not correspond exactly with ZIP codes.

### Drug Positivity by Age, Gender, and Drug

[Figure 2](#) shows drug positivity by age, gender, and drug to understand multivariate relationships in the data. Certain patterns are evident, such as generally lower positivity rates for heroin in females than in males, and age and positivity differentials regarding cocaine.

Feedback on this design included that it was easy to tell which groups are high-risk and whether these groups were stable over time. It was perceived as difficult to tell how important or statistically significant the differences were between rectangles of different colors. An alternative design suggestion was a bar graph by age as an initial visual, with a drill-down option to look at time trends.



**Figure 2.** Visualizations for drug positivity by age, gender, and specific drug for Marion County, Indiana, United States. Data are from September 1, 2018, to August 31, 2019.



### Toxicology Results as Predictive Signals

We used the ESSENCE platform to determine the potential relationship between changes in toxicology results' positivity and opioid-related chief complaints in emergency departments. We included toxicology results from our data set likely to be predictive for future overdoses, such as those generated in health care and jail facilities. We excluded data that were likely to

have been collected after overdoses, such as emergency department and coroner data. During the 12 months of overlap between the data sets, ESSENCE generated 4 alerts for emergency department visits and 3 for toxicology results. We counted the combination of 1 alert each as an "episode" if (1) the toxicology result alert occurred prior to the emergency department visit alert and (2) both alerts occurred within a 30-day window but not on the same day. We chose 30 days as



the time window because we considered toxicology results alerts outside of that window as not actionable. Only 1 episode occurred in the data set, with the toxicology results alert preceding the emergency department alert by 9 days. The sample size was not sufficient to conduct statistical tests for comparison.

## Discussion

The purpose of this project was to elucidate whether analyzing toxicology results may be useful in monitoring the opioid epidemic. Our key findings are summarized below.

### Challenges in Aggregating, Preparing, and Managing Toxicology Test Data From Multiple Sources

We aggregated data from 24 health care company clients, all of whom sent us data in varying formats and degrees of completeness. Attempts to combine data sources for population surveillance need to account for differing formats, rates of completeness, and missingness.

Changes in the client base and data feeds affected data availability. Where possible, we imputed missing data by matching to a more complete version of the patient record from another client, or using addresses of ordering providers and accessioning location as proxies. However, such imputations carried the risk of introducing bias.

Linking data was relatively easy because data were fully identified and could be matched across clients. However, we could not link toxicology results to external data such as nonfatal overdoses, overdose deaths, or naloxone administrations due to privacy constraints. This limitation reduced our ability to develop a more complete picture of the epidemic.

### Factors Increasing the Effort Required to Clean and Synthesize Data

Test names are often not standardized among laboratories, requiring significant computational or manual inferencing. While initial test mapping took considerable effort, we partially automated the process as the set of test names mapped to the hierarchy grew. Artificial intelligence methods using the training data generated in this project may facilitate test mapping in the future.

Toxicology test orders often include component tests for multiple drugs. The component tests, in turn, can have multiple instances such as screening (qualitative) and confirmatory (quantitative) tests for the same drug. Many confirmatory tests are a collection of metabolites that can indicate 1 or more parent drugs. We counted 1 or more positive results for the same drug within the same test order as a single result.

Toxicology results can sometimes be difficult to interpret with respect to the source substances introduced into the patient's system and the metabolites detected at various time points.

### Representativeness of Toxicology Test Data for Larger Trends in the Opioid Epidemic

Toxicology tests are typically not administered to a random sample of the population. For instance, pain management patients are more likely to be tested when drug testing is required

for chronic opioid therapy. Such consistency testing necessarily reflects the expectations of the clinician, such as a positive result when the patient is on opioid therapy. On the other hand, drug screening related to employment or Department of Transportation monitoring samples a different demographic with the expectation that most test results are negative. Inclusion or exclusion of data sets generated for various purposes will likely skew positivity rates. This may be partially addressed by only including data sources that are not likely to be strongly biased with regard to the test result, and weighting included data sources according to their demographic composition, to approximate the demographics of the population of interest. Encouragingly, the gender distribution in our results resembled that found in the results of a large, national laboratory test provider, providing some evidence of external validity. Unfortunately, demographic information is often missing in laboratory test records.

### Potential Approaches to Visualizing Toxicology Test Data

Our project generated several potentially useful ideas for visualizing toxicology test data. Summary statistics that include unique individuals, the number of orders and tests, and positive or negative test results for various analytes could help monitor drug use or abuse prior to serious events, such as overdoses and overdose deaths. A variety of visualization techniques can help show relationships among and trends for selected variables.

However, limitations in being able to integrate and interlink different data sets was a key obstacle for generating insights. For instance, several of our organizational participants had access to highly relevant data, such as prescriptions, fatal and nonfatal overdoses, emergency medical service runs, and drug seizures related to opioids. Interlinking these data on an individual basis (where possible) was perceived as potentially useful but challenging with regard to governance, record linking, and time and effort required.

### Using Toxicology Test Data as a "Signal" in Surveillance

Our results are inconclusive regarding the question of whether surveillance of toxicology results at the urban county level can serve as an effective predictor for spikes in opioid overdose cases admitted to emergency departments. While we focused on data likely to be predictive for such events, the proportion of overdose cases for which a toxicology test result is available prior to or after an overdose is unknown. In addition, chief complaints and discharge diagnoses for Marion County vary considerably by hospital with regard to specificity about overdoses and specific drugs involved. Individual-level data linkage may be a promising option to answer such questions and elicit more meaningful signals than possible in our study.

### Scaling Our Approach to Other Municipalities and States for Public Health Surveillance Purposes

Due to variation in data set content, availability, granularity, and linkability, our approach is likely difficult to scale easily to other municipalities and states. The health care company's market position in Indiana provided a strong foundation for attempting to explore the utility of test results for tracking the

opioid epidemic. However, even given that, it is unknown to what degree toxicology results in Marion County are indicative of trends in the opioid epidemic.

Currently, toxicology tests among living individuals appear to play only a small role in surveillance of the opioid epidemic. However, such tests might be important and timely indicators for drug use disorder trends in the general population. Further work should address issues identified in our study, such as aggregating, preparing, and managing toxicology test data; representativeness of these data; potential approaches to visualizing them; and using toxicology test data as a “signal” in surveillance.

## Conclusions

Analyzing toxicology results of living individuals from a variety of sources may be useful as an indicator of trends in opioid use. Important findings to consider include the following: (1) there are multiple challenges in aggregating, preparing, and managing toxicology test results for population trend analysis; (2) the representativeness of these data for the general population must be assessed carefully; (3) leveraging toxicology test results as a “signal” in surveillance likely requires robust data sets and sophisticated analyses. Individual-level data linkage may be a promising option to elicit more meaningful signals than is currently possible; and (4) a variety of visualization techniques can help show relationships among and trends for selected variables.

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## Conflicts of Interest

None declared.

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**Abbreviations**

**ESSENCE:** Electronic Surveillance System for the Early Notification of Community-Based Epidemics

**HL7:** Health Level 7

**LOINC:** Logical Observation Identifiers Names and Codes

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Viewpoint

# Framework for Classifying Explainable Artificial Intelligence (XAI) Algorithms in Clinical Medicine

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## Abstract

Artificial intelligence (AI) applied to medicine offers immense promise, in addition to safety and regulatory concerns. Traditional AI produces a core algorithm result, typically without a measure of statistical confidence or an explanation of its biological-theoretical basis. Efforts are underway to develop explainable AI (XAI) algorithms that not only produce a result but also an explanation to support that result. Here we present a framework for classifying XAI algorithms applied to clinical medicine: An algorithm's clinical scope is defined by whether the core algorithm output leads to observations (eg, tests, imaging, clinical evaluation), interventions (eg, procedures, medications), diagnoses, and prognostication. Explanations are classified by whether they provide empiric statistical information, association with a historical population or populations, or association with an established disease mechanism or mechanisms. XAI implementations can be classified based on whether algorithm training and validation took into account the actions of health care providers in response to the insights and explanations provided or whether training was performed using only the core algorithm output as the end point. Finally, communication modalities used to convey an XAI explanation can be used to classify algorithms and may affect clinical outcomes. This framework can be used when designing, evaluating, and comparing XAI algorithms applied to medicine.

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**KEYWORDS**

explainable artificial intelligence; XAI; artificial intelligence; AI; AI medicine; pathology informatics; radiology informatics

## Introduction

Algorithmic classifiers like artificial neural networks were first implemented many years ago [1]. Recently, unsupervised neural networks have allowed context-agnostic training and deployment. Without the need to embed a priori knowledge of the real-world system being studied, the use of these applications has expanded rapidly, and there has been much excitement about artificial intelligence (AI) algorithms in nearly every industry, including medicine.

Meanwhile, government policy that incentivizes the use of electronic medical record systems expanded the availability of digital health care information [2]. This created an environment where data analysis, predictive analytics, and ultimately AI can readily influence the interpretation of patient data and potentially prevent errors in real time during the course of clinical care [3]. Along these lines, radiologists, and to a lesser extent pathologists, are increasingly using image analysis algorithms as an assistive technology for image interpretation [4-6]. These technologies, rather than feeding into misconceptions about



threats and capabilities of AI, could potentially put radiologists and pathologists at the forefront of purposeful AI innovation [7].

Initially, AI may seem like a threat to health care jobs, removing providers from the decision-making process by introducing algorithms that function as a “black box” [8]. With this perceived threat are concerns about patient safety, some stemming from comparisons to non-health care applications of AI. Like any system, AI is not infallible. For example, early versions of self-driving automobile algorithms may have caused accidents [9].

The practice of clinical medicine remains an “art” where decisions of licensed providers are relied upon to ensure patient safety. Unfortunately, in contrast to transparent, rule-based systems, a trained AI model is not transparent to a clinician [10]. Therefore, there are currently efforts to find a middle ground that combines human involvement and AI in a complementary manner [11]. For example, AI might be used to generate insights not always or easily identified by a human, but a human would still determine their significance [12,13]. In this way, AI becomes a tool used by a clinician.

Multiple countries have passed or proposed regulations on the use of algorithms in clinical medicine. Under the US Food, Drug, and Cosmetic Act, an algorithm can be classified as a “nonregulated medical device” if it meets certain criteria; otherwise, it may represent a regulated medical device. One of the key criteria is whether the algorithm is “intended for the purpose of enabling such health care professional to independently review the basis for such recommendations that such software presents so that it is not the intent that such health care professional rely primarily on any of such recommendations to make a clinical diagnosis or treatment decision regarding an individual patient” [14]. It remains to be seen how the FDA enforces this criterion on a case-by-case basis, and regulations may change over time. Similarly, the UK Department of Health and Social Care has issued robust guidance for best practices in digital health care innovation [15]. One of the key elements of this guidance is transparency about algorithm limitations, algorithm type, and evidence of effectiveness. Because of these regulatory frameworks, concerns about medical malpractice issues, and the general awareness that algorithm predictions are not always correct, there is a growing recognition that AI

algorithms should allow health care providers to independently review some form of explanation of their core results [16].

