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Online Health Information–Seeking Among Older Adults and Predictors of Use, Motivations, and Barriers in the Context of Healthy Aging: Cross-Sectional Study

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Abstract

Background: Considering the rapid digital transformation, older adults are increasingly relying on online health information–seeking (OHIS) to support healthy aging. However, disparities in their digital competence levels (the ability to effectively use digital tools) and health literacy (the ability to access, understand, appraise, and apply health information) may influence engagement in OHIS.

Objective: This paper examines the prevalence of OHIS among older adults in Switzerland and identifies their motivations, barriers, and predictors of use. The objective is to determine key factors that promote or hinder OHIS use among older internet users.

Methods: A cross-sectional survey was conducted with 1261 internet users aged 60 years and older living in Switzerland (mean age 70.1, SD 7.3 years; 539/1261, 42.7% female). Descriptive analyses and hierarchical binary logistic regression models were used.

Results: Overall, 77.6% (969/1248) of participants engaged in OHIS in their everyday lives. Subjective health status, internet use frequency, trust in online health information (OHI), and digital competence level significantly influenced OHIS use. Participants reporting good to very good health were less likely to engage in OHIS compared to those in poorer health (odds ratio [OR] 0.496, 95% CI 0.307-0.801; *P*=.004). Higher likelihood of OHIS use was associated with (almost) daily versus less frequent internet use (OR 1.550, 95% CI 1.011-2.376; *P*=.04), general trust versus distrust in OHI (OR 5.784, 95% CI 4.044-8.272; *P*<.001), and advanced versus low digital competence (OR 3.108, 95% CI 1.385-6.975; *P*=.006); health literacy was not a significant predictor of OHIS use (OR 0.912, 95% CI 0.393-2.117; *P*=.83, excellent vs deficient [reference]). Among OHIS users (n=969), the most common frequently indicated motivation for use (672/969, 69.3%) was to gain a better understanding of health conditions. Among nonusers (n=279), the most frequently indicated barriers were difficulties in assessing the credibility of information (159/279, 57%), distrust in the effectiveness of information provided (129/279, 46.2%), and concerns about dubious providers or spam (93/279, 33.3%).

Conclusions: Digital competence, frequent internet use, and trust in OHI are critical for OHIS engagement among older adults. Programs to strengthen digital competencies in later life and initiatives to enhance the credibility of online health resources are essential to reduce digital disparities and support healthy aging. Notably, health literacy did not emerge as a significant factor in OHIS use, but digital competence did, suggesting that digital competence is most critical to OHIS use.

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KEYWORDS

online health information seeking; healthy aging; digital competence; older adults; health literacy; aging; cross-sectional study; internet; Switzerland

Introduction

Background

With a growing older population, aging presents significant health policy and societal challenges. In response, the World Health Organization's (WHO) "Healthy Aging" [1] framework promotes well-being in later life, emphasizing that functional ability can be maintained despite health challenges. This requires physical and cognitive capacity alongside supportive physical, social, and digital environments [2]. To cope with everyday life, digital competence must increasingly be considered since digital competence not only is needed for using modern technologies but also enables digital access to health information. The rapid digital transformation, driven by modern information and communication technologies (eg, internet and smartphones), is reshaping knowledge dissemination [3]. While digital solutions enhance quality of life, health, and independence, older adults still use them less than younger groups [2,4]. This digital divide extends beyond access to include disparities in digital competence and use [5]. Indeed, many older adults face challenges due to limited digital competence. Effective digital health promotion requires both access and competencies, highlighting the critical role of digital and health literacy in using digital health services [6].

Online Health Information Seeking Among Older Adults

Digital access is increasingly seen as a key solution for overcoming barriers to obtaining timely health information for older adults [4]. Online health information seeking (OHIS) offers a fast and convenient way to obtain qualitative health-related information but poses challenges due to limited digital competence. Older adults may struggle with navigating sources, formulating queries, and evaluating information and misinformation [7]. Despite greater health concerns, they engage in OHIS less than younger generations, partly due to age-related impairments and digital competence gaps and also because a considerable share of older adults remains offline or does not use internet-enabled devices in the first place. However, even those who use OHIS can benefit from improved access to health information, supporting healthy aging goals [8-10].

Research Questions and Hypotheses

Despite attempts by previous studies [10] to identify the determinants of OHIS in general, the prevalence, motivations, barriers, and predictors of OHIS among older internet users (hereafter referred to as “onliners”) remain largely unclear [7,8,10]. This underscores the need for further investigation to address these gaps.

The aim of this study was to examine the prevalence, motivations, and barriers of OHIS among older onliners in Switzerland and to identify key predictors of OHIS use. Specifically, this study addressed the following research questions: (1) What proportion of onliners aged 60 years and older use OHIS? (2) What are the key determinants of OHIS use? (3) What are the motivations and barriers related to OHIS use?

Regarding the key determinants of OHIS, we proposed hypothesis 1, which assumed that sociodemographic and health-related factors influenced the likelihood of OHIS use. Specifically, we expected that female participants [7], younger individuals (aged 60 - 69 years) [4,11], and participants with higher education levels [12], better financial resources [13], and urban (or intermediate) residency [14] were significantly more likely to use OHIS compared to their counterparts. Regarding health-related factors, we assumed that self-reported health status and the number of medical treatments were associated with OHIS use. While existing evidence was mixed, we expected that individuals with poorer self-reported health statuses [15] and those with more medical treatments [16] in the past year were more likely to use OHIS. Hypothesis 2 assumed that behavioral and attitudinal factors—particularly the frequency of internet use and trust in online health information (OHI)—significantly predicted OHIS use. Specifically, individuals who used the internet daily [16] and those who expressed at least some level of trust in OHI [12,17] were expected to have a greater likelihood of engaging in OHIS. Hypothesis 3 assumed that individual competencies played a critical role in OHIS use. Specifically, higher levels of digital competence [18] and health literacy [19] were expected to increase the probability of OHIS use.

Methods

Study Design and Participants

We conducted a cross-sectional survey within the “Regional Health Promotion in an Age-Friendly Digital World” project with individuals aged 60 years and older living in private households across Switzerland. Participants were sampled by using a stratified random sampling approach using official address data from the Swiss Federal Statistical Office in combination with an additional sampling from the private address provider AZ Direct. Surveys were carried out by Demo Scope AG, an external Swiss pooling provider.

A total of 8311 individuals were invited by mail to participate in the survey, which was available in the 3 official languages of Switzerland (German, French, and Italian). Of these, 1367 (16.4% response rate) completed the survey between June 27 and August 20, 2024, either online (computer-assisted web interviewing: n=1237) or in paper format (paper-and-pencil interviewing: n=130). Incomplete or invalid responses were excluded through rigorous data cleaning, resulting in 1325 valid questionnaires. Of these, 1261 (95.2%) respondents were classified as onliners. For the analyses, we included only the onliners because they had met the basic access requirement for OHIS use.

The questionnaire was developed based on insights from our systematic review [10] and the workshop (n=11) with older adults, family caregivers, and professionals working at the interface of age and health.

Ethical Considerations

The Ethics Committee Northwest and Central Switzerland (Req-2023 - 00727) reviewed this study and determined that it does not fall under the Human Research Act (Art.2). The survey did not collect sensitive health-related personal data, responses were fully anonymized, and participants provided informed consent at the beginning of the survey. No compensation was provided to participants. As such, authorization from the ethics committee was not required.

Measures

The dependent variable, OHIS, was measured via a single item: “In a typical week, how many days do you use websites for getting health-related information?” The question was adapted with minor modifications from the digital health literacy survey instrument developed by the Health Literacy Survey 2019

(HLS19) Consortium of the WHO Action Network on Measuring Population and Organizational Health Literacy [20]. Response options included "more than once per day," "once a day," "4 - 6 days per week," "1 - 3 days per week," "less than once per week," "I don't use it, but it's interesting," and "I don't use it, and I'm not interested in it, either." For analysis, responses indicating any frequency of use ("More than once per day" to "Less than once per week") were recoded as users, while responses indicating no use were recoded as nonusers, resulting in a binary variable (use or nonuse); this approach followed established methods in prior research on OHIS [21].

To explain OHIS use, a range of sociodemographic, health-related, and individual competence factors was considered. Sociodemographic variables included sex (female or male), age group (60 - 69, 70 - 79, and 80 - 100 years), residence location (rural, intermediate, and urban), living arrangement (living alone or with others), education level (compulsory education, secondary education, and tertiary education), and financial situation. The financial situation was assessed through a question adapted from the Swiss Survey on Income and Living Conditions, asking participants how difficult it was for their household to make ends meet with their available income, with responses categorized into "very difficult to rather difficult," "rather simple," and "easy to very easy" [22].

Subjective health status was measured by asking participants to rate their general health, with responses dichotomized afterward into "very poor to mediocre" and "good to very good" categories. To assess the number of medical treatments, participants were asked how often they had received medical treatment (including from general practitioners but excluding dentists) in the previous 12 months. The number of treatments ranged from 0 to 90 (mean 7.28, SD 12.68) and was dichotomized into "below the mean value (of the sample)" and "above the mean value (of the sample)." Both measures were adapted from the Swiss Federal Statistical Office Health Survey [23].

Frequency of internet use was measured by asking how often participants used the internet, with responses dichotomized into "(almost) daily use" and "less than (almost) daily use." Trust in OHI was assessed using participants' responses when asked how trustworthy they found health information from the internet, using a question adapted from Link and Baumann [12], with responses categorized as "rather or very trustworthy, or both trustworthy and not" versus "rather or not at all trustworthy."

Health literacy, defined as the competencies to access, understand, appraise, and apply health information in order to make judgments and take decisions in health care, disease prevention, and health promotion, was assessed using the validated HLS19-Q12 instrument developed by the HLS19 Consortium of the WHO Action Network on Measuring Population and Organizational Health Literacy and categorized into "deficient," "problematic," "sufficient," and "excellent" levels [24]. Digital competence, defined as the ability to use digital technologies in a critical, collaborative, and creative way, was measured using the DigCompSAT tool developed by Clifford et al [25], which was adapted for this study following the approach of Weinhold et al [26] and translated into German, French, and Italian by Stürz et al [27]. The overall score was divided into 4 levels: "low," "basic," "intermediate," and "advanced."

Additionally, OHIS users were asked about their motivations for and nonusers about their barriers to using OHIS, both assessed through multiple response options. The specific response categories for motivations are presented in Table S2 in Multimedia Appendix 1; categories for barriers are in Table S3 in Multimedia Appendix 1.

Analytical Strategy

Statistical analyses were performed using SPSS (version 28; IBM Corp). Descriptive analyses comparing OHIS users (n=969) and nonusers (n=279) and their stated motivations and barriers were conducted using chi-square tests (*P* values) and Cramér *V* (effect size) to assess associations between categorical variables. To identify predictors of OHIS use, a binary logistic regression was performed, allowing for the multivariate analysis of sociodemographic, health-related, and individual competence factors.

Results

Sociodemographic Characteristics of the Sample

The final study sample consisted of 1261 internet users aged 60 years and older, of whom 57.3% (722/1261) were male (Table 1). A total of 52.8% (666/1261) were aged 60 - 69 years, with the overall mean age being 70.1 (SD 7.3) years. Most participants lived in urban areas (718/1261, 57%), and the majority did not live alone (936/1228, 76.2%). Regarding educational attainment, 57.5% (714/1242) had completed secondary school, and 36.9% (458/1242) held a tertiary degree.

Table . Sample characteristics (N=1261) among participants aged 60 years and older who use the internet (onliners, aged 60 years and older).

	Sample, n (%)
(Registered) sex	
Female	539 (42.7)
Male	722 (57.3)
Age groups (years)	
60 - 69	666 (52.8)
70 - 79	438 (34.7)
80 - 100	157 (12.5)
Residence location	
Rural	265 (21)
Intermediate	278 (22)
Urban	718 (57)
Living arrangement	
Living alone	292 (23.8)
Not alone	936 (76.2)
No information	33
Education	
Compulsory	70 (5.6)
Secondary school II	714 (57.5)
Tertiary level	458 (36.9)
No information	19
Financial situation	
Very difficult to rather difficult	236 (19.5)
Rather simple	334 (27.6)
Easy to very easy	639 (52.9)
No information	52
Subjective health status	
Very poor to mediocre	294 (23.5)
Good to very good	959 (76.5)
No information	8
Number of medical treatments	
Below the mean value	910 (75.9)
Above the mean value	289 (24.1)
No information	62

Financial situation was described as easy to very easy by 52.9% (639/1209), rather simple by 27.6% (n=334), and rather to very difficult by 19.5% (n=236). Most participants reported good to very good health (959/1253, 76.5%). The number of medical treatments in the previous 12 months ranged from 0 to 90; 75.9% (910/1199) were below and 24.1% (289/1199) above the sample mean (mean 7.28, SD 12.68). Table 1 provides the sample characteristics.

Use of OHIS

Among onliners aged 60 years and older, 77.6% (969/1248) reported engaging in OHIS, while 22.4% (279/1248) did not. OHIS use was more frequent among female users (429/534, 80.3%) than male users (540/714, 75.6%), and this difference was statistically significant. Age differences were also significant, with the highest OHIS use among participants aged 60 - 69 years (531/658, 80.7%), compared to 70 - 79 years (320/434, 73.7%) and 80 years and older (118/156, 75.6%). Education level showed a significant association with OHIS use, with the highest use among those with tertiary education

(384/455, 84.4%) compared to secondary (523/707, 74%) and compulsory schooling (49/68, 72.1%).

No significant bivariate associations were observed for residence location, living arrangement, financial situation, subjective health status, or number of medical treatments. See Table 2 for full distributions.

Table . Characteristics of online health information seeking (OHIS) users (n=969) and nonusers (n=279) among participants aged 60 years and older who use the internet (onliners, aged 60 years and older).

	OHIS user (n=969), n (%)	OHIS nonuser (n=279), n (%)	Cramér *V*[a]	*P* value
(Registered) sex			0.056	.048
Female	429 (80.3)[b]	105 (19.7)		
Male	540 (75.6)	174 (24.4)		
Age groups (years)			0.079	.02
60 - 69	531 (80.7)	127 (19.3)		
70 - 79	320 (73.7)	114 (26.3)		
80 - 100	118 (75.6)	38 (24.4)		
Residence location			0.043	.31
Rural	201 (76.4)	62 (23.6)		
Intermediate	206 (74.9)	69 (25.1)		
Urban	562 (79.2)	148 (20.8)		
Living arrangement			0.032	.27
Living alone	219 (75.5)	71 (24.5)		
Not alone	728 (78.6)	198 (21.4)		
Education			0.123	<.001
Compulsory	49 (72.1)	19 (27.9)		
Secondary school II	523 (74)	184 (26)		
Tertiary level	384 (84.4)	71 (15.6)		
Financial situation			0.048	.25
Very difficult to rather difficult	174 (74)	61 (26)		
Rather simple	261 (78.9)	70 (21.1)		
Easy to very easy	501 (79.1)	132 (20.9)		
Subjective health status			0.047	.10
Very poor to mediocre	237 (81.2)	55 (18.8)		
Good to very good	726 (76.6)	222 (23.4)		
Number of medical treatments			0.001	.98
Below the mean value	701 (77.5)	203 (22.5)		
Above the mean value	222 (77.6)	64 (22.4)		

[a]Reported Cramér *V* values with corresponding *P* values indicate the strength and significance of group differences.

[b]Percentages are calculated within subgroups (users vs nonusers).

Predictors of OHIS

To identify significant predictors of OHIS, 3 hierarchical binary logistic regression models were conducted. These models sequentially examined the effects of sociodemographic (sex, age, education, financial situation, residence location, and living arrangement) and health-related (subjective health and number of medical treatments) factors (model 1), internet use and trust in OHI (model 2), and individual health literacy and digital competence (model 3; Table 3).

Table . Binary logistic regression[a] models predicting online health information seeking (OHIS) use among onliners aged 60 years and older (n=1043) across sociodemographic and health-related factors, internet use and online health information (OHI) trust, and individual competence[b].