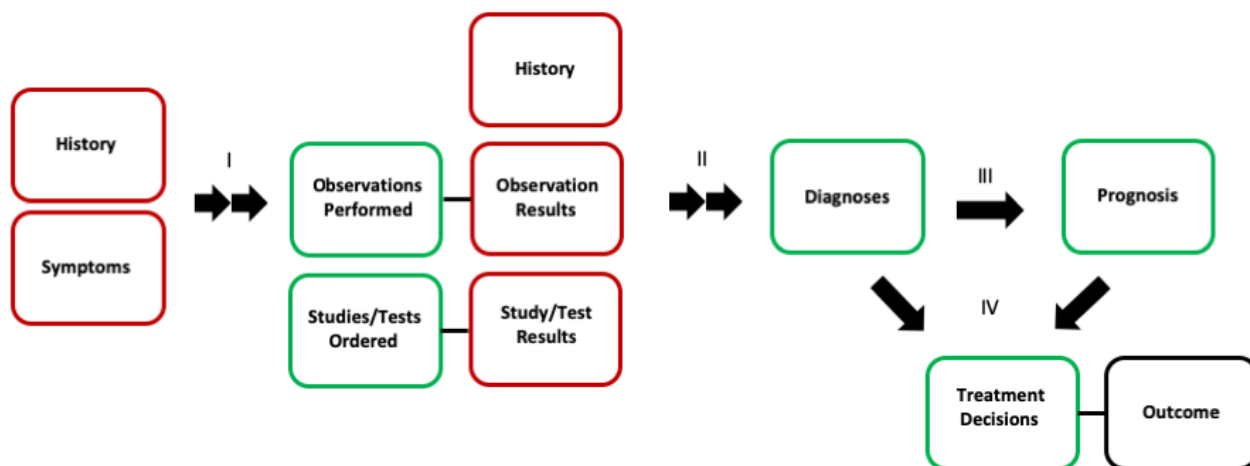
Recently, efforts began to build AI algorithms that allow humans to evaluate the significance of their results, with the goal of better integration and communication between the two. Most notably, the US Defense Advanced Research Projects Agency (DARPA) has called for further development of “explainable artificial intelligence” (XAI) [17]. The core algorithmic result or prediction is provided to the user along with an explanation that is intended to convey insight into the confidence of the core prediction, increase a user’s understanding of the real-world process being studied, or both [18].

With its many benefits, XAI also brings added complexity in the form of process-specific outputs and integration with a subject matter expert end user. Not only does this elevate the importance of partnerships between clinicians and AI developers, it also raises the somewhat paradoxical possibility that algorithms with inferior core predictive power may perform better if the explanations provided result in superior outcomes overall. Furthermore, the clinical decision points supported by XAI as well as the manner in which explanations are provided to the user may differ greatly between algorithms and influence their efficacy. Here, we propose a framework for classifying XAI algorithms in clinical medicine in order to simplify this additional complexity and allow for performance evaluation of XAI in clinical practice.

## *Clinical Scope*

The ultimate scope of clinical medicine is to prolong and improve the quality of human life. Within this, there are many decisions and actions that can be evaluated independently (eg, ordering a test, prescribing a medication, performing a surgery). XAI algorithms can be classified based on which step(s) in the clinical care pathway they support (see [Figure 1](#)). A single algorithm may provide outputs that encompass multiple areas of clinical scope. Defining clinical scope is critical for XAI, because it will determine which individuals on clinical care teams will be best suited to interact with the algorithm and evaluate the explanations provided. Furthermore, the ultimate impact of XAI on clinical outcomes will be limited by the potential impact of the process steps that an algorithm supports.

**Figure 1.** Clinical scope for XAI algorithms. XAI algorithms can be classified based on which steps in the clinical decision-making process they support. A simplified process flow map divides clinical decision-making into information (boxes) and information processing (arrows). Information processing steps (I-IV) can involve both human cognitive processing and computerized algorithms. Disease process evolution introduces biologic time dependency (red boxes), leading to a requirement for repeated information processing over time (double arrows). Some recorded information more directly reflects underlying disease (red boxes), while some is mainly the result of information processing (green boxes). Clinical outcome reflects underlying biology, the performance of the entire process, and the effectiveness of treatments. XAI fundamentally influences the information processing steps (I-IV) in partnership with clinicians. XAI performance can be evaluated at each information processing step or studied in the context of overall outcome. Performance of tests and treatments (black lines) are assumed to be static; however, they can be incorporated as inputs into a decision process. XAI: explainable artificial intelligence.



### Clinical Insight

Explanations provided by XAI algorithms should aim to provide evidence and ultimately insight to the end user. In the case of pathology, generation of insight to assist clinicians can assist with formation of differential diagnoses, quantitative classification of features, risk prediction, and identification of features imperceptible to the human observer [19]. Both the content of the information and its delivery will determine effectiveness. Evidence can be presented in the form of empiric assessments of statistical confidence, such as a *P* value. Alternatively, an algorithm could provide an assessment of the degree of association between the current patient’s data and

historical groups of patients or established disease mechanisms (see Table 1).

Clinical providers evaluate empiric assessments of confidence differently than associative power, and the existence of a high degree of uncertainty in any patient-specific medical prediction necessitates a continued role for the “art of medicine” in the form of decision-making by end users. This is due to an incomplete accounting for biological factors that influence disease processes, incomplete documentation of observable factors in the electronic medical record, and the importance of the doctor-patient relationship in clinical care [20]. As a result, associative explanations may be more powerful in certain situations, since an association may support a nonquantifiable opinion held by provider or patient.

**Table 1.** Classifying explainable artificial intelligence explanations by type. The explanations produced by an explainable artificial intelligence algorithm can provide additional information to a clinician in 3 general ways.

XAI <sup>a</sup> explanation type	XAI explanation output	Primary task for clinician	Benefit to clinician
Empiric	Statistical confidence based on historical sample data	Weigh the degree of confidence provided with risks, benefits, and training data used	Assess the validity of the prediction
Population associative	Association between signs and symptoms of a patient with historical groups of patients	Assess the validity of associating this patient with historical groups of patients	Consider alternative options processed by the algorithm
Mechanism associative	Association with known pathologic mechanism(s)	Assess the validity of the pathologic mechanism(s) and diagnoses proposed	Assess validity of the prediction and consider alternatives using established medical paradigms

<sup>a</sup>XAI: explainable artificial intelligence.

### Training and Validation

The loss of context and end user agnostic efficiency of traditional AI algorithms remains a great challenge to the initial design and implementation of XAI. In fact, the meaning of

model validation in medicine differs from the traditional validation process typically undertaken in technology fields in that it refers to validation relative to patient outcomes and evidence-based medicine principles—not just whether outcomes are technically correct, match a reference method, or agree with

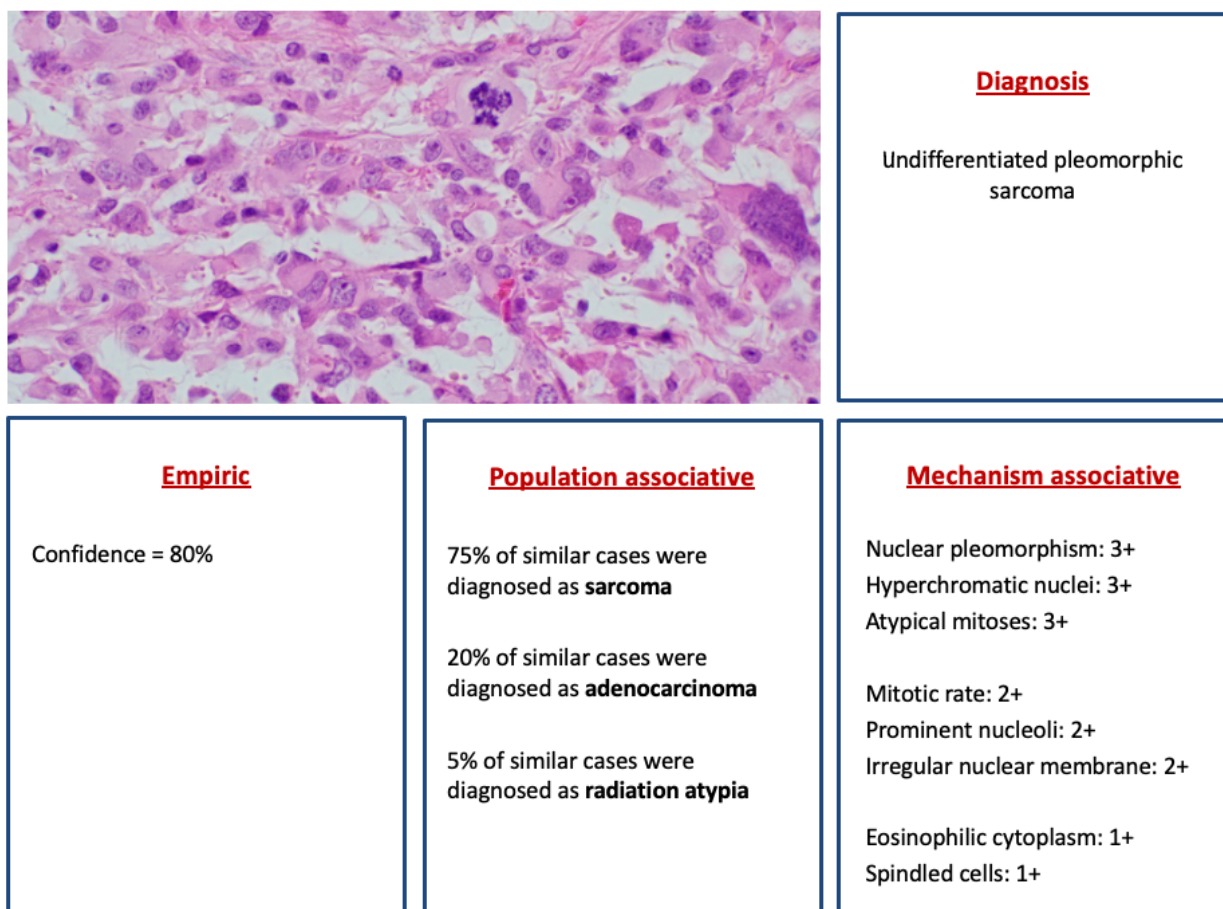
expectations [21]. Ultimately, only patient outcomes can confirm whether the model is valid and whether AI investment is or was a worthy investment. Therefore, XAI takes special meaning in such evidence-based validation processes, since explainable analytics will help support outcomes or facilitate corrections and adjustments. Likely, the development of context-specific XAI will evolve from traditional AI in phases, each supposing a core algorithm output in addition to some form of explanation: phase I will involve traditional AI training and validation; phase II will involve traditional AI training and XAI validation, taking into account end-user actions; and phase III will involve XAI training and validation, both taking into account end-user actions.

During the final phase of XAI development as described above, the algorithm will train not to maximize the predictive power of the core algorithm output but to maximize the outcome of the combined effects of core output, explanation, and end-user actions. It is during this phase of development that XAI implementations may regain some degree of the context-agnostic advantages of traditional AI, since the behavior of the end-user context expert can be studied by the algorithm during validation.

### Example 1: Anatomic Pathology

Anatomic pathologists interpret microscopic tissue morphology based on architectural and cytomorphologic criteria shown to correlate with pathologic diagnoses such as cancer. Criteria may include features such as hyperchromatic nuclei, high mitotic rate, and irregular nuclear membrane contours. Unfortunately, none of these features are 100 percent specific for a particular diagnosis like cancer, since nonneoplastic conditions may produce similar cellular features. Additionally, noninvasive premalignant conditions such as carcinoma in situ can contain individual cells that appear morphologically identical to cells within an invasive cancer. Incorporating concepts of XAI into digital anatomic pathology workflows will aid pathologists not only in making the correct diagnosis, but also in considering alternative diagnoses and recognizing potential diagnostic pitfalls (see Figure 2). Potentially, XAI systems can also incorporate ancillary information, such as clinical history, immunohistochemistry staining, and genomic testing, to aid the pathologist.

**Figure 2.** Illustrative example of 3 types of XAI output applied to anatomic pathology. XAI core algorithm output is shown as a diagnosis. Several forms of output explanation are succinctly outlined beneath the image, enabling a physician to make a visual interpretation in conjunction with immediate access to an explanation under multiple categories. “Empiric” information provides overall accuracy expressed as a single number; “population associative” provides a more detailed glimpse into the “black box” result; “diagnosis” relates to other cases an algorithm has access to; “mechanism associative” maps the AI process onto clinically relevant features found in the image (scored based on degree of association, 1 to 3+). XAI: explainable artificial intelligence.

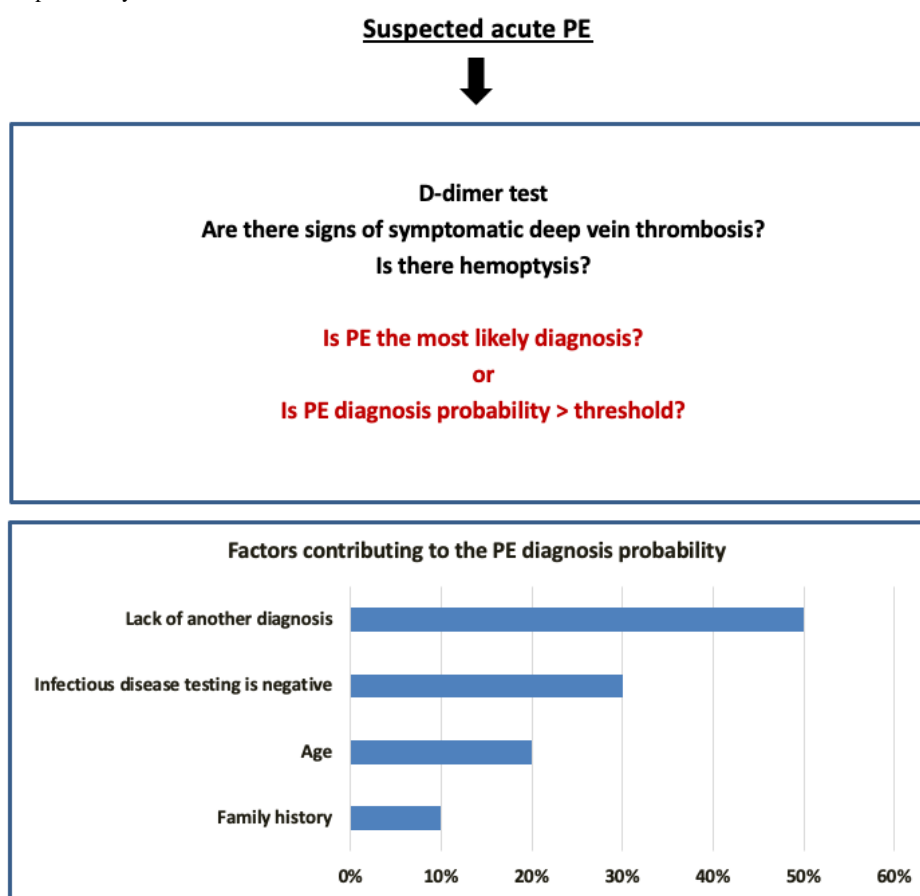


### Example 2: Diagnostic Management

One of the most difficult tasks for a clinician is to identify which patients should undergo screening tests and which should not [22]. This is particularly difficult when the condition screened for has a high mortality rate if not recognized, but the screening test is expensive and not without risks. Such a situation exists

in deciding whether to screen for pulmonary embolism using computed tomography pulmonary angiography [23]. As a result, algorithms have been developed to aid clinical decision-making, but a clinician’s assessment of whether pulmonary embolism is the most likely diagnosis plays a large role in determining a patient’s score and management. Scenarios like this represent an opportunity for XAI to contribute toward more accurate assessments of pretest diagnostic likelihood (see Figure 3).

**Figure 3.** Diagnostic management. Possible modification to the YEARS algorithm for decisions on screening for PE by computed tomography. Rather than relying on clinician assessment of whether PE is the most likely pretest diagnosis, simple scoring algorithms can use an explainable artificial intelligence core algorithm output to assess pretest probability in the context of well-defined historical patient populations. Furthermore, the contribution of factors contributing to the core probability assessment can be displayed. Users can then assess whether each factor is valid, which may influence their assessment of the core algorithm output. For example, factors may be considered invalid if the electronic medical record is recognized as being incomplete or inaccurate. PE: pulmonary embolism.



### Conclusions

The 2 recognized advantages of XAI over traditional AI can be summarized as insight into the statistical significance of a core algorithm output and mechanistic insight into the process being studied. It has been suggested that forcing AI to provide mechanistic understanding could decrease the predictive power of the algorithm itself. This may be true in a situation where algorithm inputs include all data relevant to the real-world process; however, clinical medicine remains an area where digitized information is incomplete relative to the totality of factors influencing human disease. Therefore, humans will likely remain the ultimate “trusted” decision-makers during critical, high-risk decisions in clinical care for the foreseeable future. In this framework, even clinical algorithms that are approved as regulated medical devices will remain ancillary to the human

practice of medicine. XAI offers the potential to improve not the predictive power of black box algorithms but rather their usefulness as a tool for clinical providers, offering the opportunity to classify and categorize data [24], as well as ensure meaningful feedback that fits clinical workflows [25]. Information should include identification of tasks, the nature and purpose of the tasks, their outcome, and methods applied to produce the outcome [26].

Medical leaders have discussed the need for a “learning health care system” for many years. The development of XAI offers the potential to build algorithms that learn with clinical care providers. To realize the potential of XAI, we must understand how each type of algorithm might fit into the real-world process of care delivery and the minds of medical decision-makers. At least initially, this will challenge algorithm developers to



understand clinical information and clinicians to efficiently integrate algorithms into their workflow.

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## Data Availability

All data generated or analyzed during this study are included in this published article.

## Authors' Contributions

TG contributed clinical expertise and major ideas for the manuscript, wrote and influenced several sections of the paper, helped edit the paper, and compiled materials and visualizations. J Kang contributed clinical expertise for the manuscript, leadership for the project, and perspectives into applications of artificial intelligence in pathology. TT contributed to visualizations in the manuscript, added ideas for application of technology in clinical pathology, and edited the manuscript. J Krive contributed major ideas, literature review, provided clinical informatics and artificial intelligence expertise, compiled materials and supporting visualizations, helped edit the paper, and oversaw development of the manuscript.

## Conflicts of Interest

J Kang is employed by Abbott Laboratories in their Tranafusion Medicine business unit. TG is employed by Fenwal, a Fresenius Kabi company. The knowledge shared in the manuscript is not influenced by any of these companies. All the other authors declare no conflicts of interest.

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## Abbreviations

**AI:** artificial intelligence

**DARPA:** US Defense Advanced Research Projects Agency

**XAI:** explainable artificial intelligence

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Original Paper

# Health Information Seeking Behavior on Social Networking Sites and Self-Treatment: Pilot Survey Study

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## Abstract

**Background:** Social networking site use and social network-based health information seeking behavior have proliferated to the point that the lines between seeking health information from credible social network-based sources and the decision to seek medical care or attempt to treat oneself have become blurred.

**Objective:** We contribute to emerging research on health information seeking behavior by investigating demographic factors, social media use for health information seeking purposes, and the relationship between health information seeking and occurrences of self-treatment.

**Methods:** Data were collected from an online survey in which participants were asked to describe sociodemographic factors about themselves, social media use patterns, perceptions about their motivations for health information seeking on social media platforms, and whether or not they attempted self-treatment after their social media-related health information seeking. We conducted a binomial logistic regression with self-treatment as a dichotomous categorical dependent variable.

**Results:** Results indicate that significant predictors of self-treatment based on information obtained from social networking sites include race, exercise frequency, and degree of trust in the health-related information received.

**Conclusions:** With an understanding of how sociodemographic factors might influence the decision to self-treat based on information obtained from social networking sites, health care providers can assist patients by educating them on credible social network-based sources of health information and discussing the importance of seeking medical advice from a health care provider.

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**KEYWORDS**

health care seeking behavior; online social networking; sociodemographic factors; community survey; logistic regression; self-treatment

## Introduction

Health information seeking behavior (HISB) has garnered much research attention during a time of nearly ubiquitous access to information. The digital landscape is continuously evolving, and people are constantly “plugged in.” The seemingly free-flowing availability of information from numerous digital platforms has begun to influence how people seek out health-related information and how this information is used in

the context of subsequent health-related behaviors. While concrete definitions of HISB remain mixed, there is some research consensus that HISB can be understood as having two dimensions: one dimension is associated with the extent to which health information is sought and the other dimension is associated with the method by which the information is sought [1]. This research study aims to add to the existing body of knowledge concerned with this second dimension, the method by which HISB occurs. Extant research related to HISB tends

to focus primarily on the use of the internet as the method of information seeking. In our context, we specifically explore the role that social networking platforms play in HISB.

Percheski and Hargittai [2] studied the HISB exhibited among college students and found that HISB was more likely to occur in younger women. This finding signals a recurring theme in HISB-related research as it concerns the factors that predict HISB. Wang et al [3] investigated social determinants of HISB and demonstrated that sociodemographic factors (ie, age, gender, education level, physical activity, smoking status, and income level) can explain the likelihood that an individual will engage in HISB. Some of these determinants are consistent even when the locale, the sample characteristics, and the information platforms are changed. The study by Wang et al [3] benefited from a relatively general population sample of adults in Hong Kong, and it explored a number of different platforms by which HISB was conducted, including television, radio, and the internet. Basch et al [4] conducted a study that sampled college students and found that HISB was more likely to be exhibited by students who identified as female and students who identified as non-White. The findings from Basch et al [4] are similar to the findings from Percheski and Hargittai [2], with both studies having focused on HISB among college students. Both Percheski and Hargittai [2] and Basch et al [4] highlight a greater likelihood of HISB occurring among younger women. These prior studies demonstrate the influence that demographic factors have on HISB.

Other research has been dedicated to understanding the motivations behind HISB. Motivation to engage in HISB has been attributed to the information seeker possessing a known health concern [5]. In some cases, health information seekers have sought health information on social networks prior to actually being seen by a health care provider [6]. HISB has been linked to the presence of chronic illnesses. Health information seekers with chronic illnesses, particularly those who have more than one chronic illness, tend to be more frequent users of the internet for health information seeking purposes [7]. In addition to these intrinsic motivations to seek health information, HISB is often encouraged by health care providers. Much has been researched in the way of promoting self-engagement in one's own care. HISB has been promoted by health care providers as a means to facilitate patient engagement [8].

As more and more people have turned to social network-based resources, researchers have cautioned us about 2 salient issues with this type of HISB: the quality of the health-related information available on social networks and disparities in access to this information across different groups of people [9]. Because the level of expertise and credibility of some social network-based health information sources are highly subjective, there are mixed perceptions about the amount of trust that health information seekers put into the quality of the information that they find [10]. As it relates to disparate access to social network-based health information, information seekers who have limited internet access or limited literacy in the use of the internet are unable to access this health information in the same way as literate users with unlimited access to the internet. This digital divide and the resulting inequity across sociodemographic groups has been studied in a broad context as it relates to the

internet [11-14]. Feng and Xie [15] have gone as far as to say that this digital divide also manifests in disparate access to online health information as a function of disparate access to social networking sites.

We incorporate what we have learned from extant research about HISB and aim this study at filling gaps in the existing body of knowledge for HISB. Specifically, we explore the sociodemographic determinants of HISB with the hope of identifying some new, previously undocumented determinant or alternatively, adding to the generalizability of previous researchers' work by conducting our study with a relatively general population sample of health information seekers. The study also aims to create a better understanding of the influence that perceptions about chronic diseases and the trustworthiness of health information obtained from social networking sites have on a health-related outcome, in this case self-treatment. We also consider the role that provider trust may play in affecting how HISB may result in an occurrence of self-treatment. We position this study as a response to the call for additional research into how health information seeking might influence health management and to elucidate additional facets of HISB [16].

The study poses 4 research questions (RQs). RQ1: What are the sociodemographic factors that influence social networking site use for social network-based HISB? RQ2: Is health information seeking with social networking sites a function of perceived health condition or a function of trust in the information found? RQ3: What is the role of provider trust in the use of social networking sites for health information seeking? RQ4: Does health information seeking using social networking sites result in episodes of self-treatment?

## Methods

### Overview

A pilot survey was developed to capture responses from participants that would provide insight into sociodemographic factors, perceptions about social networking site use to obtain health-related information, perceptions about their own health status, trust in the health-related information received from social media platforms, level of trust in their health care provider, and whether or not they attempted self-treatment after seeking health-related information on social networking platforms.