Predictors	Model 1: sociodemographic and health-related factors		Model 2: model 1 factors plus internet use and OHI trust		Model 3: model 2 factors plus digital competence and health literacy	
	OR[c] (95% CI)	*P* value	OR (95% CI)	*P* value	OR (95% CI)	*P* value
(Registered) sex						
Male	Reference	Reference	Reference	Reference	Reference	Reference
Female	1.369 (0.981-1.912)	.06	1.295 (0.902-1.860)	.16	1.409 (0.972-2.043)	.07
Age groups (years)						
60 - 69	Reference	Reference	Reference	Reference	Reference	Reference
70 - 79	0.696 (0.498-0.972)	.03	0.757 (0.527-1.088)	.13	0.782 (0.540-1.132)	.19
80 - 100	0.989 (0.424-1.122)	.13	0.790 (0.465-1.343)	.38	0.884 (0.512-1.524)	.66
Residence location						
Rural	Reference	Reference	Reference	Reference	Reference	Reference
Intermediate	1.020 (0.641-1.621)	.94	1.032 (0.625-1.706)	.90	1.010 (0.607-1.681)	.97
Urban	1.094 (0.740-1.618)	.65	0.998 (0.652-1.528)	.99	0.983 (0.638-1.514)	.94
Living arrangement						
Living alone	Reference	Reference	Reference	Reference	Reference	Reference
Not alone	1.271 (0.876-1.844)	.21	1.325 (0.886-1.982)	.17	1.319 (0.877-1.982)	.18
Education						
Compulsory	Reference	Reference	Reference	Reference	Reference	Reference
Secondary school II	1.115 (0.566-2.196)	.75	0.943 (0.442-2.009)	.88	0.748 (0.346-1.619)	.46
Tertiary level	1.994 (0.964-4.1259)	.06	1.353 (0.601-3.050)	.47	0.996 (0.432-2.293)	.99
Financial situation						
Very difficult to rather difficult	Reference	Reference	Reference	Reference	Reference	Reference
Rather simple	1.356 (0.860-2.138)	.19	1.332 (0.813-2.182)	.26	1.310 (0.794-2.162)	.29
Easy to very easy	1.394 (0.917-2.120)	.12	1.381 (0.873-2.186)	.17	1.322 (0.824-2.121)	.25
Subjective health status						
Very poor to mediocre	Reference	Reference	Reference	Reference	Reference	Reference
Good to very good	0.537 (0.344-0.837)	.006	0.505 (0.315-0.811)	.005	0.496 (0.307-0.801)	.004
Number of medical treatments						
Below the mean value	Reference	Reference	Reference	Reference	Reference	Reference
Above the mean value	0.780 (0.522-1.167)	.23	0.753 (0.488-1.162)	.20	0.774 (0.501-1.198)	.25
Internet use						
Less than (almost) daily	—[d]	—	Reference	Reference	Reference	Reference
(Almost) daily internet use	—	—	1.970 (1.321-2.937)	<.001	1.550 (1.011-2.376)	.04
Trust in OHI						

Predictors	Model 1: sociodemographic and health-related factors		Model 2: model 1 factors plus internet use and OHI trust		Model 3: model 2 factors plus digital competence and health literacy	
	OR[c] (95% CI)	*P* value	OR (95% CI)	*P* value	OR (95% CI)	*P* value
Rather or not at all trustworthy	—	—	Reference	Reference	Reference	Reference
OHI are rather or very trustworthy, or both trustworthy and not	—	—	6.026 (4.252-8.542)	<.001	5.784 (4.044-8.272)	<.001
Health literacy (HLS19-Q12)						
Deficient	—	—	—	—	Reference	Reference
Problematic	—	—	—	—	0.733 (0.400-1.346)	.32
Sufficient	—	—	—	—	0.669 (0.349-1.282)	.23
Excellent	—	—	—	—	0.912 (0.393-2.117)	.83
Digital competence (DigCompSAT)						
Low	—	—	—	—	Reference	Reference
Basic	—	—	—	—	1.811 (0.990-3.316)	.05
Intermediate	—	—	—	—	2.660 (1.467-4.824)	.001
Advanced	—	—	—	—	3.108 (1.385-6.975)	.006

[a]Dependent variable: user OHIS=1, nonuser OHIS=0. For detailed statistical values (CIs), please refer to Table S1 in Multimedia Appendix 1.

[b]Model fit: model 1: Nagelkerke R^2=0.045; χ^2_{12}=30.2; *P*=.003; model 2: Nagelkerke R^2=0.217; χ^2_{14}=154.3; *P*<.001; and model 3: Nagelkerke R^2=0.234; χ^2_{20}=167.4; *P*<.001.

[c]OR: odds ratio.

[d]The predictor was not included in the respective model.

Model 1 (Nagelkerke R^2=0.045; χ^2_{12}=30.2; *P*=.003) was statistically significant and revealed that only age was a significant predictor within the sociodemographic variables. Participants aged 70 - 79 years were significantly less likely to use OHIS compared to those aged 60 - 69 years (odds ratio [OR] 0.696, 95% CI 0.498-0.972; *P*=.03). Notably, no significant difference was observed between participants aged 80 - 100 years and those aged 60 - 69 years (OR 0.989, 95% CI 0.424-1.122; *P*=.13). In contrast, other sociodemographic factors that were significant in the bivariate analysis—sex and education level—did not retain significance in the multivariate model. Besides age, subjective health was also a significant predictor. Participants who rated their health as good to very good were less likely to use OHIS compared to those with poor to mediocre health (OR 0.537, 95% CI 0.344-0.837; *P*=.006). Conversely, the number of medical treatments in the previous year showed no significant association with OHIS engagement (OR 0.780, 95% CI 0.522-1.167; *P*=.23). These results provide mixed support for hypothesis 1.

Model 2 (Nagelkerke R^2=0.217; χ^2_{14}=154.3; *P*<.001) introduced internet use frequency and trust in OHI as predictors. The analysis revealed that both factors were significant predictors of OHIS use, providing full support for hypothesis 2. Participants who reported using the internet (almost) daily were nearly twice as likely to use OHIS compared to those who used it less frequently (OR 1.970, 95% CI 1.321 - 2.937; *P*<.001). Additionally, participants who perceived OHI as rather or very trustworthy, or both trustworthy and not, were over 6 times more likely to use OHIS than those who distrusted OHI (OR 6.026, 95% CI 4.252 - 8.542; *P*<.001). Notably, the previously significant effect of age became nonsignificant after including these 2 model 2 variables (OR 0.757, 95% CI 0.527-1.088; *P*=.13).

Model 3 (Nagelkerke R^2=0.234; χ^2_{20}=167.4; *P*<.001) added health literacy and digital competence to the analysis. Compared to adults with low digital competence levels, those with intermediate competence were more than twice as likely to use OHIS (OR 2.660, 95% CI 1.467 - 4.824; *P*=.001), and those with advanced competence were over 3 times more likely (OR 3.108, 95% CI 1.385 - 6.975; *P*=.006) to use OHIS. In contrast, health literacy was not a significant predictor. Additionally, subjective health status, daily internet use, and trust in OHI continued to be significant predictors in model 3.

The model's explanatory power increased with each step, as indicated by the rising Nagelkerke R^2, from 0.045 in model 1 to 0.234 in model 3. This progression highlights how the inclusion of internet use, trust in OHI, and digital competence substantially improved the model's ability to predict OHIS use.

Motivations for OHIS

Among the 969 OHIS users, the most commonly indicated reason for use was to gain a better understanding of certain health conditions or illnesses (672/969, 69.3%), followed by learning about medications and their possible side effects (538/969, 55.5%) and searching for treatment options or therapies for specific health problems (528/969; 54.5%; Table

4). Additionally, searching for alternative or complementary medical approaches (424/969, 43.8%) and seeking information out of general interest (402/969, 41.5%) were notable motivations. Fewer participants indicated using OHIS to obtain a second opinion (180/969, 18.6%) or for other reasons (9/969, 0.9%; eg, assisting family members and searching for information when health professionals are unavailable).

Table . Motivations for engaging in online health information seeking (OHIS) among OHIS users (n=969) within the onliner population (aged 60 years and older), including chi-square tests for sex and age differences[a,b].

Motivation (multiple response options)	Total, n (%)	Male, n (%)	Female, n (%)	Chi-square test for differences in sex, *P* value	60 - 69 years, n (%)	70 - 79 years, n (%)	80 - 100 years, n (%)	Chi-square test for differences in age, *P* value
Understanding health conditions	672 (69.3)	372 (68.9)	300 (69.9)	.73	370 (69.7)	216 (67.5)	86 (72.9)	.54
Medications and side effects	538 (55.5)	284 (52.6)	254 (59.2)	.04	268 (50.5)	197 (61.6)	73 (61.9)	.002
Treatment options or therapies	528 (54.5)	262 (48.5)	266 (62)	<.001	274 (51.6)	190 (59.4)	64 (54.2)	.09
Alternative or complementary medicine	424 (43.8)	192 (35.6)	232 (54.1)	<.001	239 (45)	139 (43.4)	46 (39)	.49
Just out of interest	402 (41.5)	233 (43.1)	169 (39.4)	.24	241 (45.4)	112 (35)	49 (41.5)	.01
Second opinion	180 (18.6)	118 (21.9)	62 (14.5)	.003	89 (16.8)	63 (19.7)	28 (23.7)	.18
Other reasons	9 (0.9)	8 (1.5)	1 (0.2)	N/A[c]	4 (0.8)	3 (0.9)	2 (1.7)	N/A

[a]Detailed effect sizes (Cramér *V*) and full answer options from the survey are reported in Table S2 in Multimedia Appendix 1.

[b]Sorted by total.

[c]N/A indicates that no calculation was performed because cells had a frequency of fewer than 5.

Sex differences were significant for several motivations. Female participants were more likely than male participants to search for information on treatment options or therapies (266/429, 62% vs 262/540, 48.5%), alternative or complementary medical approaches (232/429, 54.1% vs 192/540, 35.6%), and medications and side effects (254/429, 59.2% vs 284/540, 52.6%). Conversely, male participants were more inclined to search for a second opinion (118/540, 21.9% vs 62/429, 14.5%).

Significant age-related differences also emerged. Older participants, particularly those aged 70 - 79 (197/320, 61.6%) and 80 - 100 years (73/118, 61.9%), were more likely to seek information about medications and side effects compared to the 60 - to 69-year age group (268/531, 50.5%). In contrast, younger participants (aged 60-69 years) were more likely to search for OHI out of general interest (241/531, 45.4%) than older groups.

Barriers to OHIS

The most commonly indicated barrier to use among OHIS nonusers was difficulty assessing the credibility of information (159/279, 57%), followed by distrust in the effectiveness of the information provided (129/279, 46.2%), concerns about dubious providers or the risk of spam and advertising (93/279, 33.3%), lack of experience with searching for information on the internet (87/279, 31.2%), and challenges related to technical or difficult-to-understand language in health information (46/279, 16.5%; Table 5). Fewer participants indicated barriers such as lack of support in using digital services (20/279, 7.2%), negative past experiences with online searches (17/279, 6.1%), physical limitations when using digital devices (10/279, 3.6%), and other reasons (51/279, 18.3%, eg, outdated or unclear publication dates and lack of personal interest in health information). Sex- or age-related differences did not attain statistical significance for any of the barriers.

Table . Barriers to engaging in online health information seeking (OHIS) among OHIS nonusers (n=279) within the onliner population (60 years and older), including chi-square tests for sex and age differences[a,b].

Barriers (multiple response options)	Total, n (%)	Male, n (%)	Female, n (%)	Chi-square test for differences in sex, *P* value	60‐69 years, n (%)	70‐79 years, n (%)	80‐100 years, n (%)	Chi-square test for differences in age, *P* value
Credibility	159 (57)	96 (55.2)	63 (60)	.43	71 (55.9)	64 (56.1)	24 (63.2)	.71
Distrust	129 (46.2)	84 (48.3)	45 (42.9)	.38	61 (48)	51 (44.7)	17 (44.7)	.86
Dubious offers	93 (33.3)	60 (34.5)	33 (31.4)	.60	47 (37)	39 (34.2)	7 (18.4)	.10
Lack of experience	87 (31.2)	56 (32.2)	31 (29.5)	.64	32 (25.2)	38 (33.3)	17 (44.7)	.06
Technical language	46 (16.5)	31 (17.8)	15 (14.3)	.44	20 (15.7)	20 (17.5)	6 (15.8)	.93
Lack of support	20 (7.2)	12 (6.9)	8 (7.6)	.82	8 (6.3)	8 (7)	4 (10.5)	N/A[c]
Negative experiences	17 (6.1)	12 (6.9)	5 (4.8)	.47	10 (7.9)	4 (3.5)	3 (7.9)	N/A
Physical limitations	10 (3.6)	4 (2.3)	6 (5.7)	N/A	3 (2.4)	5 (4.4)	2 (5.3)	.59
Other reasons	51 (18.3)	30 (17.2)	21 (20)	.56	20 (15.7)	23 (20.2)	8 (21.1)	.60

[a]Detailed effect sizes (Cramér *V*) and full answer options from the survey are reported in Table S3 in Multimedia Appendix 1.

[b]Sorted by total.

[c]N/A indicates that no calculation was performed because cells had a frequency of fewer than 5.

Discussion

Principal Findings

The study findings revealed that OHIS occurred widely among older adults in this demographic, with 77.6% (n=969) of older onliners using OHIS. This aligns with prior research demonstrating high engagement with digital health resources among older adults [28]. Notably, no significant difference in OHIS engagement was found between individuals aged 80‐100 years and the younger age groups, although a drop in use was observed in the 70‐ to 79-year age group compared to the 60‐ to 69-year group. This suggests that the oldest age group may have adapted to digital tools similarly to younger older adults [4]. One potential explanation for this negligible discrepancy may be that the younger age group (60-69 years) was more inclined to experiment with technology and explore digital tools, consequently resulting in higher OHIS use. In contrast, the oldest group (80-100 years) may be more predisposed to seek information online for health reasons [29]. Furthermore, this study revealed a marginally elevated propensity among female participants to use OHIS, aligning with the extant literature suggesting that female participants exhibit a heightened propensity to proactively seek health-related information [7].

Education emerged as a significant predictor of OHIS use. Individuals with tertiary education were more likely to seek health information online, supporting the theory of the digital divide, where higher education correlates with better digital competence and greater access to online resources [5].

In the multivariate analysis, the effects of education, sex, and age lost statistical significance. This suggests that, while these sociodemographic factors may initially appear associated with OHIS use, their explanatory power diminishes when health, behavioral, and competence-related variables, such as subjective health status, digital competence, and trust in OHI, are considered. This pattern aligns with previous findings that highlight the centrality of these more proximal determinants [21]. This highlights the importance of broader structural and individual determinants in shaping OHIS use.

Markedly, individuals with poorer self-reported health statuses were more likely to use OHIS, supporting findings that health concerns drive proactive information seeking [30]. However, the number of medical treatments was not associated with OHIS engagement, suggesting that health care use alone does not motivate OHIS. Instead, sufficient information from health care providers may reduce the need for additional online searches, while other providers may encourage OHIS use [16].

The predictive role of digital competence was shown within our analyses; people with higher levels of digital competence were more often within the group of OHIS users. A higher level of digital competence can facilitate the ability to search for OHI, while those with low competence levels remained disengaged, despite internet access, underscoring that mere access is insufficient for effective use [6,18].

Moreover, regular use of the internet also predicted OHIS use and can be regarded as a behavioral indicator of technological familiarity, thereby further supporting the application of OHIS. However, digital competence encompasses a more extensive ability to effectively engage with digital tools across various contexts.

Contrary to the findings of other studies, health literacy was not a significant predictor of OHIS use in this research [7,19]. This suggests that, while individuals with lower health literacy may face challenges in comprehending and critically evaluating health information, these difficulties do not necessarily prevent them from OHIS engagement. The ease of access and widespread availability of OHI may encourage use regardless of comprehension levels. However, this raises concerns about the potential risk of misinterpretation or reliance on misleading information, particularly among those with lower health literacy levels. This highlights that OHIS primarily reflects the act of searching rather than the quality of comprehension or application, a finding consistent with Wang et al [21], who emphasized that instrumental factors, such as utility and trust, are far stronger predictors of OHIS than psychological or cognitive abilities related to processing health information. As a result, individuals with lower health literacy may still use OHIS without necessarily deriving meaningful health benefits. This underscores the need for integrated strategies that strengthen both digital competence and health literacy to ensure that access to information translates into informed decision-making and improved health outcomes.

Of the variables included, trust in OHI proved to be the strongest predictor of OHIS use. Participants who perceived OHI as trustworthy were significantly more likely to engage in OHIS, underscoring the central role that perceived credibility plays in online health behaviors. This finding aligns with prior research, which has consistently shown that trust is a key determinant in digital health use [7,21,31,32].