### Ethical Considerations

The survey was reviewed by the institutional review board at the University of North Carolina at Charlotte (18-0521). Links to the survey were distributed electronically on social media platforms, including Facebook, Instagram, Twitter, Google+, and LinkedIn. The survey link was also distributed via direct email to contacts known by the authors. The survey link also included an informed consent form for respondents to acknowledge in order to proceed to the survey. Participation in the survey was completely optional, and responses were anonymized so that individuals who participated in the survey could not be identified.

## Sociodemographic Factors

The electronic survey captured 6 sociodemographic factors that were used to describe characteristics of the survey respondents. Each factor was measured as a categorical variable and subsequently dummy coded for the logistic regression. These factors were all treated as independent variables in the logistic regression model. Sociodemographic factors included race, age, gender, education level, health status, and exercise frequency.

### Race

Respondents were able to self-identify their race by choosing from 1 of 7 options. The categories for race included Native American, Hispanic, African American, White, multiracial, Asian, and other. For the purposes of the logistic regression, White was designated as the reference category to which all the other racial categories would be compared.

### Age

The age of each respondent was measured as 1 of 5 different age groups. The age groups that were provided for respondents to choose were 18-20 years, 20-30 years, 30-40 years, 40-50 years, and >50 years.

### Gender

Three options to record gender were provided. Respondents self-identified as either male, female, or other. The provision of only 3 options to record gender will be addressed later in the paper as a limitation of the study in fully capturing the expanding options that are available for individuals to self-identify their gender.

### Education

There were 6 options available for respondents to record the highest level of education that they had achieved. The options included “did not complete high school,” “diploma (high school),” “2-year degree,” “4-year degree,” “master’s degree,” and “doctoral degree.”

### Health Status

Health status was recorded as 1 of 5 options that allowed respondents to self-report whether they were in perfect health or had a chronic disease. This survey item was analyzed as the variable “HealthStatus” and identified whether a person reported being in perfect health, had 1 chronic illness, had 2 chronic illnesses, had 3 chronic illnesses, or had more than 3 chronic illnesses.

### Exercise Frequency

In an effort to understand the impact that exercise, identified here as a measure of health-seeking behavior, has on health information seeking, and ultimately the propensity to attempt self-treatment, respondents were asked to report the frequency with which they engaged in some form of exercise. Responses to this survey item were “never,” “once per week,” “2-3 times per week,” and “>3 times per week.”

### Provider Trust

To obtain perceptions about the level of provider trust among the survey respondents, the survey included the item “Describe your level of trust in your health care provider.” Responses were

measured with a 3-point Likert scale. The response options were 1=“I do not trust what my health care provider tells me,” 2=“I somewhat trust what my health care provider tells me,” and 3=“I trust everything that my health care provider tells me.”

## Social Network Health Information Impact

A survey item was included to assess perceptions about the potential impact that health information received from social networking sites might have on actual health seeking behavior. Respondents were asked, “To what degree does information from social media sites affect your health seeking behavior?” Response options were 1=“not much,” 2=“somewhat,” and 3=“very much.” The item was intended to capture the level at which respondents incorporate health information received from social networking sites into their self-treatment.

## Social Network Health Information Trust

To explore respondent perceptions about the level of trust that they had in health-related information obtained from social networking sites, respondents were asked, “Describe the level of trust that you have in health-related information that you obtain from social media sites.” Response options were 1=“I do not trust the information,” 2=“I somewhat trust the information,” and 3=“I trust the information.”

## Perceived Susceptibility

Perceived susceptibility represents the level to which a person believes that they might be at risk of contracting a particular health condition [17]. Respondents were asked to indicate their self-perception of the likelihood that they would contract a serious condition by responding to the following survey item: “Using the scale below, rate how susceptible you think you are to disease.” Response options were chosen from a 7-point Likert scale with the terminal values of 1=“very strongly disagree” to 7=“very strongly agree.”

## Improvement in Health Status Because of Social Network Health Information

Respondents were asked explicitly if they believed that they had improved their health status because of information that they obtained while seeking health-related information on social networking sites. The survey item was presented as, “I believe that I have improved my health because of information that I have found on social media.” Available response options for this survey item were presented on a 7-point Likert scale with terminal values of 1=“very strongly disagree” and 7=“very strongly agree.”

## Self-Treatment

Self-treatment as a function of assimilating health information obtained from social networking sites was recorded as a binary categorical variable. The survey item was presented as “Do you try to treat yourself after obtaining health information from social media?” Respondents selected 1 for “yes” and 0 for “no.” This application of the dependent variable as a dichotomous measure lends itself to the use of logistic regression as a method of analysis [18]. The logistic regression was conducted in RStudio (Posit Software).

## Results

Data were obtained from 166 respondents. After eliminating 28 incomplete surveys, another 31 surveys were eliminated from the study because of missing values. The elimination of incomplete surveys and surveys with missing values resulted in a sample size of n=107. The sample of survey respondents represents a cross-section of social network-based health

information seekers in the United States. Representation of the survey respondents by race was skewed, however, due to the majority of the respondents identifying as predominantly African American or White. The race of the survey respondents was nearly evenly distributed between African American (n=44, 41.1%) and White (n=50, 46.7%) individuals, with smaller percentage distributions for the other racial groups that were represented (Table 1).

**Table 1.** Sociodemographic characteristics of survey respondents (n=107).

Characteristics	Respondents, n (%)
<b>Race</b>	
African American	44 (41.1)
Asian	3 (2.8)
Hispanic	3 (2.8)
Multiracial	4 (3.7)
Native American	2 (1.9)
Other	1 (0.9)
White	50 (46.7)
<b>Age group (years)</b>	
>50	14 (13.1)
18-20	7 (6.5)
20-30	38 (35.5)
30-40	21 (19.6)
40-50	27 (25.2)
<b>Gender</b>	
Female	77 (71.9)
Male	29 (27.1)
Other	1 (0.9)
<b>Education</b>	
Diploma (high school)	16 (14.9)
2-year degree	15 (14)
4-year degree	38 (35.5)
Master's degree	31 (29)
Doctoral degree	7 (6.5)
<b>Health status</b>	
1 chronic illness	25 (23.4)
2 chronic illnesses	8 (7.5)
3 chronic illnesses	2 (1.9)
>3 chronic illnesses	1 (0.9)
Perfectly healthy	71 (66.4)
<b>Exercise frequency</b>	
>3 times per week	22 (20.6)
2-3 times per week	34 (31.8)
Once per week	27 (25.2)
Never	24 (22.4)



Respondents were primarily aged between 20-30 years (n=38, 35.5%). The second largest age group represented in the respondent sample was the group of respondents who identified as being aged between 40-50 years (n=27, 25.2%). Respondents identified predominantly as female (n=77, 71.9%). The remaining survey respondents identified as male (n=29, 27.1%) or other (n=1, 0.9%). The majority of survey respondents had obtained a degree from a 4-year institution (n=38, 35.5%). Most respondents indicated that they were in perfect health (n=71, 66.4%). Frequency of exercise was reported as occurring most often between 2 to 3 times per week.

Most respondents (n=62, 58%) indicated that they somewhat trust the health-related information that they receive from their health care provider (Table 2). When asked whether they thought that the health-related information that they found on social networking sites was impactful to their health-seeking behavior, most respondents (n=58, 54.2%) selected the option “not much.”

Most respondents (n=75, 70.1%) “somewhat trust” the health-related information that they obtain from social networking sites. When asked if they felt that they were susceptible to disease, respondents provided mixed responses with a nearly even split between “neutral” (n=32, 29.9%) and “agree” (n=33, 30.8%). The majority of respondents (n=43, 40.2%) were “neutral” in their responses about whether the health information that they obtained on social networking sites actually helped them improve their health status.

Episodes of self-treatment after social network-based health information seeking were reported by a minority of survey respondents (n=41, 38.3%). The majority of respondents reported that they did not attempt to treat themselves after obtaining health information from social networking sites (Table 3).

**Table 2.** Distribution of responses (n=107).

Responses	Respondents, n (%)
<b>Provider trust</b>	
Do not trust information from provider	2 (1.9)
Somewhat trust information from provider	62 (58)
Trust information from provider	43 (40.2)
<b>Impact of information</b>	
Not much	58 (54.2)
Somewhat	40 (37.4)
Very much	9 (8.4)
<b>Trust in social network health information</b>	
Do not trust the information	26 (24.3)
Somewhat trust the information	75 (70.1)
Trust the information	6 (5.6)
<b>Perceived susceptibility</b>	
Very strongly disagree	4 (3.7)
Strongly disagree	16 (15)
Disagree	16 (15)
Neutral	32 (29.9)
Agree	33 (30.8)
Strongly agree	5 (4.7)
Very strongly agree	1 (0.9)
<b>Improved health status</b>	
Very strongly disagree	10 (9.4)
Strongly disagree	5 (4.7)
Disagree	13 (12.2)
Neutral	43 (40.2)
Agree	25 (23.4)
Strongly agree	9 (8.4)
Very strongly agree	2 (1.2)

**Table 3.** Self-treatment among respondents (n=107).

Responses	Respondents, n (%)
<b>Self-treatment</b>	
No	66 (61.7)
Yes	41 (38.3)

Although the majority of survey respondents reported that they did not attempt self-treatment after seeking health information from social networking sites, a moderately accurate predictive model was able to be defined. Assessing the number of “true positives” (the number of actual and predicted respondents who admitted self-treatment) along with the number of “true negatives” (the number of actual and predicted respondents who did not self-treat) resulted in an overall model accuracy of 78.5% and a sensitivity rate of 70.73% (Table 4).

Prior to conducting the logistic regression, we assessed our variables of interest to determine if there were any significant interitem correlations. We include the correlation matrix in Multimedia Appendix 1. We noted significant correlations between ExerciseFreq\_3 and ExerciseFreq\_2 ( $r=-.396$ ;  $P<.001$ ). ExerciseFreq\_4 was significantly correlated with both ExerciseFreq\_2 ( $r=-.296$ ;  $P=.002$ ) and ExerciseFreq\_3 ( $r=-.347$ ;  $P<.001$ ). Depending on the frequency at which respondents indicated that they exercised, they were less likely to exercise in a lower frequency category. SMITrust2 was significantly correlated with ExerciseFreq\_2 ( $r=.191$ ;  $P=.048$ ). For respondents who indicated that they “somewhat trust” the information that they found on social media networks, they were also likely to indicate that they exercised approximately one time per week. SMITrust3 was significantly correlated with SMITrust2 ( $r=-.373$ ;  $P<.001$ ), indicating that if a respondent indicated that they “trust the information” that they found on social media network sites, they were less likely to respond that they “somewhat trust” the information that they found on social networking sites.

The results of the binomial logistic regression revealed that significant predictors of self-treatment after health information seeking on social networking sites include the level of trust in the information obtained from the social networking site, race (African American), and exercise frequency (Table 5).

Trust in the health-related information obtained from social networking sites was represented by the variables SMITrust1=“do not trust the information,” SMITrust2=“somewhat trust the information,” and SMITrust3=“trust the information.” Of these trust variables, only SMITrust2 ( $\beta=1.8695$ ;  $P=.01$ ) and SMITrust3 ( $\beta=3.7162$ ;  $P=.02$ ) were statistically significant. Respondents who “somewhat trust” the health information they obtain from social networking sites were 6.5 times (odds ratio [OR] 6.4849, 95% CI 1.66-3.52E+01) more likely to self-treat as compared to the reference group of individuals who did not trust the information on social networking sites. Individuals who “trust” the health information that they obtain from social networking sites were nearly 41 times (OR 41.1090, 95% CI 2.78-1.51E+03) more likely to self-treat than those who did not trust health information from social networking sites.

Race significantly predicted self-treatment but only among respondents who identified as African American ( $\beta=1.4413$ ;  $P=.005$ ). African Americans were 4 times (OR 4.2261, 95% CI 1.59-1.20E+01) more likely than their White counterparts to self-treat after obtaining health-related information from social networking sites.