Conversely, a lack of trust in OHI was among the barriers most frequently cited by nonusers. This distrust often stems from concerns about misinformation, unreliable sources, and commercial influences [31]. In line with previous studies, respondents expressed apprehension regarding the credibility of online health resources, which aligns with findings from Sbaffi and Rowley [33], who emphasized that website design, intrusive advertisements, and complex language negatively affect the perceived trustworthiness of OHI.

Importantly, sex and age differences indicated distinct information-seeking patterns, with female participants more focused on treatment-related topics and alternative medicine and male participants more likely to seek second opinions, while younger participants demonstrated a broader, more general interest in health-related content compared to older age groups. Therefore, digital health information should always consider the different audiences and, if necessary, tailor its content to specific audiences.

Implications for Practice and Policy

Enhancing digital competence through targeted training could improve OHIS use, especially among older adults with low digital competence levels [7]. Public health campaigns should build trust in OHI by promoting credible and user-friendly digital health platforms. Addressing individual capabilities and improving the quality of digital health information can help bridge gaps in OHIS use [30]. As highlighted by Jacob et al [34], the effectiveness of digital health interventions depends not only on providing information but also on ensuring user trust through privacy, security, and credibility. For offline individuals, the challenge lies in gaining access to digital resources. Expanding digital infrastructures and providing accessible training are essential first steps toward enabling digital engagement [10]. However, reliable offline health information (eg, flyers and brochures from government health organizations) must continue to be available to meet the needs of those who do not engage with digital platforms.

Limitations

This study has several limitations. As it focuses on Switzerland alone, the generalizability of our findings to other contexts may be limited. The cross-sectional design prevents time comparisons and, therefore, causal conclusions about factors influencing OHIS use. Hence, future longitudinal studies should investigate factors that influence changes in OHIS use over time. Self-reported data, such as subjective health, may introduce recall or social desirability bias, potentially affecting the accuracy of responses. Additionally, the content and quality of the accessed health information were not assessed, limiting insights into the variance of the individual user profiles.

Conclusions

This paper highlights the significant correlation of subjective health status, digital competence, daily internet use, and trust in OHI with OHIS use among older adults. Health literacy and sociodemographic characteristics showed no significant correlation when examined alongside other factors. Addressing digital competence and enhancing trust in OHI are essential for reducing digital inequalities and empowering older adults to manage their health more actively, thereby promoting healthy aging.

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Data Availability

The datasets generated or analyzed during this study are available from the corresponding author on reasonable request.

Authors' Contributions

Conceptualization: YB, AS
Data curation: YB, AS
Formal analysis: YB, AS
Funding acquisition: AS, CF
Investigation: YB, AS
Project administration: CF
Visualization: YB
Writing—original draft: YB
Writing—review and editing: YB, AS, SS, CF

Conflicts of Interest

None declared.

Multimedia Appendix 1
Supplemental tables for detailed statistical values.
[DOCX File, 60 KB - ojphi_v18i1e77557_app1.docx]

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Abbreviations

HLS19: Health Literacy Survey 2019
OHI: online health information
OHIS: online health information seeking
OR: odds ratio
WHO: World Health Organization

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Original Paper

Demonstrating a Social Intelligence Analysis Framework for Loneliness: Infodemiology Approach

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Abstract

Background: Loneliness is a dynamic phenomenon that can be investigated using social media and web data.

Objective: This study aims to introduce a framework for studying loneliness through social media and online data sources. A case study is presented to demonstrate the deployment of this framework and its effectiveness in collecting and analyzing data related to loneliness.

Methods: Our proposed framework involves collecting data from various social media and online sources. We discuss the modalities of analyzing the collected data based on the framework's defined purpose. The analysis was conducted using tools such as Google Trends, the News application programming interface, X (formerly known as Twitter), Reddit, and other social media platforms. Different types of data were categorized according to the proposed framework to understand and study loneliness comprehensively.

Results: The results demonstrate the effectiveness of our proposed framework in collecting various types of data related to loneliness. Tools such as Google Trends and the News application programming interface provided insights into loneliness trends in specific regions. Social media platforms offered behavioral data on loneliness, which were analyzed using sentiment analysis and social intelligence techniques. Correlations between loneliness and personal-emotional and socioeconomic categories were identified through this analysis.

Conclusions: The framework and tools discussed in this paper complement psychosocial approaches to loneliness, which typically rely on self-report measurements. By incorporating online data perspectives, our framework provides valuable insights into loneliness dynamics, enhancing our understanding of this complex phenomenon.

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KEYWORDS

health informatics; loneliness informatics; loneliness theory; health effects; loneliness interventions; ICT-based interventions; social media–based interventions; social media; ICT; lonely; loneliness; social isolation; analysis framework; Twitter; Reddit; behavioral data

Introduction

Background

Loneliness has global public health consequences. Loneliness not only affects the mental health of people worldwide but also has consequences for physical health [1]. Loneliness is a dynamic phenomenon that is understood from multiple perspectives and disciplines [2]. It can be studied from an information and health informatics perspective. Applying data and data science disciplines to study health in rapidly changing scenarios has led to the development of fields such as infodemiology and infoveillance [3]. There is a demand for a framework that is based on the tools of infodemiology to study loneliness through data sources available online and from social media.

The proposed social intelligence analysis framework for loneliness in this paper has four parts: (1) identifying trends, (2) monitoring the news, (3) exploring the breadth of topics, and (4) finally analyzing the depth of topics. In the first stage, it is important to know how the phenomenon being investigated has a general trend. This stage gives us the overall scope of the topic and its temporal dimensions. When the temporal dimensions are known, we can go to the second stage of analysis, which is to know whether the phenomenon is getting coverage in a specific geographical area. The third stage of the analysis is to use social media data to analyze the correlations and associations of the phenomenon in the geographical area. This part can focus on the breadth or the variety of related topics and correlations. The fourth stage, which can compound the third stage, is to provide details on the topics and correlations of the phenomenon.

This paper aims to provide a demonstration through data collection and data analysis according to the proposed framework. Social media and online sources can help us understand the prevalence of loneliness to devise technology-based and community-oriented strategies to address it. While technology may have resulted in a fragmented and individualized existence, it can also be a great healer. The rise of social media has transformed the way in which we interact with others, offering new opportunities for social connection and communication. Loneliness is a common experience that can have negative effects on mental and physical health, and social media use has been implicated as a potential contributor to loneliness [4]. Governments such as Japan and the United Kingdom have designated positions dedicated to loneliness. In response to rising concerns about social isolation, particularly among older adults and young people, Japan appointed a Minister of Loneliness in 2021 [5]. As can be seen, in addition to piquing the interest of scholars, with the engagement of governments, loneliness has become a component of public health.

Objectives

The proposed framework uses Google Trends, the News application programming interface (API), and data from X (formerly known as Twitter) and Reddit under the interdisciplinary field of infodemiology. Further studies and discussions in infodemiology can be found in the works by Jia et al [6], Eysenbach [7], and Yu et al [8]. We make a distinction between web and social media sources because social media sources are self-reported and can provide an intimate and personal perspective. By web sources, we mean sources other than social media. Although the main focus of this work was on the United States, country-specific filtering can be used for Google Trends, the News APIs, and X data. The Reddit API does not provide the data for a particular country, so Reddit data on loneliness only includes worldwide posts. This is one of the limitations of this demonstration of the social intelligence analysis framework. Nonetheless, Reddit data can still provide useful insights for the study of loneliness. We used the sentiment intensity analyzer contained in the Natural Language Toolkit (NLTK; Team NLTK) and Valence Aware Dictionary and Sentiment Reasoner (VADER) [9] from the NLTK for various analyses in this study.

This study aims to introduce a framework for studying loneliness through social media and online data sources. The framework is important to understand loneliness using data available online and to complement the theoretical and psychosocial understanding of loneliness.

Methods

Overview

Most researchers in the fields of sociology, public health, and psychology have studied loneliness using the University of California, Los Angeles (UCLA), Loneliness Scale [10-12]. The UCLA Loneliness Scale is a measuring instrument developed by Russell [13] at UCLA. It is an essential instrument for assessing subjective perceptions of loneliness. The scale comprises 20 items. The UCLA Loneliness Scale investigates various dimensions of loneliness involving social isolation, relational quality, and self-reliance. Its core domains—social connectedness, relational connectedness, and self-reliance—investigate the availability and depth of social interactions and assess an individual's capacity to manage loneliness. It has been broadly used in psychological research, specifically in assessing the effects of loneliness on mental health and social behaviors across diverse demographic groups. The UCLA Loneliness Scale is a valued quantitative measure [13]. The proposed framework provides a complete assessment of loneliness, helping to identify, recognize, and theoretically address feelings of isolation, thereby generating discussions about social associations and guiding possible interventions to allay loneliness.

The UCLA Loneliness Scale is a set of questions, whereas our framework collects behavioral information and unstructured text data, in addition to other online data, to understand loneliness. For the sake of brevity, a detailed explanation of the proposed framework is not included in this paper.

Proposed Framework

The proposed social intelligence analysis framework for studying loneliness leverages a wide range of data sources from across the web and social media, addressing the challenges of extracting meaningful information from the overwhelming volume of available online content. Traditional measures of loneliness, such as the UCLA Loneliness Scale, have long been used in scientific and psychosocial research to assess individuals' subjective feelings of social isolation, well-being, and connection to others. However, these measures rely heavily on self-reported survey data, which while valuable, only capture loneliness in controlled, specific contexts. In contrast, the proposed framework uses real-time, publicly available online data to offer a more dynamic and expansive perspective on loneliness as it naturally occurs in society. The framework is divided into four key parts: identifying trends, following the news, analyzing the range of topics, and examining the depth of discussion.

In the first stage, identifying trends, Google Trends is used to track the frequency with which people search for loneliness-related terms over time. This tool allows for the analysis of temporal patterns in public interest, offering insights into the external factors—such as societal events, economic downturns, or health crises—that may cause fluctuations in loneliness. For example, spikes in searches for loneliness-related terms might coincide with lockdowns during the COVID-19 pandemic, indicating increased public concern. In addition, Google Trends provides regional data on where these searches originate, helping researchers and policymakers target resources and interventions to the areas most affected by loneliness. Google Trends also offers related search queries, enabling the discovery of connected terms such as "loneliness in older adults" or "loneliness and mental health," which can guide further research and exploration.

The second stage, following the news, involves analyzing news articles using news APIs, such as the News API, Google News API, and Bing News Search API. News coverage of loneliness reflects broader societal interest and how loneliness is framed and discussed in the media. By examining trends and patterns in news reporting, researchers can gain insights into the causes, consequences, and public perceptions of loneliness. Media coverage often highlights demographic variations, such as the loneliness of older adults or teenagers, and reveals how loneliness is discussed within the context of mental health, social isolation, or public health crises. News stories often feature personal experiences, providing a deeper look into how loneliness affects individuals. In addition, news analysis allows researchers to monitor how public awareness of loneliness evolves and how media framing might influence public attitudes or contribute to the stigma surrounding loneliness.

In the third stage, analyzing the range of topics, the focus shifts to social media platforms, particularly X, where users express their personal feelings and opinions in real time. Through keyword searches and sentiment analysis of X data, researchers can observe the range of experiences and emotional responses associated with loneliness. The short-form, real-time nature of posts on X allows for the collection of self-reported loneliness experiences, capturing personal, emotional, and psychological aspects of the phenomenon. Furthermore, the wide range of topics and hashtags related to loneliness can help researchers understand the broader social, economic, and political factors influencing loneliness, providing a more diverse understanding of the issue.

Finally, in the fourth stage, examining the depth of discussion, platforms such as Reddit provide a more in-depth exploration of loneliness through longer, more detailed posts and discussions. Reddit users often engage in communities, or subreddits, dedicated to specific topics, such as *r/loneliness* or *r/depression*, where they share personal experiences and seek advice. This detailed, often anonymous sharing allows for more honest and comprehensive insights into the complexities of loneliness. The depth of these discussions makes Reddit a valuable tool for uncovering the more nuanced, personal dimensions of loneliness, particularly its emotional and psychological impacts. Reddit's forum-based structure also allows researchers to track the evolution of discussions over time and identify recurring themes and subtopics, contributing to a deeper understanding of loneliness.

Demonstrating the Proposed Framework

In the initial implementation of the framework, the aim is to gain an understanding of the underlying patterns associated with the phenomenon under investigation. This initial stage provides a comprehensive view of the topic and its temporal aspects. Once these temporal dimensions are determined, we can proceed to the second stage of analysis, which involves assessing whether the phenomenon is receiving attention within specific geographic regions. The third stage of the analysis entails using social media data to explore the relationships pertaining to the phenomenon within these geographical areas. This stage can either focus on the diversity and the broad spectrum of the associated topics and correlations or delve into specific aspects.

Building on the insights gained in the third stage, the fourth stage involves a more in-depth examination of the topics and correlations associated with the phenomenon. In the following sections, we will explain each of these stages in detail, outlining the tools and methodologies that will be used to facilitate their execution.

This paper aims to demonstrate the social intelligence analysis framework through a case study in which data on loneliness were collected from online data sources. The major contributions of this paper are as follows: (1) demonstrating how data can be collected in an organized way and how to analyze them to gain meaningful insights about the nature of loneliness, (2) demonstrating how different online and social media data sources can provide varied information on the dynamic and changing nature of loneliness, and (3) categorizing the themes and topics associated with loneliness into socioeconomic and personal-emotional or other relevant categories from the data collected and processed through the social intelligence analysis framework.

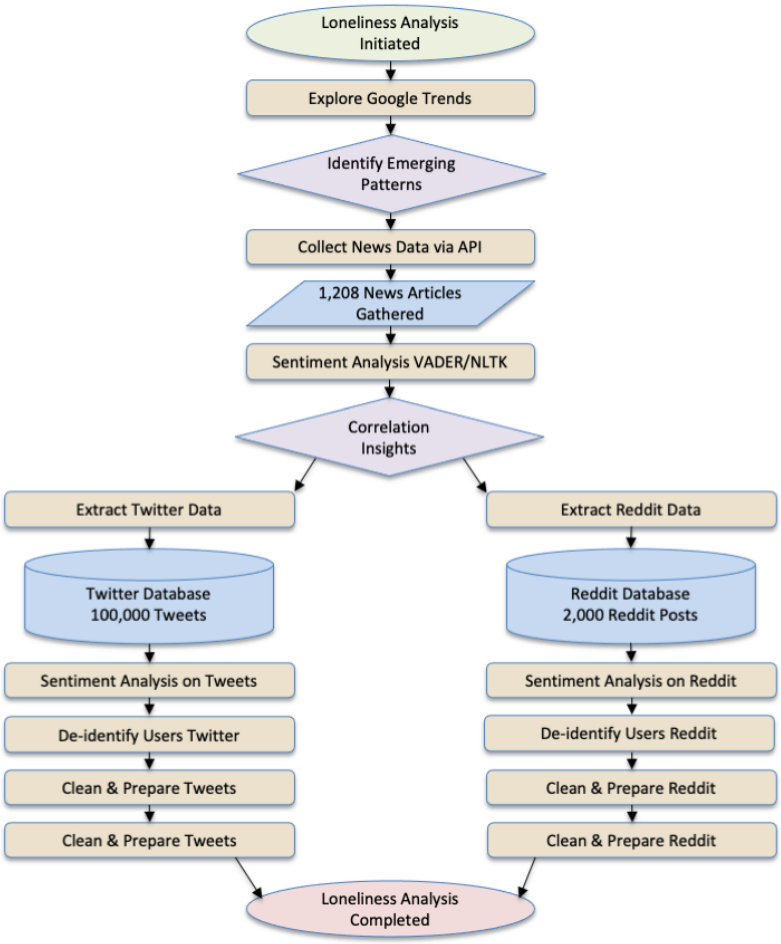
Data Collection

As this framework involves four different data sources, the data collection for each data source followed the specifics of the associated API and the rules of the data source. The data sources were Google Trends, the News API, X, and Reddit. First, data from Google Trends were collected for the year 2022. The dashboard of Google Trends allows for searching for a particular country using keywords, as well as searching for a specific year. For the news analysis, we used the News API in Python (Python Software Foundation). The data were collected for the keyword "loneliness" in the United States. On the basis of the data collected in this stage, the analysis could focus exhaustively on specific cities or countries to collect more data about them. However, we did not want to limit the search to one specific country to allow for the collected data to be a proof of concept. The collected data on X were merged based on location, user ID, and post ID to identify posts from the United States. The total number of posts was 100,000. The words "lonely," "loneliness," "alone," "isolated," and "isolation" were used to retrieve the posts.

The Reddit data collection methodology is relatively straightforward. Reddit is a forum-based social media platform where people post about a topic on a subforum dedicated to it. These subforums are called subreddits. The Reddit API provides access to individual subreddits to download the top posts on a topic, which is determined by the number of upvotes and other parameters of engagement. The posts from the *r/loneliness* subreddit were collected through the Reddit API. The *r/loneliness* subreddit has 13,000 members who can post and comment in this subforum. Reddit has its own algorithm for giving scores (ie, higher visibility to posts), which also contains input from other users in the form of upvoting.

We collected the top 2000 posts from the *r/loneliness* subreddit with all their comments. The comments varied for each post, both in number and size. It is worth noting that some of the comments were of the same length or even longer than the original posts. Thus, the comments constituted valuable data on loneliness. In total, more than 2000 individual texts were analyzed, which was estimated by multiplying the posts by the average number of comments per post. While some posts did not have comments, the maximum number of comments for a single post was 55. The average number of comments was 4.51, and the total number of comments was 8570. When combined with the posts, this resulted in more than 10,000 unique texts or personal expressions of loneliness from Reddit. We analyzed both the posts and the comments to determine the frequency of occurrence of words to locate the correlations of topics and themes with loneliness. The flowchart in Figure 1 shows the details of the data collection and analysis process used in this study.

Figure 1. Loneliness framework flowchart. API: application programming interface; NLTK: Natural Language Toolkit; VADER: Valence Aware Dictionary and Sentiment Reasoner.



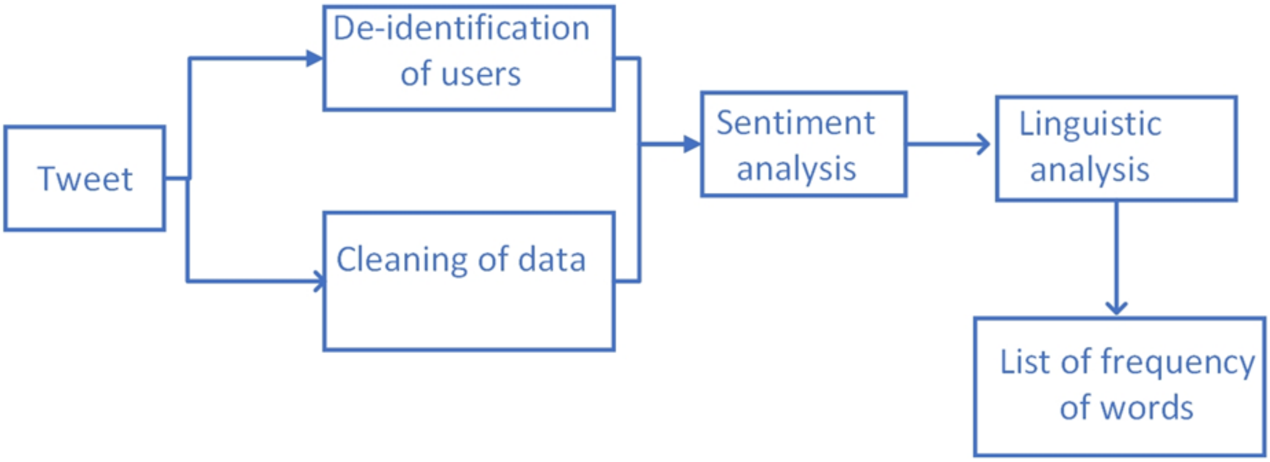
Data Analysis

X Data Analysis

We collected a particular number of X posts using keywords related to loneliness. If we reported all the X posts that contained feelings of loneliness, we would not have required a further stage, but the question here is how the expression of loneliness can imply negative consequences, such as mental health problems. In that case, the problem becomes determining the association or correlation between themes (which may represent loneliness) and keywords representing loneliness. For instance, we had to determine the relationship between "hurt," "sick," "tired," and "sleep" and the expression of loneliness. This task is usually carried out by associating lexicon categories with posts including the words "lonely" or "alone."

The problem we formulate in this paper is broader in scale. Thus, the limited scale of representative X posts had to be interpreted in a novel way to provide meaningful insight into loneliness. All the posts in the dataset contained keywords representing loneliness. These data could be analyzed to find the association between loneliness and other socioeconomic or personal-emotional categories worldwide or for individual countries. Analyzing these data is important to provide a global picture of the determinants of loneliness and to provide a tool for policymakers to address loneliness in their specific countries. However, "lonely" or "alone" can also be mentioned in a nonnegative way. Using sentiment analysis and manual analysis of the topic and themes of negative posts allowed us to look at the relationship between mentioning keywords representing loneliness and negative emotions, which may ultimately be linked to psycholinguistic features of mental well-being (Figure 2).

Figure 2. Pipeline for processing Twitter data.



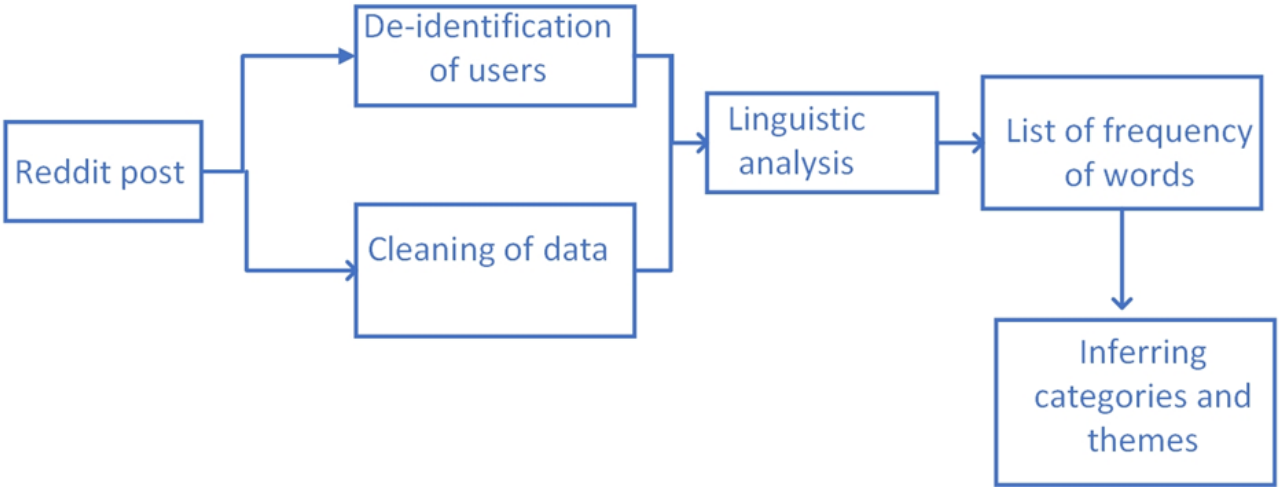
Loneliness in the context of mental health is a negative emotion, which is why the sentiment analysis stage is required—to find out how loneliness is expressed. For an analysis of loneliness in the context of mental health, we filtered out the X posts in which the expression of loneliness was negative. The collected posts also contained metaphorical uses of "lonely" or "loneliness" that did not pertain to our use of loneliness. Such mentions of loneliness were present in positive- and neutral-sentiment posts. The definition of loneliness in this paper connotes a negative feeling. While loneliness can also be a positive or neutral feeling for some people or at certain times, when it comes to its association with mental health issues, the negative consequences of loneliness must be considered.

We conducted sentiment analysis on both news articles and X data. The news articles were analyzed using the sentiment intensity analyzer contained in the NLTK. The collected posts were stored in a database, and a sentiment analysis was conducted using VADER from the NLTK. VADER is a lexicon and rule-based model for sentiment analysis. The lexicon-based algorithm is constructed using a dictionary that contains a detailed list of sentiment features. In addition, VADER complements the lexicon-based dictionary with grammatical rules that are heuristic in nature and used to determine the polarity of the sentiment. The resulting polarity of the sentiment analysis was used as an indication of loneliness in the dataset. For the sake of brevity, we will not go into the details of using VADER and sentiment analysis. For interested readers, we recommend referring to our previous work [14-16].

Reddit Data Analysis

Figure 3 shows the pipeline for processing Reddit posts. The difference between Figures 2 and 3 is the absence of sentiment analysis on the Reddit posts. After going over the subreddit *r/loneliness*, we found that the posts were about the emotional expression of loneliness and did not involve metaphorical or non-sequitur uses of "loneliness." Reddit and its subreddits are characterized by serious engagement on the topics that the subreddits are designed for. Therefore, no sentiment analysis of the Reddit data was deemed important, and the posts were analyzed using the frequency of occurrence of words to find out the themes and topics that were most highly associated with loneliness.

Figure 3. Pipeline to process Reddit data.



Manual Coding and Analysis of X and Reddit Data

The authors cleaned the data before analysis. We ensured that the X posts were deidentified by removing usernames and IDs as part of the data cleaning process. While the data are publicly available, we did not disclose any collected data without first anonymizing them. Sentiment analysis was conducted after cleaning the data, which included removing redundant characters, numbers, special characters, users' profile IDs, and information such as reposts. For the Reddit data, direct analysis was possible. However, posts from bots or other automated and potentially malicious agents were not filtered out in this study, a limitation that we plan to address in future work by removing such posts before analysis.

We stored X posts with a negative sentiment separately for further analysis, focusing on identifying prominent themes and categories through manual coding. After removing stop words and applying lemmatization to reduce word count, we generated a compact list of word occurrences. This list was manually analyzed to identify larger socioeconomic or emotional-personal categories guided by the literature, although the process remained subjective, relying on the researchers' judgment. For Reddit data, we followed a similar process, collecting posts and comments, removing stop words, applying lemmatization, and generating a word occurrence list for analysis without conducting sentiment analysis on the data from this platform.

Manual coding and analysis were used to assess expressions of loneliness on X and Reddit objectively. This topic-based categorization was more effective in identifying meaningful similarities and differences. Unlike the n-gram method, which focuses on word co-occurrence, our inductive approach allowed themes to emerge organically, providing a thorough analysis without being constrained by predefined keywords. This method, being quantitative, avoids subjective interpretation, relying instead on the frequency of word occurrences and their classification into relevant categories grounded in existing literature. The detailed analysis method and the use of sentiment analysis for Reddit and X data can be found in our previous work [14-16].

News and Google Trends Analysis

The methodology used in this study involved using the News API tool for data analysis. The News API provides programmatic access to a vast collection of news articles from various sources. The data analysis process began by formulating relevant search queries and parameters to retrieve news articles specifically related to loneliness. These parameters included keywords such as "loneliness." The News API facilitates the retrieval of a significant volume of news articles encompassing different geographical regions and periods. The collected data underwent preprocessing, including cleaning, filtering, and removing duplicate or irrelevant articles. Subsequently, sentiment analysis was used on the news articles. Sentiment analysis for news articles was used for the same reasoning explained previously for the analysis of X posts. These analyses aimed to identify prevalent themes, trends, and sentiments associated with loneliness.

Google Trends provides access to a vast database of search queries and allows for the analysis of search interest over time and across different regions. The data analysis process for Google Trends began by selecting relevant keywords related to loneliness. These keywords were used to retrieve search interest data from Google Trends. The retrieved data were then processed and analyzed to identify temporal patterns, regional variations, and related queries associated with loneliness. The analysis involved examining trend graphs, comparing search interests across different regions, and identifying related topics and queries.

Ethical Considerations

All data such as usernames, tweets, quotes, etc, in the paper have been deidentified.

Results

As the first stage involved knowing the trends, we carried out a search for the term "loneliness" on Google Trends, shown in Figure 4. We selected a longer period starting before the COVID-19 pandemic, specifically from November 1, 2019, to August 31, 2023. Figure 4 shows a snapshot of the trend graph for "loneliness." The "Note" breakpoint in the graph represents the improvement to Google's data collection system on January 1, 2022. The y-axis represents interest over time in the topic. A value of 100 represents peak interest in and popularity of the topic, whereas a value of 50 means that the term had half the popularity. The data points were collected weekly. There was a peak in interest in the topic on May 7, 2023, which did not correspond to a particular event and seems to be an outlier or an anomaly. On the other hand, the interest in the topic was at higher levels during the months of lockdowns related to the COVID-19 pandemic, peaking around the end of March 2020. Overall, the graph shows that the interest in loneliness remained at approximately half the peak levels throughout this period. This shows a sustained interest in the topic. Although the number of searches for the term and its volume are not provided, the popularity rates provide an insight into the trends for loneliness (or any other term) over time.

Figure 4. Google Trends chart for the term "loneliness." The "Note" breakpoint in the graph represents the improvement to Google's data collection system on January 1, 2022.

Google Trends also provides *Related queries* for the topic. In case of the search term "loneliness," the related queries were "covid loneliness," "loneliness during covid," "my loneliness is killing me tiktok," "is the cure to male loneliness," and "surgeon general loneliness epidemic." These terms can express different socioeconomic, personal-emotional, or other phenomena associated with loneliness. If further insight into loneliness is required, these terms can be searched separately, and the results can be compared. Google Trends also provides a tool in which two different topics or queries can be searched.

In the second stage, following the news, we used the News API in Python to retrieve news articles containing mentions of loneliness. In total, we retrieved 956 articles. Table 1 includes a random selection of 25 articles. We carried out a sentiment analysis of the news articles retrieved. An overall negative sentiment score means that the article discussed topics or themes that were negatively associated with either loneliness or broader mental health issues. The news articles with negative sentiment scores can be read for further trend analysis.

Table 1. A list of news articles with their sentiment analysis scores.

Article title	Sentiment score
Meet The People Who Listen to Podcasts Crazy-Fast	−0.766
MORABITO: Hillary Clinton Just Gave Away the Left's playbook for censorship and oppression	0.681
The Connection Cure: 6 Ways to Beat Loneliness	−0.661
Official Trailer for Babak Jalali's 'Fremont'	0.077
4 Signs Trauma Has Affected Your Self-Worth	−0.944
Why Historian Jill Lepore Hated Barbie	−0.166
MJ Lenderman Nods to Bob Dylan on New Single "Knockin"	0.700
How Athletic Beer Won Over America	0.215
4 ways simulation training alleviates team burnout	−0.681
Nessa Barrett ON: How to Overcome Loneliness	−0.851
5 Ways Men Can Build Strong Connections	0.971
Gywneth Paltrow saw you from across the bar and wants you to stay with her	−0.296
Album Of The Week: Ratboys The Window	0.250
What is the 'Joy' in the Joy of Missing	0.212
Self checkout could be making Americans Lonelier	0.772
Leave it to the dogs (13 Photos)	−0.700
An Easy Way to Reduce Depression And Loneliness	−0.968
Perils of not being attractive or athletic	−0.908
Parents Are Almost as Depressed and Anxious as Teens	−0.900
Bike Happy Hour, listening, and loneliness	0.908
3 Ways Teachers Can Instill Belonging in Students	0.898
Let It Be Sunday, 325!	0.338
How to Overcome Feeling Lonely and Powerless	−0.953
Edinburgh Fringe: The Life and Times of Michael K	0.869

Another analysis that can be carried out on the collected news articles is a list of bigrams in collocations. A collocation is a series of words that co-occur more often than would be determined by chance. In Textbox 1, we collected the bigram collocations (ie, a combination of 2 words that occurred together in the collected news articles). Although the list is a small sample and contains words that may connote difficulties regarding loneliness, collecting bigrams in collocations can provide a wider impression of what themes and topics are discussed in conjunction with loneliness. This, in turn, can point to other directions for exploring the dynamics of loneliness.

Textbox 1. Bigram collocations.

- "Relationship" and "loneliness"
- "Insomnia" and "symptoms"
- "Loneliness" and "purpose"
- "Depression" and "bitterness"
- "Anxiety" and "disorder"
- "Isolation" and "silence"
- "Alcohol" and "misuse"
- "Anxiety" and "loneliness"
- "Epidemics" and "obesity"
- "Loneliness" and "long"
- "Help" and "loneliness"
- "Insomnia" and "symptoms"

For stage 3, the analysis of the range of topics and topic analysis was conducted on the X posts. Table 2 shows the results of relevant themes and categories from analyzing the word occurrence in posts, whereas Figure 5 shows a visualization of the most dominant themes. We carried out sentiment analysis on 200,000 posts and found that 30.7% (n=61,400) had a negative sentiment. Table 2 breaks down the text of these negative-sentiment posts into the resultant words. Posts containing the keywords mentioned in the Methods section were collected. Sentiment analysis was then carried out. Sentiment analysis differentiates between phrases and topics that carry meaningful information on loneliness and those that use the term in a metaphorical or non-sequitur manner.

Figure 5. Visualization of highly correlated themes obtained from X posts.