Frequency of exercise significantly predicted self-treatment among respondents who stated that they exercised more than 3 times per week ( $\beta=-2.5437$ ;  $P=.005$ ). We note the negative coefficient for exercising more than 3 times per week and interpret this inverse relationship between frequent exercise and self-treatment. This finding suggests that respondents who more frequently engage in some form of exercise are actually less likely to self-treat as a result of health information seeking with social networking sites. While the odds ratio for this group of respondents was small (OR 0.0786, 95% CI .011-4.11E-01), the negative association between exercising more than 3 times per week and self-treatment is still statistically significant.

In terms of goodness-of-fit, the final model demonstrated a statistically significant improvement over the null model. Results of the log likelihood ratio test were as follows:  $\Delta_{df}=-11$ ;  $\Delta\text{LogLikelihood}=-21.756$ ;  $\chi^2_{11}=43.513$  ( $P<.001$ ). The final model resulted in a pseudo  $R^2$  of 0.3055. Because of the nature of logistic regression, we are cautious about stating that the model explains 31% of the variance in self-treatment. The pseudo  $R^2$  reported here is based on the McFadden  $R^2$ . The same model produced a pseudo  $R^2$  of 0.331432 according to the Cox and Snell method and a pseudo  $R^2$  of 0.454083 according to the Nagelkerke method.

Sociodemographic factors identified in this study as predictors of social network-based health information seeking include trust in the information obtained from the social networking site, race, and exercise frequency. Health information seeking on social networking sites appears to be motivated by trust in the health information more than the criticality of the current health condition. We included provider trust as a variable in our logistic regression models, but provider trust did not significantly predict self-treatment as a result of social network-based HISB. Our final regression model supports a significant association between self-treatment and social network-based health information seeking.

To compare the results of our logistic regression to other methods of analysis, we conducted a number of post hoc tests. These post hoc tests serve as a robustness check of our findings. For the relationship between race and self-treatment, we conducted a chi-square test. The chi-square test supported a significant relationship between identifying as African American and identifying as someone who sought self-treatment

( $\chi^2_{1,107}=10.822$ ;  $P<.001$ ). Similar chi-square tests were done for exercise frequency and social media information trust. For social media information trust, SMITrust2 ( $\chi^2_{1,107}=5.450$ ;  $P=.02$ ), and for exercise frequency, ExerciseFreq >3 times per week ( $\chi^2_{1,107}=7.138$ ;  $P=.008$ ) were found to be significantly associated with self-treatment. We observed similar results

when we applied the Fisher exact test with each of the independent variables of race, exercise frequency, and social media information trust. The results of the Fisher exact tests were all significant ( $P=.001$ ) indicating a significant association between the independent variables and the dichotomous dependent variable, self-treatment.

**Table 4.** Classification table. Accuracy:  $(29 + 55) / 107 = 0.7850$ ; sensitivity:  $29 / (29 + 12) = 0.7073$

	Predicted self-treatment	Predicted absence of self-treatment
Actual self-treatment (n=41)	29	12
Actual absence of self-treatment (n=66)	11	55
Total (n=107)	40	67

**Table 5.** Factors that influence self-treatment after social network-based health information seeking.

	$\beta$	SE	z	P value	Odds ratio (95% CI <sup>a</sup> )
(Intercept)	-1.7536	0.8001	-2.192	.03	0.1731 (0.030-7.42E-01)
SMITrust2	1.8695	0.7603	2.459	.01	6.4849 (1.66-3.52E+01)
SMITrust3	3.7162	1.5485	2.4	.02	41.1090 (2.78-1.51E+03)
<b>Race</b>					
African American	1.4413	0.5125	2.812	.005	4.2261 (1.59-1.20E+01)
Asian	-16.3986	2161.7013	-0.008	.99	0.0000 (N/A <sup>b</sup> -7.18E+114)
Hispanic	-16.4948	2027.1618	-0.008	.99	0.0000 (N/A-1.33E+107)
Multiracial	2.2025	1.3613	1.618	.11	9.0472 (0.760-2.41E+02)
Native American	-16.4862	2162.8038	-0.008	.99	0.0000 (N/A-3.03E+1.39)
Other	-15.8124	3956.1804	-0.004	.99	0.0000 (N/A-inf <sup>c</sup> )
<b>ExerciseFreq</b>					
>3 times per week	-2.5437	0.899	-2.83	.005	0.0786 (0.011-4.11E-01)
2-3 times per week	-1.177	0.7094	-1.659	.09	0.3082 (0.072-1.20E+00)
Once per week	-0.6136	0.7327	-0.837	.40	0.5414 (0.122-2.23E+00)

<sup>a</sup>Some CIs were incalculable because of how the software used treats dummy-coded variables for race.

<sup>b</sup>N/A: not applicable.

<sup>c</sup>inf: infinite.

## Discussion

While health information seeking theory remains fragmented, we have identified that sociodemographic factors can at least partially predict self-treatment as a result of health information seeking on social networking sites. Our findings highlight the need for caution as it relates to the quality of health information that is made available on social networking sites. Providers can capitalize on the level of trust that health information seekers place in the information that they find on social networking sites by developing a web presence for their medical practices on social media networking sites. Our results demonstrate that when health information seekers trust or even somewhat trust the information they obtain on social networking sites, self-treatment is more likely to occur. Whether this self-treatment is efficacious lies beyond the scope of this research study.

Our research also emphasizes the need to be concerned with the use of social networking sites for health information seeking purposes among the African American community. Our results suggest that African Americans are more likely to self-treat after obtaining health-related information from social networking sites. This assumes that the health information seeker has successfully navigated the digital divide that historically has been an obstacle in the African American community [19-23].

Within our pilot study, we note a number of limitations. Among these limitations is the unbalanced representation of different racial groups. Our study results were based on responses from people who identified predominantly as White or African American. A more comprehensive study should include a broader sampling strategy with more equitable representation between racial groups. Similarly, gender was captured in a predominantly binomial fashion. Future research on health

information seeking should consider multiple gender classifications in an effort to understand more nuanced HISB. A more comprehensive study should also attempt to achieve a much larger sample size to improve the generalizability of the findings that we report. An additional complicating factor that must be considered for future research on health information

seeking is the likely emergence of a propensity for individuals to increase their use of social networking sites as a source of health-related information in a postpandemic era, wherein attempts at self-treatment might increase as a direct result of fear of contracting COVID-19 as a result of seeing a provider.

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## Conflicts of Interest

None declared.

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## Multimedia Appendix 1

Correlation matrix.

[[DOCX File, 16 KB - ojphi\\_v15i1e51984\\_app1.docx](#)]

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## Abbreviations

**HISB:** health information seeking behavior

**OR:** odds ratio

**RQ:** research question

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Original Paper

# Machine Learning Model for Predicting Mortality Risk in Patients With Complex Chronic Conditions: Retrospective Analysis

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## Abstract

**Background:** The health care system is undergoing a shift toward a more patient-centered approach for individuals with chronic and complex conditions, which presents a series of challenges, such as predicting hospital needs and optimizing resources. At the same time, the exponential increase in health data availability has made it possible to apply advanced statistics and artificial intelligence techniques to develop decision-support systems and improve resource planning, diagnosis, and patient screening. These methods are key to automating the analysis of large volumes of medical data and reducing professional workloads.

**Objective:** This article aims to present a machine learning model and a case study in a cohort of patients with highly complex conditions. The object was to predict mortality within the following 4 years and early mortality over 6 months following diagnosis. The method used easily accessible variables and health care resource utilization information.

**Methods:** A classification algorithm was selected among 6 models implemented and evaluated using a stratified cross-validation strategy with k=10 and a 70/30 train-test split. The evaluation metrics used included accuracy, recall, precision,  $F_1$ -score, and area under the receiver operating characteristic (AUROC) curve.

**Results:** The model predicted patient death with an 87% accuracy, recall of 87%, precision of 82%,  $F_1$ -score of 84%, and area under the curve (AUC) of 0.88 using the best model, the Extreme Gradient Boosting (XGBoost) classifier. The results were worse when predicting premature deaths (following 6 months) with an 83% accuracy (recall=55%, precision=64%  $F_1$ -score=57%, and AUC=0.88) using the Gradient Boosting (GRBoost) classifier.

**Conclusions:** This study showcases encouraging outcomes in forecasting mortality among patients with intricate and persistent health conditions. The employed variables are conveniently accessible, and the incorporation of health care resource utilization information of the patient, which has not been employed by current state-of-the-art approaches, displays promising predictive

power. The proposed prediction model is designed to efficiently identify cases that need customized care and proactively anticipate the demand for critical resources by health care providers.

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## KEYWORDS

machine learning; mortality prediction; chronicity; chronic; complex; artificial intelligence; complexity; health data; predict; prediction; predictive; mortality; death; classification; algorithm; algorithms; mortality risk; risk prediction

## Introduction

Current health care systems are evolving toward a more patient-centered approach, ensuring continuity of care between primary and hospital care. Their goal is to work toward implementing strategies that favor integrated health and social care of excellent quality for individuals with chronic conditions, such as frailty, multimorbidity, or advanced illness, by prioritizing community care led by primary care teams to improve quality of life across the different stage of disease pathways—especially at the end of life [1-3]. This change in health care provision brings out a series of challenges such as predicting populations' needs, selecting high-risk cases, and tracking illness trajectories, as well as tools to analyze which factors determine high patients' needs in different stages, with the aim of optimizing resources, [4,5]. In Institut Català de la Salut (ICS), Catalonia's main public health provider, this model has been designed and is being implemented by the Chronic Care Management Team in Barcelona's North Metropolitan Area under the name "Community-Based Integrated Care Program for People With Complex Chronic Conditions" (ProPCC) [6] with promising results in terms of the decrease in emergency department attendance and hospitalizations [7]. In this scenario, the research team recognizes the necessity of developing supportive tools for care activities and data exploration. These tools aim to predict resource utilization for individual patients, their progression, and the variables influencing it. This initiative is geared toward enhancing resource planning within the program.

The exponential increase in the availability of health data is enabling the application of advanced statistics and artificial intelligence (AI) techniques for the health care system to evolve toward data-driven policy-making and develop decision support systems to improve efficiency in resource planning, prevent diagnoses evolutions, predict patient progression, and make screenings. However, most data currently being collected are not analyzed, either due to a lack of resources or professionals. AI and machine learning (ML) techniques are key to solving these challenges and automating the analysis of large volumes of medical data to reduce professionals' workload and save resources [8,9]. Moreover, there is a severe shortage of professionals in the health care system, which these algorithms could help alleviate. They could greatly aid health care professionals by optimizing resource use and decreasing systemic gaps, with a particular focus on improving structure for the care of high-needs populations. The developed AI models must be robust, ensure privacy, and be easily generalized to other data and contexts in the health care field [10].

In the context of chronic care planning, predicting patient mortality in a short period of time could help the system better plan critical resources, most of which are spent in the last years of life, and provide closer accompaniment during the last phase of a patient's life [11]. In the medical field, predicting mortality has always been carried out in controlled contexts or in groups of patients with a specific disease. Most of this research has focused on predicting intensive care unit (ICU) mortality. Various studies have advocated the use of ML techniques over the use of logistic regression methods for prediction [12-14], achieving promising results, with an area under the receiver operating characteristic (AUROC) curve of 0.9 [13]. In a hemodialysis cohort, ML techniques were applied to predict death in patients who were critically ill (AUROC=0.86) [15].