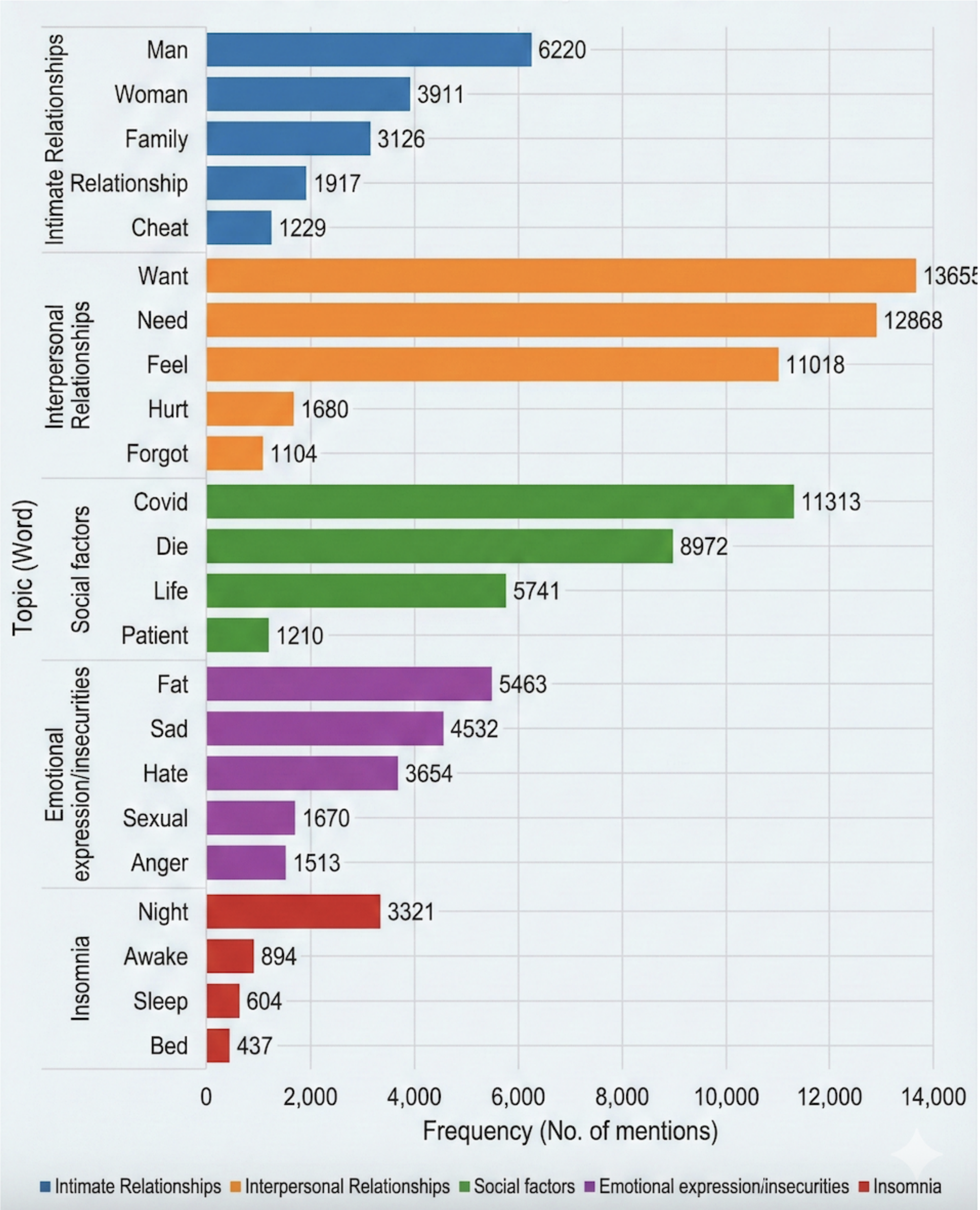


Table 2. Words highly correlated with mentions of loneliness in X posts. Topics are categorized under a broader thematic area.

Thematic area and topic	Mentions, n
Intimate relationships	
“Cheat”	1229
“Man”	6220
“Family”	3126
“Woman”	3911
“Relationship”	1917
Interpersonal relationships	
“Want”	13,655
“Need”	12,868
“Feel”	11,018
“Hurt”	1680
“Forgot”	1104
Social factors	
“Covid”	11,313
“Die”	8972
“Life”	5741
“Patient”	1210
Emotional expressions or insecurities	
“Sad”	4532
“Hate”	3654
“Fat”	5463
“Anger”	1513
“Sexual”	1670
Insomnia	
“Night”	3321
“Awake”	894
“Sleep”	604
“Bed”	437

The results show that most of the X posts containing keywords associated with loneliness from the United States were neutral, which means that they did not meaningfully contribute to the analysis of loneliness. Before conducting the detailed analysis of the posts on loneliness, it was important to identify uses of “loneliness” as a metaphor or non sequitur (ie, those posts that would not add meaningfully to the analysis of negative consequences related to loneliness). Neutrality can also represent the mention of loneliness in descriptive terms.

The basic analysis of the Reddit data for stage 4, examining the depth of the discussions, is provided in Table 3. We collected the top 2000 Reddit posts from the *r/loneliness* subreddit with all their comments. Thus, we analyzed more than 2000 total individual texts. The breakup of the data into words resulted in more than 25,000 words. For the sake of meaningful mentions of topics and brevity, we set a threshold of 50 topics that gave us 411 words to be analyzed. It should be noted that a significant number of these words were language constructs. Only the words that were meaningful in terms of emotions or other expressive qualities were included in the analysis.

Table 3. Analysis of frequency of occurrence of words in the Reddit data (N=35,057).

	Words, n (%)
Words occurring >100 times	611 (1.74)
Words occurring >1000 times	78 (0.22)

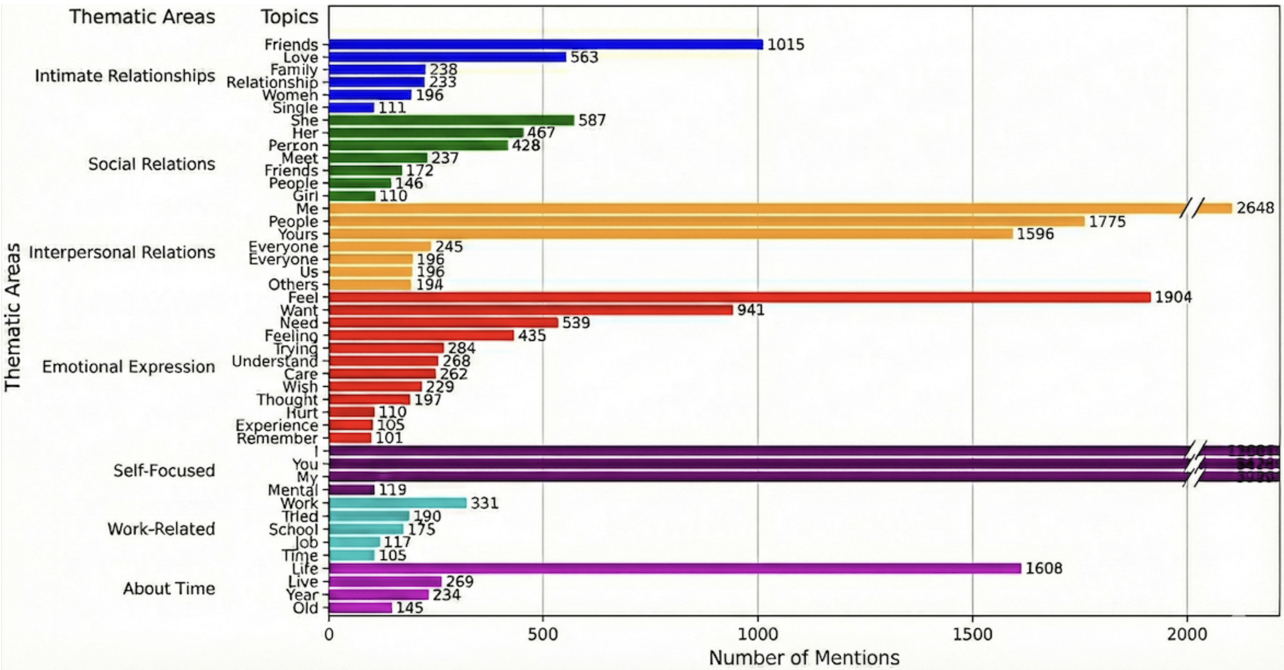
In addition, we want to note that the Reddit posts on loneliness were not specific to the United States. The posts were not divided by country, and the Reddit API does not allow for country-specific downloads. Some methods provide the ability to find the country of the post from the Reddit data, but this involves processes that are beyond the scope of this paper [17]. Table 4 and Figure 6 list and visualize the correlations between themes and loneliness in the *r/loneliness* subreddit. It can be observed from the table that the themes are mostly focused on relations and emotional expression. Because of the longer posts, it is expected that people would have more space to open up and express their feelings. Social media platforms such as Reddit provide spaces where individuals can express their vulnerabilities without facing backlash that can come in the form of social ostracization.

Table 4. Correlations of themes with loneliness in the Reddit data. Topics are categorized under a broader thematic area.

Thematic area and topic	Mentions, n
Intimate relationships	
“Love”	563
“Women”	196
“Relationship”	233
“Family”	238
“Single”	111
“Friends”	1015
Social relations	
“Friends”	172
“Girl”	110
“She”	587
“Her”	467
“People”	146
“Online”	106
“Meet”	237
“Person”	428
Interpersonal relations	
“Me”	2648
“He”	101
“Yours”	1596
“Us”	196
“Everyone”	245
“People”	1775
“Others”	194
Emotional expression	
“Thought”	197
“Hurt”	110
“Trying”	284
“Pain”	114
“Experience”	105
“Remember”	101
“Understand”	268
“Feeling”	435
“Want”	941
“Need”	539
“Feel”	1904
“Wish”	229
“Care”	262
Self-focused	
“I”	13,604
“Mental”	119
“My”	3989

Thematic area and topic	Mentions, n
“You”	5424
Work related	
“Work”	331
“Job”	117
“Tried”	190
“Time”	105
“School”	175
Time related	
“Life”	1608
“Year”	234
“Live”	269
“Old”	145

Figure 6. Visualization of highly correlated themes obtained from Reddit posts.



Discussion

Principal Findings

This paper demonstrates our social intelligence analysis framework for studying loneliness from online and social media data sources, and presents an overall picture of how a varied topic such as loneliness can benefit from multiple levels of analysis. In this study, we adopted a comprehensive approach, integrating data from Google Trends, news articles, X, and Reddit to examine the multifaceted concept of loneliness within the framework of social intelligence analysis. The demonstration of the social intelligence analysis framework for loneliness revealed interesting patterns, such as in Google Trends, and provided the topics related to mentions of loneliness.

Analysis of Google Trends data exposed intriguing temporal patterns in the public’s interest in loneliness. We observed notable spikes in loneliness-related search queries at various junctures, suggesting that external events, cultural shifts, or seasonal influences may significantly impact the prevalence and perception of loneliness in society. Our examination of news articles provided a broader contextual understanding of loneliness. The sentiment analysis of news articles provided a helpful tool to gather news articles that discuss the negative and health consequences of loneliness.

From a psychological perspective, the increases in the Google Trends graph indicate elevated public interest in loneliness that can be explained as societal reactions to noteworthy or unexpected events [13]. These events, such as the COVID-19 pandemic and the social and physical restrictions that followed, made people feel more emotionally and psychologically alone. Our sentiment analysis of news items revealed that media coverage frequently reflects this elevated awareness. In addition to reporting on these occurrences, the media also influences public opinion by highlighting the psychological results of loneliness, particularly its detrimental consequences on mental health. This combination of social factors and psychological reactions, as observed in media coverage and Google Trends, highlights the multifaceted nature of loneliness [3].

The analysis of X posts and Reddit posts revealed associations between socioeconomic and personal-emotional factors and loneliness. These factors included emotion, sentiment, emojis, and topic modeling. This analysis demonstrated that such factors could help gather evidence and analyze interactions on the topic of loneliness and other related topics. The first factor was emotion, which can serve as a guide in understanding people's reactions. The second most common factor was relationships. Other thematic areas such as health, work, self-focused topics, and insomnia-related topics indicate the intimate nature of loneliness.

The difference that was observed between the data from X and Reddit (ie, stage 3 and stage 4 of the framework) was in their diversity and extensiveness. In the X data, a range or diversity of topics and themes could be observed. Because of the limited character expression on X, people express their thoughts or opinions in a compact manner; however, through analysis of the terms used and the overall sentiment of the sentences, an association with loneliness can be found. There can be a range of such themes in which there are direct mentions of loneliness in a negative context. On the other hand, Reddit data can be useful for finding the depth of a theme associated with loneliness (ie, what subthemes or topics under a broader category are related to loneliness). These data are important for investigating the possible causes of loneliness. The diversity of the discovered topics and themes from X and the depth of topics that were found on Reddit can be used in complementary ways.

The framework delineated in this paper provides a versatile, multistep approach to analyzing loneliness through online and social media data. Beyond studying loneliness, this framework can be expanded to explore other complex societal issues, such as mental health conditions (eg, anxiety and depression), misinformation, or public reactions to crises. In addition, it can be used for early detection of public health trends or social phenomena by monitoring real-time data. The framework's capacity for sentiment analysis and topic modeling can offer valuable insights into emotional and psychological responses, which can be applied to develop targeted interventions, inform policies, or enhance public health programs.

The results of this framework reveal the complex, multifaceted nature of loneliness, highlighting its emotional, psychological, and socioeconomic dimensions. These insights can be used in mental health applications by enabling early identification of loneliness trends and allowing for real-time monitoring of at-risk groups. For mental health patient care, these data can be integrated into artificial intelligence–driven tools that personalize interventions, offer resources, or connect patients with support networks. It can also help inform health care providers about socioenvironmental triggers contributing to loneliness. Future research can incorporate more advanced natural language processing tools and extend the use of this framework to cross-cultural studies, improving understanding of how societal factors impact loneliness and other issues across different populations.

The proposed framework can be used in future research endeavors to deepen the understanding of loneliness and its societal implications by providing a systematic approach to analyze diverse and large-scale data from online platforms. By capturing both temporal trends and geographic relevance, researchers can identify key moments and regions where loneliness spikes, enabling a more focused examination of societal or environmental triggers. Expanding the framework to include more detailed demographic information will allow researchers to study how loneliness impacts specific groups, such as older adults or the younger generations, across various cultural contexts. In addition, the framework's ability to integrate multiple data sources, including social media platforms, news articles, and search trends, offers a more holistic perspective of how loneliness is discussed and experienced at both personal and collective levels. This could lead to a deeper exploration of the role that socioeconomic factors, public health crises, or policy changes play in exacerbating or alleviating loneliness. Furthermore, the sentiment and thematic analysis components can be refined to investigate emotional undercurrents related to loneliness, helping uncover the psychological and emotional dimensions of social isolation.

This framework can support the development of artificial intelligence–driven tools for real-time monitoring and intervention, ultimately informing policy and community-based solutions to address loneliness more effectively. The proposed framework could be adapted to investigate various other societal and public health issues that are influenced by dynamic social and environmental factors. For instance, mental health conditions such as anxiety and depression, which often correlate with loneliness, could be explored by tracking online discourse, sentiment, and search patterns. The framework could also be applied to study the societal impacts of major events such as pandemics, economic downturns, or political crises, where real-time social media analysis could provide insights into public emotions, coping mechanisms, and socioeconomic concerns. In addition, issues such as misinformation, public perceptions of health interventions, or even social phenomena such as digital addiction or climate anxiety could be investigated. By analyzing data from different online platforms, researchers can gain a more comprehensive understanding of public reactions and trends related to these complex, evolving issues.

Limitations

While our research yielded valuable insights into loneliness using an innovative approach, there are also some limitations. First, our reliance on digital data sources such as X and Reddit may introduce biases. These platforms primarily represent individuals comfortable with sharing their experiences online, potentially excluding those who are less active or lack internet access. This is a limitation of the proposed framework that can be overcome through in-depth interviews or surveys to provide a more holistic understanding of individuals' emotions, motivations, and coping mechanisms.

In addition, the study's temporal analysis of Google Trends data lacks causality. While we identified spikes in search queries, determining the specific reasons behind these fluctuations requires further investigation. Furthermore, the focus of the study on English-language data may not fully capture the global diversity of loneliness experiences, potentially limiting the generalizability of our findings. Another limitation lies in the demonstration itself, which relied on data from Reddit, in which the country cannot be specified. For a nuanced understanding of data from Reddit, the data first need to be categorized by region.

Conclusions

In this paper, we introduced a comprehensive framework for analyzing loneliness through the lens of social intelligence analysis. The framework uses data from diverse online sources, including search engines, news articles, X, and forum websites. This paper provides a demonstration of our proposed framework and reveals correlations between loneliness and online news and posts through sentiment analysis. We provided details on how data can be collected and analyzed according to the umbrella of our proposed framework for studying loneliness through social media and online data. In addition, sentiment analysis of news articles sheds light on the negative health consequences of loneliness, whereas the analysis of X posts and Reddit posts revealed associations between loneliness and various socioeconomic and personal-emotional factors.

Despite the framework limitations, our study provides valuable insights into the multifaceted nature of loneliness through the demonstration of our proposed framework. This study can be used in future research endeavors that can further deepen our understanding of loneliness and its societal implications.

Conflicts of Interest

None declared.

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Abbreviations

API: application programming interface
NLTK: Natural Language Toolkit
UCLA: University of California, Los Angeles
VADER: Valence Aware Dictionary and Sentiment Reasoner

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Associations Between Hospital Structural Characteristics and Adoption of Public Health Data Integration and Automation: National Cross-Sectional proofsStudy

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Abstract

Background: Public health data integration and automation systems are crucial for effective health care delivery and public health surveillance. However, the factors associated with hospitals' adoption and successful implementation remain inadequately explored.

Objective: This study aims to examine how hospital characteristics influence the adoption of public health data integration and automation.

Methods: We analyzed 2277 hospitals from the 2023 American Hospital Association Annual Survey and its Health Information Technology supplement, focusing on 6 public health reporting categories. Multivariable logistic regression models were used to examine the association between hospital characteristics and the 2 primary outcomes: active electronic data submission and use of automated transmission processes.

Results: System-affiliated and not-for-profit hospitals demonstrated significantly higher rates of electronic data submission and automated reporting across most categories (odds ratio [OR] 1.70 - 2.27; *P*<.001). Rural hospitals showed lower adoption rates in immunization registry (OR 0.77, 95% CI 0.61-0.97), public health registry (OR 0.67, 95% CI 0.46-0.97), and clinical data registry reporting (OR 0.77, 95% CI 0.60-0.98). Larger hospitals were more likely to implement electronic reporting, with medium and large hospitals showing stronger engagement in syndromic surveillance reporting (OR 1.52, 95% CI 1.06-2.19 and OR 2.29, 95% CI 1.17-4.46, respectively). Teaching status was significantly associated only with clinical data registry reporting (OR 2.66, 95% CI 1.56-4.52 for major teaching hospitals).

Conclusions: Hospital characteristics, particularly system affiliation, ownership type, and geographic location, are strongly associated with public health data integration and automation capabilities. Findings suggest targeted interventions are needed to address disparities in smaller and rural facilities to ensure equitable advancement of public health reporting infrastructure.

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KEYWORDS
public health data; data reporting; automation; active reporting; hospitals

Introduction

The integration and automation of public health data have evolved from manual record-keeping to modern digital systems that enhance real-time data sharing and interoperability. Automated frameworks now combine structured and unstructured health data, improving research capabilities and public health responsiveness. The implementation of Findable, Accessible, Interoperable, and Reusable data principles has further enhanced data use for decision-making [1]. These innovations highlight the importance of technology-driven data integration in optimizing health care delivery and public health outcomes [2]. The Health Information Technology for Economic and Clinical Health Act of 2009, enacted into law by Title XIII of the American Recovery and Reinvestment Act of 2009, dramatically fueled computerization in health care through reimbursement incentives to adopt electronic health records (EHRs) as a method of standardizing and enhancing interoperability of data [3,4]. These differences reiterated that institutional resilience and organizational readiness were more critical than technology availability to successful adoption.

The 2020s have seen further advancements with artificial intelligence (AI) and machine learning technologies extending automation capabilities. AI-based software now streamlines tasks such as drug safety compliance reporting, reducing administrative burdens and human error [5]. Despite technological progress, persistent challenges remain:

interoperability gaps prevent smooth data exchange between institutions due to diverse standards and proprietary tools [6]; regulatory requirements often fail to address structural barriers such as system upgrade costs or personnel training needs [5]; and workforce preparedness is frequently overlooked, particularly in low-resource settings where staff may lack proper training to use new technologies effectively [7].

Public reporting of hospital data, such as patient outcomes, infection rates, and readmission rates, can drive improvements in health care quality by promoting transparency and accountability. Studies have shown that hospitals participating in public reporting programs tend to engage in quality improvement activities more actively [8,9]. For instance, the American College of Cardiology's voluntary public reporting program revealed that hospitals with higher participation rates demonstrated better performance in cardiac care [8,9]. Additionally, the COVID-19 pandemic highlighted the importance of standardized and automated reporting systems to ensure timely and accurate data exchange, which is essential for effective public health responses and leads to better health outcomes for patients [4].

The association between public health data integration, automation, and hospital characteristics has become a key focus in assessing reporting system effectiveness, particularly during the COVID-19 pandemic [10]. Beyond improving health care delivery, data integration can enhance hospitals' operational efficiency, potentially leading to higher profits and increased patient service capacity [11]. However, the most significant barrier to integration remains the lack of standardization in health data norms at local, national, and international levels. Many health data systems cannot communicate effectively, resulting in integration challenges when patients move between health systems [12]. Through improved data integration, public health systems can better address concerns like social determinants of health and disease monitoring for future pandemics while enhancing patient experiences through personalized care. While prior research has examined EHR adoption broadly, few studies have disaggregated public health reporting into its component categories to identify differential adoption patterns across hospital characteristics. This study addresses this gap by simultaneously examining 6 distinct public health reporting categories and analyzing both electronic submission engagement and automation processes as separate outcomes. This context situates the central question of this research: *What hospital characteristics are associated with the adoption and success of automated health reporting systems?* By identifying factors associated with successful implementation of automated health reporting systems, the findings can inform strategies to address disparities and improve public health data infrastructure across different health care settings. This research is particularly significant in light of the COVID-19 pandemic, which exposed weaknesses in current health data systems, especially regarding integration and automation [10]. A well-integrated, automated health data system will not only lead to improved patient outcomes and more patient-focused care but also enhance public health decision-making at both local and national levels [13].

Methods

Data Source

The primary data for this study were derived from the 2023 American Hospital Association (AHA) Annual Survey and its supplemental Health Information Technology Survey [14]. The AHA Annual Survey provides comprehensive information on a wide range of hospital characteristics including organizational structure, service lines, staffing, finances, and patient populations. The supplemental Health Information Technology Survey specifically captures detailed information about hospitals' health information technology capabilities, EHR implementation, and public health reporting practices.

Outcome Variables

The first set of outcome variables assessed the hospital's current stage of active engagement towards electronically submitting data for public health reporting across 6 categories: syndromic surveillance, immunization registry, electronic case reporting, public health registry, clinical data registry, and electronic reportable laboratory result reporting. For each category, respondents selected one of five ordinal response options representing implementation stages: (1) actively electronically submitting production data, (2) in the process of testing and validating electronic submission, (3) completed registration to submit data, (4) have not completed registration, or (5) do not know. This variable was operationalized as a dichotomous (yes or no) measure, with "yes" representing hospitals that reported actively electronically submitting production data and those that did not (yes or no). This dichotomization approach was used to create a clear distinction between hospitals actively engaged in electronic reporting versus those at earlier implementation stages or nonparticipants, consistent with prior AHA survey analyses examining health IT adoption [15].

The second set of outcome variables assessed the specific processes used to transmit health data, with respondents identifying whether their hospital utilized automated, manual, or mixed processes across 6 reporting categories. Response options included: (1) fully or primarily automated, (2) mix of automated and manual processes, (3) fully or primarily manual, or (4) do not know. For analysis purposes, the automated reporting variable was operationalized as a binary (yes or no) measure for each of the seven reporting categories, with "yes" representing hospitals using fully or primarily automated processes.

Confounding Variables

The analysis also included several hospital characteristics and market factors that may influence public health data reporting practices. Hospital ownership type was categorized as government (federal and nonfederal), not-for-profit (private hospitals with Internal Revenue Service 501(c)(3) tax-exempt status), or for-profit (investor-owned facilities operating as taxable business entities). Geographic location was classified as rural or nonrural (urban) based on the hospital's physical setting and Rural-Urban Commuting Area codes. Hospital size was operationalized using the total staffed bed count and stratified into 3 categories: small (fewer than 100 beds), medium (100 - 299 beds), and large (300 or more beds).

System affiliation was measured as a binary variable indicating whether the hospital was part of a larger health care system (system-affiliated) or operated independently. Teaching status was classified using the AHA criteria into nonteaching or teaching. Medicare percentage (proportion of total Medicare inpatient days) and Medicaid percentage (proportion of total Medicaid inpatient visits) were included to account for patient population characteristics that may influence hospitals' priorities and resource allocation for health IT investments. Market competition was measured using the Herfindahl-Hirschman Index (HHI), calculated based on the distribution of hospital beds within each health care market area. Higher HHI values indicate greater market concentration and less competition, with values approaching 1.0 representing highly concentrated markets [16]. This measure was included to control for the potential influence of competitive pressures on hospitals' public health reporting practices and technology adoption decisions. These variables were selected based on previous literature identifying them as potential determinants of health care technology adoption, organizational innovation, and public health reporting capabilities.

Statistical Analysis

This study used descriptive statistics and logistic regression analyses. For categorical variables, we computed frequencies and percentages. For continuous variables (Medicare percentage, Medicaid percentage, and HHI), we calculated means and SDs. We stratified these descriptive statistics by our two primary outcome measures: (1) whether hospitals were actively submitting data electronically and (2) whether hospitals used automated processes for data transmission.

For our primary analysis, we developed a series of multivariable logistic regression models to examine the adjusted associations between hospital characteristics and public health reporting practices. Separate models were constructed for each of the 6 reporting categories (syndromic surveillance, immunization registry, electronic case reporting, public health registry, clinical data registry, and electronic reportable laboratory result reporting) and for both outcome measures (active electronic submission and automated processes).

Results from the logistic regression models are presented as adjusted odds ratios (ORs). We conducted model diagnostics to ensure that all logistic regression assumptions were met. These included tests for multicollinearity using variance inflation factors, examination of influential observations using the Cook distance, and assessment of model fit using the Hosmer-Lemeshow goodness-of-fit test. All analyses were conducted using Stata (version 17.0; StataCorp), with statistical significance set at $P<.05$ for all tests. Cases with missing data on any study variables were excluded from the analysis using listwise deletion.

Ethical Considerations

In accordance with the policy of the university of North Florida, the Institutional Review Board for the Protection of Human Subjects categorized the research as exempt since the study analyzed secondary data that are publicly available.

Results

The results reveal patterns in electronic health data reporting practices between health care facilities based on their patient demographics, market concentration measures, and hospital characteristics.

Actively Submitting Data Electronically

Table 1 reports hospital categorical characteristics across hospitals that actively submit data electronically versus those that do not.

Table 2 reports hospital and market continuous characteristics across hospitals that actively submit data electronically versus those that do not (51.87%-54.14%), while actively submitting facilities demonstrate more consistent Medicare percentages (53.51%-54.13%). The SDs for Medicare percentages are generally higher in nonactive facilities (up to SD 20.15) compared to active facilities (up to SD 16.27). The HHI values for actively submitting facilities (ranging from 0.53 to 0.56, all with SD 0.36) are consistently lower than for nonactive facilities (ranging from 0.59 to 0.67, mostly with SD 0.37). Medicaid percentages are similar between active and nonactive facilities across all reporting categories, with active facilities showing slightly more consistent values (19.28%-20.02%) compared to nonactive facilities (18.6%-20.19%). SDs for Medicaid percentages are also generally higher in nonactive facilities.

Table . Hospital categorical characteristics across hospitals that actively submit data electronically versus those that do not.

Characteristics	Actively electronically submitting production data (yes or no), n (%)											
	Syndromic surveillance reporting		Immunization registry reporting		Electronic case reporting		Public health registry reporting		Clinical data registry reporting		Electronic reportable laboratory result reporting	
	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Ownership												
Government	59 (22.26)	236 (11.77)	36 (16.67)	261 (12.66)	184 (16.08)	111 (9.92)	148 (19.65)	135 (9.15)	170 (17.07)	121 (9.81)	74 (25.61)	219 (11.16)
For-profit	31 (11.7)	287 (14.31)	36 (16.67)	281 (13.63)	139 (12.15)	177 (15.82)	129 (17.13)	184 (12.47)	267 (26.81)	44 (3.57)	38 (13.15)	279 (14.21)
Not-for-profit	175 (66.04)	1482 (73.92)	144 (66.67)	1519 (73.7)	821 (71.77)	831 (74.26)	476 (63.21)	1157 (78.39)	559 (56.12)	1069 (86.63)	177 (61.25)	1465 (74.63)
Rural												
No	131 (49.43)	1295 (64.59)	104 (48.15)	1327 (64.39)	649 (56.73)	775 (69.26)	387 (51.39)	1010 (68.43)	574 (57.63)	828 (67.1)	134 (46.37)	1287 (65.56)
Yes	134 (50.57)	710 (35.41)	112 (51.85)	734 (35.61)	495 (43.27)	344 (30.74)	366 (48.61)	466 (31.57)	422 (42.37)	406 (32.9)	155 (53.63)	676 (34.44)
Size												
Small	167 (63.02)	887 (44.24)	135 (62.5)	923 (44.78)	585 (51.14)	463 (41.38)	437 (58.03)	600 (40.65)	517 (51.91)	512 (41.49)	190 (65.74)	850 (43.3)
Medium	81 (30.57)	819 (40.85)	66 (30.56)	836 (40.56)	425 (37.15)	475 (42.45)	245 (32.54)	637 (43.16)	373 (37.45)	514 (41.65)	78 (26.99)	818 (41.67)
Large	17 (6.42)	299 (14.91)	15 (6.94)	302 (14.65)	134 (11.71)	181 (16.18)	71 (9.43)	239 (16.19)	106 (10.64)	208 (16.86)	21 (7.27)	295 (15.03)
Part of a system												
No	99 (37.36)	377 (18.8)	61 (28.24)	418 (20.28)	303 (26.49)	171 (15.28)	231 (30.68)	238 (16.12)	283 (28.41)	184 (14.91)	115 (39.79)	355 (18.08)
Yes	166 (62.64)	1628 (81.2)	155 (71.76)	1643 (79.72)	841 (73.51)	948 (84.72)	522 (69.32)	1238 (83.88)	713 (71.59)	1050 (85.09)	174 (60.21)	1608 (81.92)
Teaching												
Not teaching	163 (61.51)	905 (45.14)	127 (58.8)	942 (45.71)	582 (50.87)	483 (43.16)	430 (57.1)	621 (42.07)	524 (52.61)	520 (42.14)	180 (62.28)	872 (44.42)
Minor	95 (35.85)	952 (47.48)	82 (37.96)	970 (47.06)	495 (43.27)	547 (48.88)	291 (38.65)	731 (49.53)	442 (44.38)	590 (47.81)	99 (34.26)	947 (48.24)
Major	7 (2.64)	148 (7.38)	7 (3.24)	149 (7.23)	67 (5.86)	89 (7.95)	32 (4.25)	124 (8.4)	30 (3.01)	124 (10.05)	10 (3.46)	144 (7.34)

Table . Hospital continuous characteristics across hospitals that actively submit data electronically versus those that do not.