In terms of predicting mortality focusing on certain diseases, there are multiple mortality risk scores for different diseases that have been used for a while in the Catalan Health system [16-18]. Regarding ML techniques, many of the models focused on diseases with a high prevalence in the population, such as cardiovascular diseases. ML algorithms such as the support vector machine-radial basis function (SVM-RBF) achieve good results in predicting the mortality onset of cardiovascular diseases [19-21]. Multiple studies use Cox proportional hazards regression models to predict the risk of death due to progressive chronic heart failure [22] and breast cancer [23]. In the case of patients with diabetes, some models have achieved good results in predicting the disease using SVM or NB algorithms, reaching an accuracy of 82% [11,24,25]. Research has prioritized identifying predictors of mortality related to diabetes, including hypercholesterolemia or serum albumin, which have been found to be significant predictors of death in patients undergoing hemodialysis [26,27].

With the COVID-19 pandemic, the need to generate prediction models at a population level has been brought to the forefront. The research paradigm has shifted from predicting mortality in a highly controlled population cohort with a specific clinical profile to the general population, with much more diverse clinical, socioeconomic, and demographic realities. The pandemic has provided the research field with a much higher volume of resources and data to develop models with acceptable accuracy. Recent studies have used deep learning (DL) models to predict the probability of entering the ICU or dying for patients diagnosed with COVID-19 (AUROC=0.84) [28]. Others have tried to predict the mortality rate of critically ill patients diagnosed with COVID-19, achieving promising results (AUROC=0.87) [29]. Other studies sought to predict mortality at the national level [30-32]. Regarding the prediction of mortality in patients with complex chronic conditions, AI and ML algorithms have not yet been used. Currently, only frailty

indexes have been used to predict mortality risk in older populations [16].

In this context, this study aims to present an ML model applied to a cohort of patients with highly complex diagnoses, categorized as either a patient with complex chronic disease (CCP) or a patient with advanced chronic disease (ACP). These terms serve as indicators of health and social complexity as defined by the Catalan public health system [17]. The aim is to predict mortality, which is indicative of the severity of their condition by utilizing easily accessible retrospective data. The model aims to predict a future event, death, by incorporating different population variables to ascertain how their progression would be in each case.

## Methods

### Data Sources and Inclusion Criteria

The data set was obtained from the administrative database of Barcelonès Nord Primary Care Centers linked to the program and the Germans Trias i Pujol Hospital, a reference hospital for the region that covers a population of 1,448,812 people belonging to 70 municipalities. It includes the period between May 2018 and December 2021 (with a slowdown of inclusion due to the COVID-19 pandemic in 2020). The observation study was focused on individuals from the ProPCC cohort, including high-needs high-cost patients cataloged as CCP or ACP based on the Catalonia Department of Health's risk stratification strategy [32,33]. This is a subanalysis from a retrospective observational study to estimate the impact of the introduction of ProPCC.

This study contains the main population characteristics of the patients, including age, sex, main diagnoses, complexity profiles (CCP or ACP), and adjusted mobility groups (ie, grupos de morbilidad ajustados, GMA). and place of habitual residence (home or nursing home). To enter the ProPCC program, patients

had to meet one of the inclusion criteria for the program: (1) easily decompensated chronic conditions, (2) frequent visits to hospital emergency rooms for the same reason, (3) dementia with cognitive/behavioral handling challenges, (4) functional dependence with difficult handling, (5) difficulty accepting the loss of health, (6) polypharmacy with handling difficulty, and (7) advanced complex disease process or caregiver burden.

The database also contains information on the duration of time spent at home and the utilization of health care resources, encompassing primary care and hospital visits within the last 12 and 6 months, specifically, primary care visits and hospital services such as emergency department visits and acute hospitalizations.

### Ethical Considerations

This study was approved by the Medicines Research Ethics Committee of the Institut Universitari d'Investigació en Atenció Primària (IDIAP Jordi Gol; 22/084-P).

### Baseline Characteristics

This study included 264 patients identified as CCP (n=116, 43.9%) or ACP (n=148, 56.1%). The average age at inclusion in the study was 83.6 (SD 10.3) years, and 50% (n=132) of the patients were female. The mean time spent in the program since inclusion was 16.73 (SD 12.8) months. Most patients belonged to the highest adjusted morbidity group (ie, GMA; group 4, n=219, 83%), and 9.1% (n=24) lived in a nursing home. Most were included in the program because they had easily decompensated chronic conditions (n=145, 54.9%). The mean number of active health problems was 24.3 (SD 8.4). [Table 1](#) summarizes all the variables used as predictors in the study. The variable death represents the variable to predict, while the rest act as predictors. Within the first 6 months after inclusion in the ProPCC program, 43.9% (n=116) of the patients in the study died. Subsequently, there were 171 (n=174, 65.9%) additional deaths in the remaining period.

**Table 1.** Clinical characteristics of the implementation cohort (N=264).

Main patient variables	Values
Age (years), mean (SD)	83.6 (10.3)
Female sex, n (%)	132 (50)
<b>Main clinical diagnoses, n (%)</b>	
Respiratory	92 (34.8)
Cardiological	112 (42.4)
Cognitive disorder	86 (32.6)
Diabetes mellitus 2	83 (31.4)
Hypertension	158 (59.8)
Musculoskeletal	156 (59.1)
Renal failure	75 (28.4)
<b>Complexity profiles, n (%)</b>	
CCP <sup>a</sup>	117 (44.3)
ACP <sup>b</sup>	147 (55.7)
<b>Adjusted morbidity groups, n (%)</b>	
Group 4	156 (83)
Group 3	30 (15.9)
Group 1-2	2 (1.3)
<b>Program inclusion criteria, n (%)</b>	
Chronic conditions easily decompensated	145 (54.9)
Frequent visits to the emergency room for the same reason	32 (12.1)
Dementia with cognitive/behavioral management difficulties	23 (8.7)
Hard-to-handle functional dependency	53 (20.1)
Difficulty accepting the loss of health	31 (11.7)
Polypharmacy with complex handling	48 (18.2)
Advanced complex disease process	51 (19.3)
Caregiver burden	31 (11.7)
<b>Consumption of previous care resources, mean (SD)</b>	
Family doctor visit 12 months prior	12.4 (17)
Family doctor visit 6 months prior	8.2 (8.3)
Nursing visit 12 months prior	13.1 (20.7)
Nursing visit 6 months prior	9.3 (11.9)
Social worker visit 12 months prior	1.5 (3.7)
Social worker visit 6 months prior	1 (2.7)
Continued care visit 12 months prior	1.2 (6.6)
Continued care visit 6 months prior	0.7 (3.7)
<b>Consumption of previous hospital care resources, mean (SD)</b>	
Home hospitalization 12 months prior	0.2 (0.6)
Home hospitalization 6 months prior	0.1 (0.4)
Acute hospitalization 12 months prior	1.1 (1.5)
Acute hospitalization 6 months prior	0.7 (1.1)
Visit to the emergency room 12 months prior	2.3 (2.6)

Main patient variables	Values
Visit to the emergency room 6 months prior	1.4 (1.7)
<b>Death (outcome variable), n (%)</b>	
Within the first 6 months of program entry	114 (43.4)
Throughout the rest of the study period	171 (64.7)

<sup>a</sup>CCP: patient with complex chronic disease.

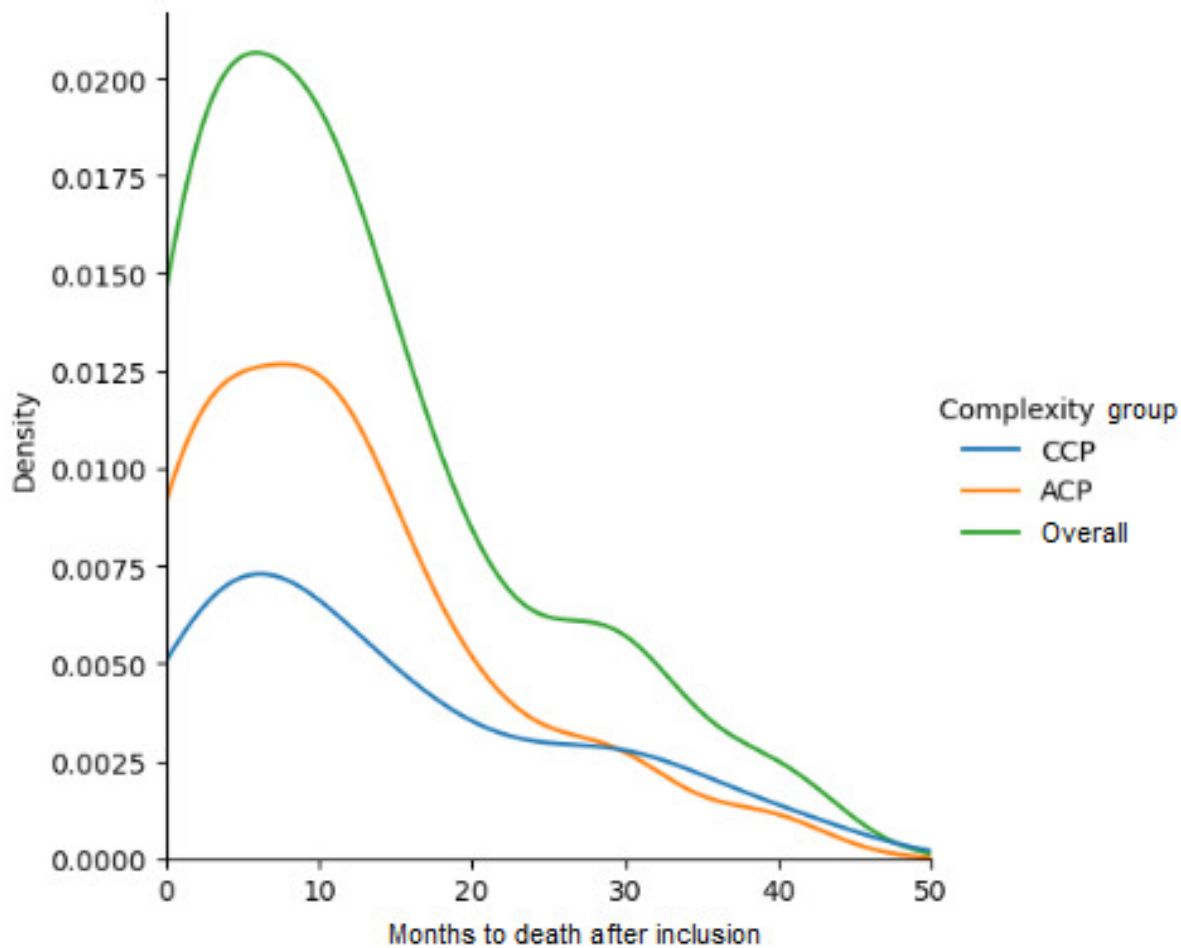
<sup>b</sup>ACP: patient with advanced chronic disease.

### Mortality in High-Risk CCP and ACP

Patients entering the ProPCC program had highly complex and chronic clinical profiles. This caused the death rate to be much higher than in any other health program, with a high probability of having died in the 2 years following the start of the program. Among the 264 patients who were monitored in the ProPCC program during the 48 months of study, 171 (64.7%) died. The case fatality ratio over the first 6 months in the program was 43.2% (n=114). The average patient died after 12.61 (SD 10.8) months. The death distribution over the study time period

representation is shown in Figure 1. Table 2 contains a description of the mortality variable, overall and by complexity subgroups. The study only considers the first 4 years to predict patient mortality. The objective of this analysis was to predict which patients would die within the first 48 months and who would experience premature death within the first 6 months. By definition, a patient with complexity transitions from CCP to ACP. Therefore, it was highly probable that an ACP would die within the first year since the complex diagnosis but less likely to be the case for a CCP.

**Figure 1.** Death distribution over the study period (overall and by complexity groups). ACP: patient with advanced chronic disease; CCP: patient with complex chronic disease.





**Table 2.** Description of ProPCC<sup>a</sup> program prediction variables (mortality up to 4 years).

Prediction variables	Value, n (%)	Mean	SD	Min	Q1	Median	Q3	Max
Months until death overall	171 (64.8)	12.6	10.8	0	4	10	18	43
Months until death for CCP <sup>a</sup>	68 (58% CCP, 39% deaths, 25.8% global)	14.2	11.9	0	4.8	10	22.5	43
Months until death for ACP <sup>b</sup>	103 (70% ACP, 60% deaths, 39% global)	11.6	10	0	3.5	10	16.5	40

<sup>a</sup>CCP: patient with complex chronic disease.