Characteristics	Syndromic surveillance (n=2270), mean (SD)	Immunization registry (n=2277), mean (SD)	Electronic case (n=2263), mean (SD)	Public health registry (n=2229), mean (SD)	Clinical data registry (n=2230), mean (SD)	Electronic reportable laboratory results (n=2252), mean (SD)
Not actively electronically submitting production data						
Medicare Percentage	51.87 (20.15)	53.41 (18.56)	54.14 (17.19)	54 (17.99)	53.62 (16.69)	53.97 (18.98)
Medicaid Percentage	20.19 (15.14)	18.6 (12.84)	20.1 (14.23)	19.6 (14.89)	19.29 (14.01)	18.76 (14.66)
Herfindahl-Hirschman Index	0.62 (0.37)	0.62 (0.37)	0.61 (0.37)	0.64 (0.37)	0.59 (0.37)	0.67 (0.36)
Actively electronically submitting production data						
Medicare Percentage	54.13 (15.87)	53.89 (16.26)	53.51 (15.65)	53.9 (15.56)	54.02 (16.27)	53.88 (16.02)
Medicaid Percentage	19.59 (13.15)	19.77 (13.46)	19.28 (12.52)	19.57 (12.37)	20.02 (12.85)	19.84 (13.15)
Herfindahl-Hirschman Index	0.56 (0.36)	0.56 (0.36)	0.53 (0.36)	0.54 (0.36)	0.55 (0.36)	0.55 (0.36)
Total						
Medicare Percentage	53.86 (16.44)	53.85 (16.48)	53.83 (16.44)	53.94 (16.42)	53.84 (16.45)	53.89 (16.43)
Medicaid Percentage	19.66 (13.4)	19.66 (13.4)	19.69 (13.41)	19.58 (13.27)	19.69 (13.38)	19.7 (13.35)
Herfindahl-Hirschman Index	0.57 (0.36)	0.57 (0.36)	0.57 (0.36)	0.57 (0.36)	0.57 (0.36)	0.57 (0.36)

The statistical analysis using logistic regression models is shown in Table 3, which revealed several significant predictors of hospitals' engagement in electronic health data reporting across different reporting categories. For-profit hospitals show significantly lower odds of engaging in clinical data registry reporting compared to government hospitals (OR 0.15, 95% CI 0.09-0.22; *P*<.001), but higher odds for immunization registry reporting (OR 1.45, 95% CI 1.02-2.07; *P*<.05). Not-for-profit hospitals demonstrate significantly higher engagement in clinical data registry reporting (OR 1.89, 95% CI 1.43-2.50; *P*<.001), electronic case reporting (OR 1.76, 95% CI 1.25-2.48; *P*<.01), and public health registry reporting (OR 1.88, 95% CI 1.41-2.49; *P*<.001) compared to government-owned facilities.

Rural hospitals show significantly reduced likelihood of electronic reporting adoption across immunization registry (OR 0.77, 95% CI 0.61-0.97; *P*<.05), public health registry (OR 0.67, 95% CI 0.46-0.97; *P*<.05), and clinical data registry reporting (OR 0.77, 95% CI 0.60-0.98; *P*<.05) compared to urban counterparts. Hospital size emerges as a significant factor, with medium-sized hospitals showing higher engagement in electronic reportable laboratory results (OR 1.55, 95% CI 1.08-2.22; *P*<.05), public health registry (OR 1.51, 95% CI 1.02-2.25; *P*<.05), clinical data registry (OR 1.35, 95% CI 1.05-1.74; *P*<.05), and syndromic surveillance reporting (OR 1.52, 95% CI 1.06-2.19; *P*<.05) compared to small hospitals. Large hospitals demonstrate even stronger engagement in public health registry (OR 2.13, 95% CI 1.03-4.38; *P*<.05) and syndromic surveillance reporting (OR 2.29, 95% CI 1.17-4.46; *P*<.05).

System affiliation consistently emerges as one of the strongest predictors, with system-affiliated hospitals showing significantly higher odds of electronic reporting engagement across 5 of 6 categories: clinical data registry (OR 2.27, 95% CI 1.80-2.88; *P*<.001), immunization registry (OR 1.70, 95% CI 1.35-2.14; *P*<.001), electronic case reporting (OR 2.16, 95% CI 1.61-2.90; *P*<.001), public health registry (OR 1.78, 95% CI 1.42-2.25; *P*<.001), and electronic reportable laboratory results (OR 1.91, 95% CI 1.41-2.59; *P*<.001). Among teaching status variables, only major teaching hospitals show significantly higher odds for clinical data registry reporting (OR 2.66, 95% CI 1.56-4.52; *P*<.001). Medicare percentage shows a small but significant effect on syndromic surveillance reporting (OR 1.01, 95% CI 1.00-1.02; *P*<.05), while Medicaid percentage shows a minimal significant effect on immunization registry reporting (OR 0.99, 95% CI 0.98-1.00; *P*<.05). These small effect sizes for payer mix variables (ORs close to 1.0) suggest limited practical significance despite statistical significance, likely reflecting the large sample size rather than meaningful clinical impact.

Table . Logistic regression model of hospitals' engagement in electronic health data reporting across different reporting categories.

Characteristics	Clinical data registry reporting, OR[a] (95% CI)	Electronic case reporting, OR (95% CI)	Electronic reportable laboratory result, OR (95% CI)	Immunization registry reporting, OR (95% CI)	Public health registry reporting, OR (95% CI)	Syndromic surveillance reporting, OR (95% CI)
Ownership (reference: government)						
For-profit	0.15[b] (0.09-0.22)	1.45[c] (1.02-2.07)	1.38 (0.86-2.22)	0.77 (0.45-1.33)	0.95 (0.66-1.36)	1.45 (0.87-2.42)
Not-for-profit	1.89[b] (1.43-2.50)	1.31 (0.99-1.72)	1.76[d] (1.25-2.48)	1.11 (0.72-1.69)	1.88[b] (1.41-2.49)	1.42 (0.99-2.03)
Rural (reference: no)						
Yes	0.8 (0.62-1.02)	0.77[c] (0.61-0.97)	0.86 (0.62-1.19)	0.67[c] (0.46-0.97)	0.77[c] (0.60-0.98)	0.89 (0.63-1.25)
Size (reference: small)						
Medium	1.22 (0.95-1.58)	1.08 (0.85-1.37)	1.55[c] (1.08-2.22)	1.51[c] (1.02-2.25)	1.35[c] (1.05-1.74)	1.52[c] (1.06-2.19)
Large	1.12 (0.75-1.67)	1.19 (0.83-1.71)	1.85 (0.97-3.53)	2.13[c] (1.03-4.38)	1.43 (0.95-2.15)	2.29[c] (1.17-4.46)
Part of a system (reference: no)						
Yes	2.27[b] (1.80-2.88)	1.70[b] (1.35-2.14)	2.16[b] (1.61-2.90)	1.23 (0.87-1.75)	1.78[b] (1.42-2.25)	1.91[b] (1.41-2.59)
Teaching (reference: not teaching)						
Minor teaching	1.04 (0.82-1.30)	1.01 (0.82-1.25)	1.15 (0.84-1.58)	1.07 (0.76-1.52)	1.14 (0.91-1.43)	1.22 (0.88-1.68)
Major teaching	2.66[b] (1.56-4.52)	1.1 (0.71-1.70)	1.34 (0.58-3.11)	1.26 (0.49-3.28)	1.46 (0.86-2.46)	2.04 (0.81-5.16)
Medicare percentage	1.00 (1.00-1.01)	0.99[c] (0.98-1.00)	1.00 (0.99-1.01)	1.01 (1.00-1.02)	1.00 (0.99-1.01)	1.01[c] (1.00-1.02)
Medicaid percentage	1.00 (0.99-1.01)	0.99[d] (0.98-1.00)	1.00 (0.99-1.02)	1.01 (0.99-1.02)	0.99 (0.98-1.00)	1.00 (0.99-1.01)
Herfindahl-Hirschman Index	0.99 (0.72-1.36)	0.82 (0.61-1.10)	0.74 (0.48-1.14)	1.17 (0.73-1.88)	0.76 (0.56-1.04)	1.17 (0.76-1.81)

[a]OR: odds ratio.
[b]*P*<.001.
[c]*P*<.05.
[d]*P*<.01.

Automated Processes to Transmit Public Health Data

Table 4 reports hospital categorical characteristics across hospitals that have automated processes to transmit public health data (71.55% - 87.03% of "yes" responses), with particularly strong adoption for clinical data registry reporting (87.03%). Government hospitals show the lowest representation among automated reporting adopters (8.10% - 11.45%), while for-profit hospitals show moderate adoption that varies by reporting type, with notably higher representation in electronic case reporting (20.35%). The rural-urban divide is substantial, with nonrural hospitals constituting the clear majority of facilities using automated processes across all reporting categories (64.83% - 71.72%). The imbalance is most pronounced for clinical data registry reporting, where rural hospitals represent only 28.28% of automated adopters despite making up 40.86% of facilities not using automation for this purpose.

Hospital size shows a clear pattern where larger hospitals are disproportionately represented among automated process adopters. Medium and large hospitals together represent 55% to 60% of facilities using automation across reporting categories, despite making up only 40% to 47% of nonautomated facilities. Small hospitals, while still numerous among automation adopters (38.6% - 43.77%), are significantly under-represented compared to their share among nonautomated facilities (49.18% - 67.37%). System affiliation emerges as one of the strongest predictors, with system-affiliated hospitals representing 81.22% to 86% of facilities using automated processes across reporting categories. This contrasts sharply with their 62.84% to 76.13% representation among nonautomated facilities. Finally, teaching status also shows consistent patterns, with minor teaching and major teaching hospitals combined representing 51.25% to 60.54% of automated adopters across reporting categories, compared to 38.49% to 48.17% of nonautomated facilities. Major teaching hospitals, despite their small numbers overall, show consistently higher representation among automated facilities (6.63% - 10.5%) compared to nonautomated ones (3.63% - 10.5%).

Table . Hospital categorical characteristics across hospitals that have automated processes to transmit public health data versus those that do not.

Characteristics	Automated processes to transmit the data (yes or no), n (%)											
	Syndromic surveillance reporting		Immunization registry reporting		Electronic case reporting		Public health registry reporting		Clinical data registry reporting		Electronic reportable laboratory result reporting	
	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Ownership												
Government	85 (20.38)	207 (11.27)	75 (22.66)	217 (11.45)	197 (18.11)	88 (8.1)	199 (18.27)	83 (8.41)	221 (15.84)	60 (8.75)	120 (23.35)	167 (10.07)
For-profit	36 (8.63)	281 (15.3)	51 (15.41)	245 (12.93)	72 (6.62)	221 (20.35)	69 (6.34)	158 (16.01)	198 (14.19)	29 (4.23)	54 (10.51)	197 (11.87)
Not-for-profit	296 (70.98)	1349 (73.43)	205 (61.93)	1433 (75.62)	819 (75.28)	777 (71.55)	821 (75.39)	746 (75.58)	976 (69.96)	597 (87.03)	340 (66.15)	1295 (78.06)
Rural												
No	228 (54.68)	1191 (64.83)	152 (45.92)	1237 (65.28)	611 (56.16)	752 (69.24)	627 (57.58)	686 (69.5)	825 (59.14)	492 (71.72)	265 (51.56)	1119 (67.45)
Yes	189 (45.32)	646 (35.17)	179 (54.08)	658 (34.72)	477 (43.84)	334 (30.76)	462 (42.42)	301 (30.5)	570 (40.86)	194 (28.28)	249 (48.44)	540 (32.55)
Size												
Small	240 (57.55)	804 (43.77)	223 (67.37)	819 (43.22)	582 (53.49)	429 (39.5)	579 (53.17)	381 (38.6)	686 (49.18)	275 (40.09)	302 (58.75)	700 (42.19)
Medium	133 (31.89)	765 (41.64)	83 (25.08)	788 (41.58)	355 (32.63)	500 (46.04)	363 (33.33)	447 (45.29)	515 (36.92)	300 (43.73)	153 (29.77)	706 (42.56)
Large	44 (10.55)	268 (14.59)	25 (7.55)	288 (15.2)	151 (13.88)	157 (14.46)	147 (13.5)	159 (16.11)	194 (13.91)	111 (16.18)	59 (11.48)	253 (15.25)
Part of a system												
No	125 (29.98)	345 (18.78)	123 (37.16)	351 (18.52)	301 (27.67)	152 (14)	299 (27.46)	154 (15.6)	333 (23.87)	117 (17.06)	171 (33.27)	295 (17.78)
Yes	292 (70.02)	1492 (81.22)	208 (62.84)	1544 (81.48)	787 (72.33)	934 (86)	790 (72.54)	833 (84.4)	1062 (76.13)	569 (82.94)	343 (66.73)	1364 (82.22)
Teaching												
Not teaching	237 (56.83)	822 (44.75)	211 (63.75)	834 (44.01)	564 (51.84)	454 (41.8)	562 (51.61)	401 (40.63)	690 (49.46)	277 (40.38)	295 (57.39)	720 (43.4)
Minor	155 (37.17)	885 (48.18)	108 (32.63)	918 (48.44)	444 (40.81)	560 (51.57)	450 (41.32)	511 (51.77)	626 (44.87)	337 (49.13)	184 (35.8)	821 (49.49)
Major	25 (6)	130 (7.08)	12 (3.63)	143 (7.55)	80 (7.35)	72 (6.63)	77 (7.07)	75 (7.6)	79 (5.66)	72 (10.5)	35 (6.81)	118 (7.11)

Table 5 reports hospital and market continuous characteristics across hospitals that have automated processes to transmit public health data versus those that do not.

The logistic regression analysis examined factors associated with hospitals' use of automated processes (EHR-generated data sent electronically or automatically) to transmit data to public health agencies across 6 reporting categories (Table 6). Hospital ownership was shown to significantly impact automated reporting practices. For-profit hospitals are 85% less likely than government hospitals to use automated processes for clinical data registry reporting (OR 0.15, 95% CI 0.09-0.22; *P*<.001), but 45% more likely to automate immunization registry reporting (OR 1.45, 95% CI 1.02-2.07; *P*<.05). Not-for-profit hospitals show significantly higher automation adoption in clinical data registry reporting (OR 1.89, 95% CI 1.43-2.50; *P*<.001), electronic case reporting (OR 1.76, 95% CI 1.25-2.48; *P*<.01), and public health registry reporting (OR 1.88, 95% CI 1.41-2.49; *P*<.001) compared to government facilities.

Rural status negatively impacts automation adoption, with rural hospitals showing significantly lower odds of automated data transmission for immunization registries (OR 0.77, 95% CI0.61-0.97; *P*<.05), public health registries (OR 0.67, 95% CI 0.46-0.97; *P*<.05), and clinical data registries (OR 0.77, 95% CI 0.60-0.98; *P*<.05). Hospital size matters, with medium-sized hospitals showing higher odds of automation across electronic reportable laboratory results (OR 1.55, 95% CI 1.08-2.22;

P<.05), immunization registries (OR 1.51, 95% CI 1.02-2.25; *P*<.05), public health registries (OR 1.35, 95% CI 1.05-1.74; *P*<.05), and syndromic surveillance (OR 1.52, 95% CI 1.06-2.19; *P*<.05) compared to small hospitals. Large hospitals show even stronger automation adoption in immunization registries (OR 2.13, 95% CI 1.03-4.38; *P*<.05) and syndromic surveillance (OR 2.29, 95% CI 1.17-4.46; *P*<.05).

System affiliation emerges as the most consistent predictor of automation adoption, with system-affiliated hospitals showing significantly higher odds of automated reporting across 5 categories: clinical data registry (OR 2.27, 95% CI 1.80-2.88; *P*<.001), immunization registry (OR 1.70, 95% CI 1.35-2.14; *P*<.001), electronic case reporting (OR 2.16, 95% CI 1.61-2.90; *P*<.001), public health registry (OR 1.78, 95% CI 1.42-2.25; *P*<.001), and electronic reportable laboratory results (OR 1.91, 95% CI 1.41-2.59; *P*<.001). Major teaching status significantly increases automation adoption for clinical data registry reporting (OR 2.66, 95% CI 1.56-4.52; *P*<.001), while Medicare and Medicaid percentages show minimal but significant effects on syndromic surveillance and immunization registry reporting, respectively. Market concentration (HHI) shows no significant association with automation adoption across all reporting categories.

Table . Hospital continuous characteristics across hospitals that have automated processes to transmit public health data versus those that do not.