<sup>b</sup>ACP: patient with advanced chronic disease.

## Data Processing

There were no missing values in the database. The numerical variables (ie, age, resource consumption, program inclusion criteria) were normalized and scaled using a min-max scaler. The rest of the categorical variables underwent a one-hot encoding transformation. The classification variable was binarized from the “months until death” variable based on the different experimentation use cases defined in the “Experimental Setup” section. Only retrospective information (up to 1 year prior to inclusion in the ProPCC program) was used to predict death in the following months (48 months or 4 years). No data collected during the response time were used for prediction.

## Model Construction and Evaluation

The developed method aimed to find classification algorithms capable of predicting the mortality of patients with high complexity using retrospective variables available within the health provider's information systems. This approach aimed to use these variables as predictors without the need to conduct surveys or use external data repositories. The ML algorithms we used included SVM with a linear kernel (SVM-Lin) with a one-versus-one decision function, SVM with RBF as a kernel (SVM-RBF, regularization parameter  $c=20$ ), a k-nearest-neighbors classifier (KNN,  $k=25$ ), decision tree classification (Tree), an Extreme Gradient Boosting (XGBoost) classifier, and a Gradient Boosting (GRBoost) classifier (learning\_rate=0.25). All parameters were optimized to identify the best parameterization strategy. All models were implemented using the open-source Python ML library *Scikit-learn* and *dmlc-XGBoost*. A stratified cross-validation (CV) strategy with  $k=10$  and a 70/30 train-test split was used to evaluate and validate the models. Evaluation metrics are averaged over all k-fold CVs.

The metrics used to evaluate the models were accuracy, which measured how many observations, both positive and negative, were correctly classified; recall and precision, extracting the ratio of death patients correctly classified as dead;  $F_1$ -score, which measures the harmonic mean between precision and recall; and AUROC curve, which provides an aggregate measure of performance across all possible classification thresholds.

To obtain the algorithm that yielded the best results in the different experiments, predicting such a critical label as death, we focused on maximizing the recall, and subsequently, the  $F_1$ -score (reducing the number of false negatives). The aim of the model was to save resources by identifying patients with a higher risk of death, and hence more severe health conditions, to participate in the ProPCC study. Thus, it was crucial to reduce

the number of false negatives, as this could imply less care for the patient than necessary.

However, emphasizing precision was not as vital since it could result in offering more services to individuals with lower mortality risk. Participation in the program did not harm the patient; thus, it was not a critical prediction for health. Nonetheless, the primary objective was to minimize the number of patients who are flagged as likely to die but do not; hence, our emphasis was more on  $F_1$ -score than overall accuracy. Employing this methodology and deriving the mean with a 10-fold CV yielded more robust results, balancing the classes and generating results less impacted by the minor imbalance in the data set. The Cochran Q test was performed to assess the robustness of the results.

Once we identified the algorithm with the best results in terms of metrics, we used the open-source Python library *Streamlit* to develop a user-friendly web app with a good user interface and user experience for health care professionals.

## Experimental Setup

This study was divided into 3 experiments based on patients' period of death. All the experiments used the same models, parametrizations, and variables described in Table 1 (ie, age and sex, clinical diagnostics, complexity profile, morbidity profile, program inclusion criteria, and consumption of primary care and hospital care resources in the 6 and 12 months before inclusion). The objective was to detect which model more accurately predicted mortality in each experiment, using the same accessible variables. These experiments were structured as binary classifications (1=death, 0=survival). The first experiment aimed to evaluate the algorithms' ability to predict patient mortality throughout the study period (48 months, 4 years). In this scenario, the binary outcomes were as follows: 1=patient death ( $n=171$ , 64.8%) and 0=patient survival ( $n=93$ , 35.2%). The second scenario was designed to evaluate the algorithms' predictive ability to detect premature mortality (within 6 months). The binary results were as follows: 1=patient death within the first 6 months of the study ( $n=58$ , 22%) and 0=patient survival after 6 months ( $n=206$ , 78%). The third scenario aims to evaluate the algorithm's ability to classify which patients will likely die prematurely (within 6 months) and which will likely die later to check for differences. The binary results were as follows: 1=patient death within the first 6 months of the study ( $n=58$ , 34%) and 0=patient death after 6 months ( $n=113$ , 66%).

## Results

### Overview

The averaged results of all models for the stratified k-fold CV, including all metrics for each algorithm in the different use case scenarios, are presented in [Table 3](#) and [Figure 2](#) to visualize the comparison between the different models.

**Table 3.** Performance results of the algorithms in the different use case scenarios.

Model	Accuracy	Recall	Precision	$F_1$ -score	AUC <sup>a</sup>
<b>Mortality prediction (48 months), mean (SD)</b>					
SVM <sup>b</sup> -Lin <sup>c</sup>	75 (7)	81 (6)	81 (10)	80 (5)	83 (8)
SVM-RBF <sup>d</sup>	74 (10)	80 (9)	81 (11)	80 (7)	82 (9)
KNN <sup>e</sup>	74 (8)	87 (6)	76 (8)	81 (5)	78 (11)
Tree <sup>f</sup>	72 (7)	79 (12)	78 (10)	78 (8)	72 (13)
XGBoost <sup>g</sup>	79 (7)	87 (7)	82 (9)	84 (6)	88 (5)
GRBoost <sup>h</sup>	71 (6)	81 (6)	75 (8)	78 (6)	75 (5)
<b>Early mortality prediction (within 6 months), mean (SD)</b>					
SVM-Lin	82 (9)	61 (31)	63 (22)	57 (22)	83 (14)
SVM-RBF	81 (7)	54 (25)	60 (20)	52 (17)	89 (5)
KNN	79 (7)	31 (18)	48 (35)	34 (23)	84 (8)
Tree	80 (9)	59 (21)	57 (17)	58 (15)	73 (11)
XGBoost	83 (5)	55 (12)	64 (19)	57 (12)	88 (5)
GRBoost	86 (8)	58 (26)	75 (20)	63 (21)	87 (8)
<b>Early mortality prediction vs late mortality (within and after 6 months), mean (SD)</b>					
SVM-Lin	68 (9)	46 (19)	57 (26)	48 (19)	76 (11)
SVM-RBF	66 (13)	45 (21)	62 (26)	47 (14)	72 (14)
KNN	56 (22)	19 (16)	46 (41)	23 (20)	63 (15)
Tree	65 (10)	53 (17)	55 (29)	50 (20)	57 (12)
XGBoost	75 (11)	49 (24)	65 (26)	54 (25)	81 (15)
GRBoost	71 (14)	52 (21)	61 (31)	55 (24)	73 (16)

<sup>a</sup>AUC: area under the curve.

<sup>b</sup>SVM: support vector machine.

<sup>c</sup>Lin: linear kernel.

<sup>d</sup>RBF: radial basis function.

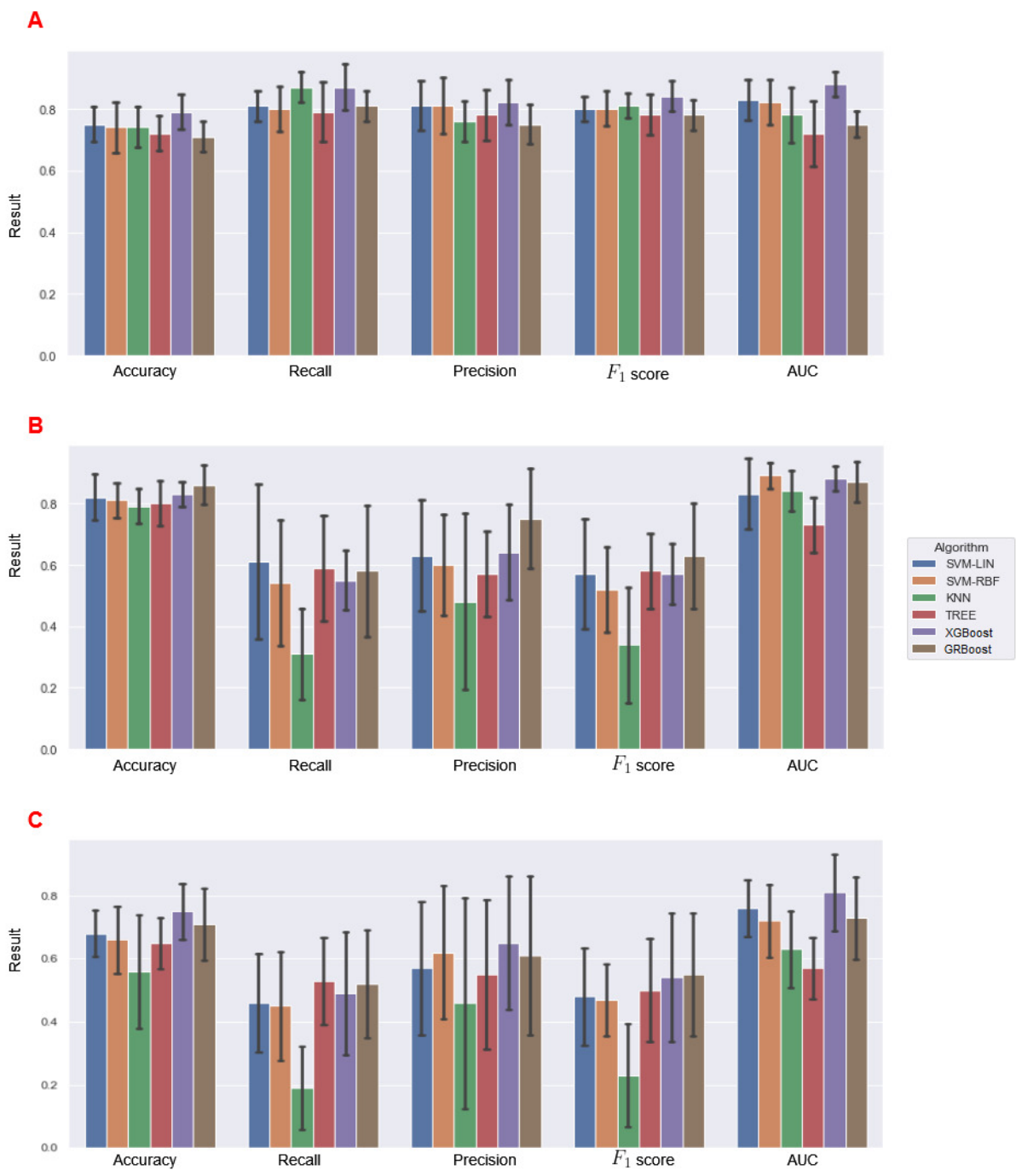
<sup>e</sup>KNN: k-nearest neighbor.

<sup>f</sup>Tree: decision tree.

<sup>g</sup>XGBoost: Extreme Gradient Boosting.

<sup>h</sup>GRBoost: Gradient Boosting.

**Figure 2.** Performance metrics comparison of the different models in the different use case scenarios. (A: mortality in the entire study period, 48 months; B: premature death, 6 months; C: premature death versus dead). AUC: area under curve; GRBoost: Gradient Boosting; KNN: k-nearest neighbor; Lin: linear kernel; RBF: radial basis function; SVM: support vector machine; Tree: decision tree; XGBoost: Extreme Gradient Boosting.



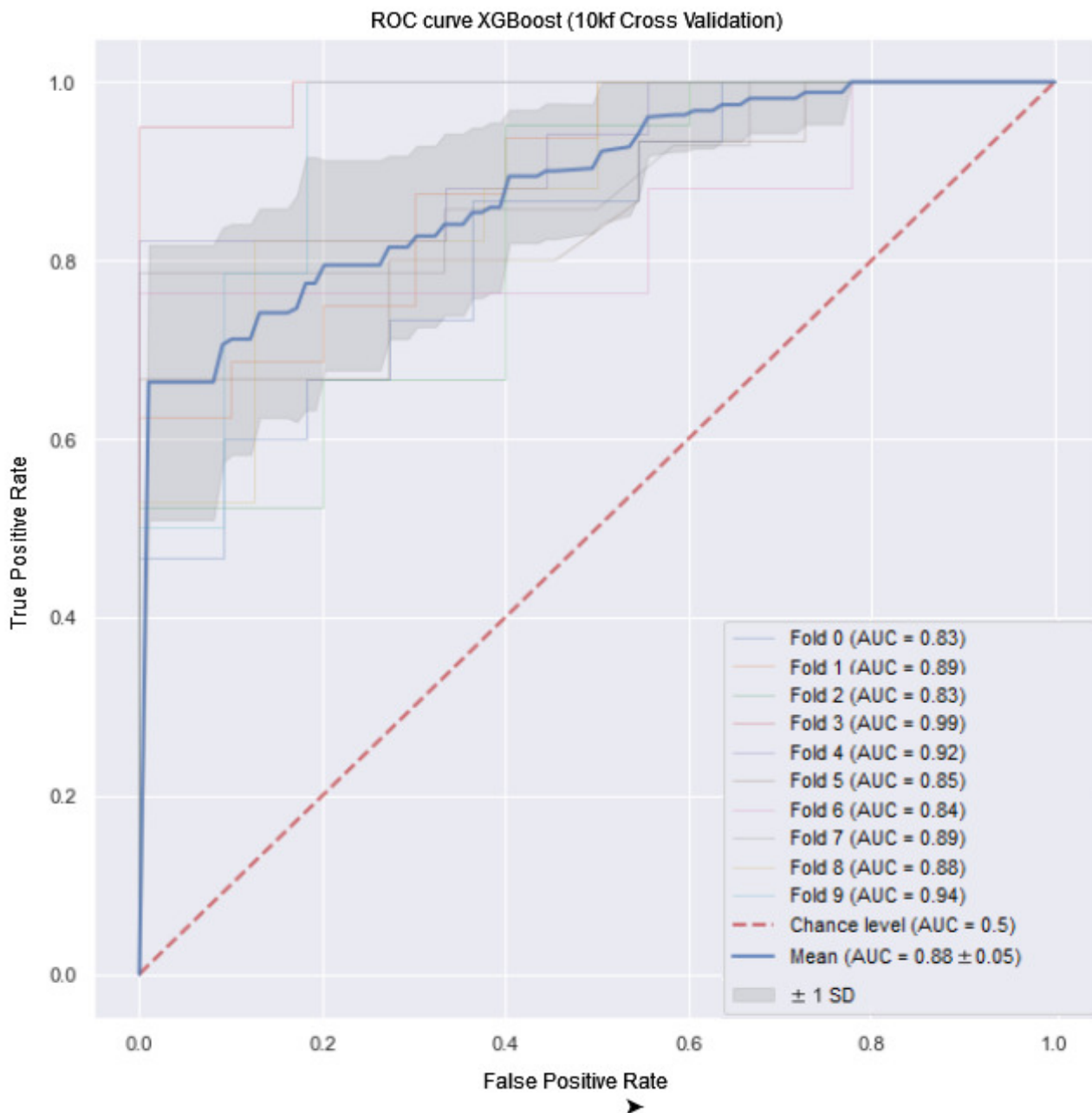
**Model Performance**

The performance of the models varied significantly depending on the use case. The best results were obtained when identifying patient mortality during the entire study period.

In the first experiment, the XBoost algorithm obtained the best results in all metrics. The results were obtained by averaging partial results from a 10 k-fold CV. The SD was small for all metrics, demonstrating robustness across different partial results.

XGBoost achieved the best result, especially in the most critical metrics (recall=87%, F<sub>1</sub>-score=84%, and AUROC=88%). The average Cochran Q test results obtained in different folds were significant in training (Q=137.7, P<.001) but not significant in testing (Q=5.3, P=.43). Regarding testing, there was no significant difference in the accuracy of the different models. However, in terms of the other metrics, the XGBoost model was best suited for predicting patient mortality throughout the study period (48 months, 4 years). Figure 3 shows the AUROC curve of this experiment,

**Figure 3.** Area under the receiver operating characteristic (AUROC) curve for the algorithm with the best performance. Extreme Gradient Boosting (XGBoost) averaged over the k-fold cross-validation (CV, k=10). First experiment (mortality prediction over the entire period: 10 k-fold area under the curve (AUC)=0.88, SD 0.05).



In the second and third experiments, the results are worse. In both cases, the SDs obtained were higher than in the first experiment, indicating that the models were not as robust and were highly sensitive to the cases found in each fold. GRBoost with a 25% learning rate obtained good results in predicting premature deaths (6 months after data collection), especially in terms of accuracy (86%) and AUC (87%), with low SDs. However, in terms of recall (58%), precision (75%), and  $F_1$ -score (63%), the results were less promising and highly sensitive to the fold used (high SDs). SVM-RBF and XGBoost also obtained good results in AUC and accuracy. The average results of the Cochran Q test obtained in the different folds were significant in the training set ( $Q=113.9, P<.001$ ) but not significant in the testing set ( $Q=7.1, P=.36$ ). Although the results were not as robust and promising as in the first use case, the

overall accuracy and AUC were very high in different models, demonstrating a correlation between the predictors and premature death.

In use case scenario 3, where we aimed to create a model capable of distinguishing between participants who would die prematurely and those who would die during the rest of the study period (without considering survivors), we obtained the poorest results. XGBoost achieved the highest accuracy (75%) and AUC (81%). However, in the other metrics, there was considerable variability across all models, demonstrating that the results were highly sensitive to the fold used. The top  $F_1$ -score (55%) was obtained by GRBoost, although it was much lower than the results obtained in the previous use cases.

As depicted in [Figure 2](#), XGBoost usually obtained the best results in all 3 scenarios. GRBoost and SVM-RBF also performed well in different scenarios.

## Discussion

### Principal Findings

Our research shows that ML and AI models can predict mortality in CCP and ACP with a high degree of accuracy (up to 89%) using easy-to-obtain real-life predictor variables not typically used in this type of experiment. This study illustrates that incorporating these variables has the potential to enhance analysis and accurately predict mortality among patients with significant health and social chronic needs. Previous studies showed similar results [12,14,26,27,29] or better ones [17,22,28,30] in terms of metrics. However, no literature has been found that specifically refers to predicting mortality within the high-need high-cost patient population. Most models for predicting mortality among chronic patients focused on cohorts with a specific diagnosis or establishing basic associations among variables linked to mortality. We have not found a similar use case in the literature that seeks to predict mortality in an identifiable yet heterogeneous group. Additionally, no identified model has been capable of predicting mortality using the consumption of primary care and hospital care resources.

The comparison was carried out with cases of prediction for specific diseases [17,22] or controlled contexts such as ICUs [12,14] or the COVID-19 pandemic outbreak [26-30].

Observing the outcomes, studies predicting mortality in ICUs obtain metrics akin to this study's findings, whereas those addressing specific pathologies present higher metrics. Unlike other death prediction models, the proposed model not only uses patient clinical data such as diagnosis or morbidity but also proposes a framework utilizing medical care resource consumption data during the previous year (visits to different clinical specialties) and sociodemographic health-related variables. These variables include difficulty accepting health loss, dementia, caregiver burden, functional dependence, polypharmacy, or frequent consultations for the same reason. Incorporating these variables as predictors alongside previously established predictive variables resulted in robust outcomes, accurately predicting cases where patients may face mortality. This model can be used to screen patients who will enter the ProPCC program when scaled to all health care areas, aiding in optimizing critical health care resources and supporting patients at a higher risk of mortality.

### Limitations

This study is subject to several limitations that warrant careful consideration. First, it is important to acknowledge the relatively small size of the cohort. The limited number of patients included in our analysis suggests that there is ample room for improvement to bolster the robustness of the findings, particularly through validation in a larger and more diverse cohort. It is worth noting that the incorporation of a 10-fold CV methodology was employed to enhance the reliability of the results and demonstrate the model's predictive capability. However, the inclusion of a larger sample size would provide

more compelling evidence and strengthen the generalizability of our study's outcomes.

Second, an inherent limitation of the study lies in the potential unbalance present within the data sets. This may introduce errors, particularly when predicting mortality, especially in scenarios 2 and 3 where the occurrence of mortality within the sample was relatively lower. Consequently, the model may not adequately capture the intricate patterns and factors associated with mortality in these specific scenarios. It is advisable to address this issue by employing appropriate techniques such as data set balancing if the data set is large enough, thereby potentially improving the model's performance and accuracy in predicting outcomes.

Third, it is essential to consider the quality of data derived from electronic health systems, particularly within noncontrolled environments. While the data set utilized herein exhibited a high standard of coding quality, which was meticulously ensured by a team of proficient professionals, it is crucial to recognize applying these models to uncured data sources within the health care system may yield less favorable results. The inherent variability and potential inconsistencies in data coding across diverse sources may substantially impact the model's performance and its ability to generalize findings to real-world scenarios.

In summary, this study has acknowledged several notable limitations, including the modest cohort size, potential errors arising from data set unbalance, and potential challenges associated with applying the models to real-world data sources characterized by lower data quality. These limitations should be duly considered when interpreting our study findings, and further endeavors should be undertaken to enhance the robustness and applicability of the models.

### Conclusion and Future Work

This study was developed under the hypothesis that mortality among high-need high-cost patients could be predicted in advance using easily accessible real-life patient variables, including clinical, economic resource use, and demographic variables. With this premise, we used an agnostic approach to develop and test a series of ML algorithms to evaluate predictive capacity in a highly controlled cohort of CCP and ACP. The models achieved robust performance in terms of AUC (88%), accuracy (87%), and  $F_1$ -score (84%), indicators that are particularly important in this prediction context.

Our model not only offers a high degree of prediction accuracy but also provides graphs with the importance of each variable in predicting the risk of mortality. The algorithm is encapsulated in a web app developed with the open-source Python library *Streamlit* to improve usability, transportability, and interpretability for medical professionals. This facilitates more efficient utilization of technology resources and enables the system to predict clinical resource usage, thereby offering better support to patients in the end-of-life stage. This type of tool enables process automation and analysis of large volumes of data, while also allowing the seamless transfer of the same infrastructure to different contexts or units.



Regarding future work, there are relevant challenges such as increasing the number of patients and including new clinical and analytical variables that can act as predictors. Our study cohort exhibits high-quality data, meticulously reviewed by multiple professionals to ensure that there are no errors or missing values. In comparison, primary databases, despite

containing a significantly larger patient pool, tend to have lower-quality data. Future objectives include testing the model using this data set and a much larger number of patients, not just from the high-need profile. Deep-learning models could also further refine the results.

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## Data Availability

The data supporting this study's findings belong to the Gerència Territorial Metropolitana Nord of the Catalan Health Institute (ICS). Restrictions apply to the availability of these data, which were used after signing a data processing agreement and an ethical agreement that complies with the requirements of the current legal framework.

## Conflicts of Interest

None declared.

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## Abbreviations

**ACP:** patient with advanced chronic disease

**AI:** artificial intelligence  
**AUC:** area under the curve  
**AUROC:** area under the receiver operating characteristic  
**CCP:** patient with complex chronic disease  
**CV:** cross-validation  
**DL:** deep learning  
**GMA:** grupos de morbilidad ajustados  
**GRBoost:** Gradient Boosting  
**ICS:** Institut Català de la Salut  
**ICU:** intensive care unit  
**IDIAP:** Institut Universitari d'Investigació en Atenció Primària  
**KNN:** k-nearest-neighbor  
**ML:** machine learning  
**ProPCC:** Community-Based Integrated Care Program for People With Complex Chronic Conditions  
**RBF:** radial basis function  
**SVM:** support vector machine  
**XGBoost:** Extreme Gradient Boosting

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