Characteristics	Syndromic surveillance (n=2254), mean (SD)	Immunization registry (n=2226), mean (SD)	Electronic case (n=2174), mean (SD)	Public health registry (n=2076), mean (SD)	Clinical data registry (n=2081), mean (SD)	Electronic reportable laboratory results (n=2173), mean (SD)
No automated processes to transmit the data						
Medicare Percentage	52.69 (19.31)	54.51 (19.31)	53.79 (18.02)	53.77 (17.71)	53.41 (17.26)	53.95 (19.03)
Medicaid Percentage	20.29 (15.27)	18.24 (14.59)	19.69 (14.45)	19.56 (14.42)	19.87 (13.98)	19.1 (14.57)
Herfindahl-Hirschman Index	0.6 (0.36)	0.64 (0.35)	0.59 (0.36)	0.59 (0.36)	0.59 (0.36)	0.61 (0.36)
Automated processes to transmit the data						
Medicare Percentage	54.23 (15.69)	53.83 (16.04)	54.04 (14.89)	53.68 (15.24)	54.57 (15.28)	53.75 (15.69)
Medicaid Percentage	19.43 (12.85)	19.8 (13.15)	19.33 (12.1)	19.65 (12.04)	19.13 (12.08)	19.83 (12.96)
Herfindahl-Hirschman Index	0.56 (0.36)	0.56 (0.36)	0.56 (0.36)	0.53 (0.36)	0.52 (0.36)	0.55 (0.36)
Total						
Medicare Percentage	53.95 (16.43)	53.93 (16.56)	53.92 (16.52)	53.73 (16.58)	53.79 (16.64)	53.8 (16.54)
Medicaid Percentage	19.59 (13.33)	19.57 (13.39)	19.51 (13.33)	19.6 (13.34)	19.63 (13.39)	19.66 (13.36)
Herfindahl-Hirschman Index	0.57 (0.36)	0.58 (0.36)	0.57 (0.36)	0.56 (0.36)	0.57 (0.36)	0.56 (0.36)

Table . Logistic regression analysis of factors associated with hospitals' use of automated processes (electronic health record [EHR]-generated data sent electronically or automatically) to transmit data to public health agencies across 6 reporting categories.

Characteristics	Clinical data registry reporting, OR[a] (95% CI)	Electronic case reporting, OR (95% CI)	Electronic reportable laboratory result, OR (95% CI)	Immunization registry reporting, OR (95% CI)	Public health registry reporting, OR (95% CI)	Syndromic surveillance reporting, OR (95% CI)
Ownership (reference: government)						
For-profit	0.15[b] (0.09-0.22)	1.45[c] (1.02-2.07)	1.38 (0.86-2.22)	0.77 (0.45-1.33)	0.95 (0.66-1.36)	1.45 (0.87-2.42)
Not-for-profit	1.89[b] (1.43-2.50)	1.31 (0.99-1.72)	1.76[d] (1.25-2.48)	1.11 (0.72-1.69)	1.88[b] (1.41-2.49)	1.42 (0.99-2.03)
Rural (reference: no)						
Yes	0.8 (0.62-1.02)	0.77[c] (0.61-0.97)	0.86 (0.62-1.19)	0.67[c] (0.46-0.97)	0.77[c] (0.60-0.98)	0.89 (0.63-1.25)
Size (reference: small)						
Medium	1.22 (0.95-1.58)	1.08 (0.85-1.37)	1.55[c] (1.08-2.22)	1.51[c] (1.02-2.25)	1.35[c] (1.05-1.74)	1.52[c] (1.06-2.19)
Large	1.12 (0.75-1.67)	1.19 (0.83-1.71)	1.85 (0.97-3.53)	2.13[c] (1.03-4.38)	1.43 (0.95-2.15)	2.29[c] (1.17-4.46)
Part of a system (reference: no)						
Yes	2.27[b] (1.80-2.88)	1.70[b] (1.35-2.14)	2.16[b] (1.61-2.90)	1.23 (0.87-1.75)	1.78[b] (1.42-2.25)	1.91[b] (1.41-2.59)
Teaching (reference: not teaching)						
Minor teaching	1.04 (0.82-1.30)	1.01 (0.82-1.25)	1.15 (0.84-1.58)	1.07 (0.76-1.52)	1.14 (0.91-1.43)	1.22 (0.88-1.68)
Major teaching	2.66[b] (1.56-4.52)	1.1 (0.71-1.70)	1.34 (0.58-3.11)	1.26 (0.49-3.28)	1.46 (0.86-2.46)	2.04 (0.81-5.16)
Medicare Percentage	1.00 (1.00-1.01)	0.99[c] (0.98-1.00)	1.00 (0.99-1.01)	1.01 (1.00-1.02)	1.00 (0.99-1.01)	1.01[c] (1.00-1.02)
Medicaid Percentage	1.00 (0.99-1.01)	0.99[d] (0.98-1.00)	1.00 (0.99-1.02)	1.01 (0.99-1.02)	0.99 (0.98-1.00)	1.00 (0.99-1.01)
Herfindahl-Hirschman Index	0.99 (0.72-1.36)	0.82 (0.61-1.10)	0.74 (0.48-1.14)	1.17 (0.73-1.88)	0.76 (0.56-1.04)	1.17 (0.76-1.81)

[a]OR: odds ratio.
[b]*P*<.001.
[c]*P*<.05.
[d]*P*<.01.

Discussion

Principal Findings

This study identifies some of the main differences in automation and integrating public health information between US hospitals driven by structural resource inequalities, institutional practice, and location. Rural, independent, and smaller hospitals lag far behind urban, system-affiliated, and larger hospitals when it comes to adopting automated reporting systems. Despite national-level attempts to standardize health IT infrastructure, these gaps underscore systemic obstacles based on financial interests, organizational capacities, and market forces.

Rural hospitals continue to face significant challenges in adopting electronic public health reporting despite national progress in health IT adoption [15]. Limited financial resources and constrained operational capacity hinder their ability to invest in the infrastructure required for automation. These facilities often serve smaller patient populations and receive lower reimbursement rates, which makes it difficult to justify the high upfront costs of implementing advanced reporting systems. Additionally, rural hospitals typically lack access to IT specialists and foundational systems that support seamless electronic data exchange, resulting in a greater reliance on manual or mixed reporting methods. These barriers not only restrict their compliance with public health reporting requirements but also widen the digital divide between rural and urban health care providers. Addressing these disparities requires targeted policy support and financial investment to ensure rural hospitals can fully participate in the public health data ecosystem.

The nonrural versus rural divide is stark in the results as both the rates of actively submitting data electronically and the adoption of automated processes to transmit that public health data show low rates of submission and adoption by rural hospitals in all reporting categories. There are many possible reasons for this difference largely relating to the differing economic environments of these hospitals. Rural hospitals often face greater financial strain due to the poorer socioeconomic conditions of their locals and thus do not have the financial capital to invest in high-tech systems. As Younis [17] shared that rural hospitals generate less revenue than urban hospitals and are significantly disadvantaged in terms of performance.

Another avenue to look at is the role of competition from other hospitals that nonrural hospitals face. As discussed in Garcia-Lacalle and Martin [18], hospitals in a market-driven environment have a keen sense of where they sit in comparison to their competition and therefore consider new strategies to better focus on patients and users. Once one hospital in a competitive environment adopts an electronic data submission system or automates their pre-existing one, it encourages other hospitals in that same environment to also adopt. Similarly, Ghiasi et al [19] found, in their literature review, that hospitals in a competitive market seek to differentiate themselves from competitors through specific services. Some of these differentiating services could be electronic data submission systems.

In our study, larger hospitals benefit from centralized IT infrastructure and specialized personnel, enabling consistent compliance with evolving standards. Medium and large hospitals show 1.5 to 2.3 times higher odds of automation across categories like syndromic surveillance and laboratory reporting. These institutions absorb upfront costs more effectively and maintain robust EHR systems, whereas smaller facilities struggle with limited staffing and budgetary flexibility. Particularly larger hospitals within multihospital systems demonstrate higher engagement in both active electronic data submission and automated reporting due to greater resource availability. These hospitals benefit from economies of scale that support investment in centralized IT infrastructures and EHR systems. In addition, system-affiliated hospitals are also more likely to have internal health IT teams and established workflows for public health communication because it reduces barriers to implementation.

Not-for-profit hospitals lead in adoption due to mission-driven commitments to population health and access to grant funding. Their focus on community benefit aligns with public health reporting goals, whereas for-profit hospitals prioritize revenue-generating technologies (eg, billing systems). Government hospitals, with the limitations of bureaucratic procurement systems, fall behind despite regulatory encouragement. The trends are indicative of findings by Tsai et al [20] that financial restrictions and fragmented workflows are the main barriers against EHR adoption in low-resource settings.

In our study, facilities not actively submitting data electronically exhibit more variable Medicare percentages (51.87% - 54.14%), suggesting that markets with less competition (higher HHI values) reduce pressure to adopt reporting technologies. Lower digital literacy among older Medicare populations may also deprioritize automation in regions serving these demographics. Conversely, hospitals in competitive, high-volume markets align IT investments with performance metrics to meet patient and regulatory expectations.

Policy Implications

A 2024 analysis by the Kaiser Family Foundation found that nearly half of US metropolitan areas are dominated by just one or two hospital systems, significantly reducing competition and, consequently, the urgency for these institutions to adopt advanced data reporting practices [21]. This aligns with findings from the BMC Health Services Research, which revealed that providers in rural or less competitive regions demonstrate lower EHR adoption and interoperability [22]. Moreover, patient population characteristics, particularly among older adults on Medicare, further influence reporting engagement. A systematic review in the Archives of Public Health emphasized the digital health literacy gap in this group, suggesting that facilities serving older or underserved populations may deprioritize electronic data initiatives due to lower patient engagement with digital platforms [23]. These studies underscore the multifactorial barriers to robust public health data reporting, suggesting the need for targeted policy incentives and infrastructure support to promote broader and more equitable adoption.

Limitations

This study's limitation lies in its reliance on secondary data from the 2023 AHA Annual Survey. Hospital characteristics are based on self-reported data which may affect accuracy. Our cross-sectional design limits causal inference. This analysis focused on US hospitals only, affecting generalizability to other types of health organizations and countries. Finally, the rural or urban classification using Rural-Urban Commuting Area codes may not fully capture rural-urban distinctions. Residual confounding may exist due to unmeasured variables such as IT staffing levels or leadership engagement.

Conclusions

The clear difference between nonrural and rural hospitals in terms of electronic data submission and automation adoption shows significant gaps caused by economic and competitive factors. Nonrural hospitals, benefiting from higher revenue and competitive pressures, are more likely to invest in advanced IT systems and automated processes. On the other hand, rural hospitals face financial constraints and lower patient volumes, limiting their ability to adopt such technologies. This divide is further worsened by the centralized resource allocation and organized workflows in system-aligned hospitals, which improve their reporting capabilities. Not-for-profit hospitals also lead in electronic health data adoption due to their mission-driven priorities and access to grant funding. Research highlights the many barriers to strong public health data reporting, shaped by market dynamics and patient demographics. Effective strategies for improving electronic data submission may include tailored incentives, strategic partnerships, and population-specific approaches. Addressing these gaps is crucial for ensuring fair access to advanced health care technologies and improving overall public health reporting. Targeted policy interventions and financial support are essential to help rural hospitals overcome structural barriers and participate more fully in the nation's public health data system.

Data Availability

Data used in this study are available from the American Hospital Association and are available for purchase through a data usage agreement.

Authors' Contributions

HH conceived and designed the study, including the research questions, methodology, and analytical approach; supervised all aspects of the research and data analysis; interpreted the results and developed the initial findings; provided critical revision of the manuscript for intellectual content; ensured all aspects of the research were accurately reflected; and took final responsibility for submission.

AA contributed to study design and analytical approach; wrote sections of the manuscript; and participated in revision and editing of the final version.

CSL assisted in developing the study design and analytical framework; participated in data analysis and interpretation; wrote sections of the manuscript; and contributed to manuscript revision for accuracy and clarity.

DB participated in data management and preparation; assisted with statistical analysis; wrote sections of the manuscript; and provided critical feedback on analytical approaches.

CSL assisted in developing the study design and analytical framework; participated in data analysis and interpretation; wrote sections of the manuscript; and contributed to manuscript revision for accuracy and clarity.

JYJ participated in data analysis and visualization; assisted with results interpretation; contributed to manuscript drafting; and provided critical feedback during revision.

Conflicts of Interest

None declared.

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Abbreviations

AHA: American Hospital Association
AI: artificial intelligence
EHR: electronic health record
HHI: Herfindahl-Hirschman Index
OR: odds ratio

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Fairness Correction in COVID-19 Predictive Models Using Demographic Optimization: Algorithm Development and Validation Study

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Abstract

Background: COVID-19 forecasting models have been used to inform decision-making around resource allocation and intervention decisions, such as hospital beds or stay-at-home orders. State-of-the-art forecasting models often use multimodal data, including mobility or sociodemographic data, to enhance COVID-19 case prediction models. Nevertheless, related work has revealed under-reporting bias in COVID-19 cases as well as sampling bias in mobility data for certain minority racial and ethnic groups, which affects the fairness of COVID-19 predictions across racial and ethnic groups.

Objective: This study aims to introduce a fairness correction method that works for forecasting COVID-19 cases at an aggregate geographic level.

Methods: We use hard and soft error parity analyses on existing fairness frameworks and demonstrate that our proposed method, Demographic Optimization (DemOpts), performs better in both scenarios.

Results: We first demonstrate that state-of-the-art COVID-19 deep learning models produce mean prediction errors that are significantly different across racial and ethnic groups at larger geographic scales. We then propose a novel debiasing method, DemOpts, to increase the fairness of deep learning–based forecasting models trained on potentially biased datasets. Our results show that DemOpts can achieve better error parity than other state-of-the-art debiasing approaches, thus effectively reducing the differences in the mean error distributions across racial and ethnic groups.

Conclusions: We introduce DemOpts, which reduces error parity differences compared with other approaches and generates fairer forecasting models compared with other approaches in the literature.

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KEYWORDS

COVID-19 forecasting; deep learning model; fairness; time series model; regression

Introduction

Background

Forecasting the number of COVID-19 cases, hospitalizations, or deaths is crucial to inform decision-making. For example, COVID-19 forecasts can be used by hospitals to evaluate medical needs and required resources, such as supplies or beds, or by public health officials to inform closure policies at various geographical scales. In the United States, COVID-19 forecasts have been used at the state and county levels to inform social distancing or masking, such as the publicly available forecasts on the COVID-19 Forecast Hub that the Centers for Disease Control and Prevention (CDC) has routinely used in their communications [1,2].

Related work over the past 4 years has shown a diverse variety of COVID-19 forecasting approaches [3-10, 11] using datasets such as the New York Times (NYT), Johns Hopkins University, COVID-19 Community Vulnerability Index, Google, and Apple [12-16], among others. Most publications focused on COVID-19 case prediction have reported results around the accuracy of the models, that is, minimizing the difference between the predicted cases and the actual number of cases reported. Nevertheless, previous work has shown that the accuracy of COVID-19 predictions can depend on various social determinants, including race or ethnicity [17], income, or age [18], revealing worse performance for protected attributes and pointing to a lack of COVID-19 predictive fairness that can affect resource allocation and decision-making. This lack of predictive fairness might be related to bias in the datasets used to train the model, that is, bias in COVID-19 case reporting [19] or bias in mobility data [20].

Given the presence of bias in the training datasets frequently used by COVID-19 forecast models, and previous work demonstrating that COVID-19 prediction accuracy can vary across social determinants, it becomes critical to devise methods to prevent data biases from percolating into the COVID-19 forecasts to guarantee fair decision-making based on case predictions. In this paper, we focus on in-processing bias mitigation approaches given their scarcity in the COVID-19 literature and propose Demographic Optimization (DemOpts), a debiasing method designed to achieve COVID-19 case prediction error parity across racial and ethnic groups in the context of deep learning models, that is, guarantee that county prediction errors are not significantly different across racial and ethnic groups. Although there exists a diverse set of COVID-19 predictive approaches, we focus on deep learning models because these are the most frequently used models in the machine learning community [21], and narrow down our choice to transformer-based architectures because they are state-of-the-art in time series predictions [22].

The main objective of DemOpts is to improve the fairness of the COVID-19 case predictions at the county level by achieving error parity in a regression setting [17]. DemOpts proposes a novel debiasing approach that leverages county racial and ethnic data during training to modify conventional deep learning loss functions to penalize the model for statistically significant associations between the predictive error and the race or ethnicity distribution of a county. Our main contributions are:

- We present DemOpts, a novel debiasing method for deep learning architectures that attempts to increase the fairness of the COVID-19 county case predictions by achieving error parity, that is, guaranteeing that prediction errors are similar across racial and ethnic groups. The DemOpts architecture is designed to optimize error parity across race and ethnicity using a novel multilabel approach that allows each county to be characterized by its own racial and ethnic group distribution during the debiasing process, instead of by a unique label.
- We propose a novel evaluation protocol for the COVID-19 context, and we show that (1) state-of-the-art COVID-19 county case prediction models based on transformer architectures with no debiasing approach lack error parity, that is, prediction errors are statistically significantly different across racial and ethnic groups, (2) DemOpts applied to transformer-based architectures improves the error parity of the prediction models, increasing the similarity between mean prediction errors across racial and ethnic groups, and (3) the DemOpts debiasing approach performs better than state-of-the-art debiasing methods for regression settings.

While COVID-19 research was particularly prominent from 2020 to early 2024, challenges related to data biases and sampling issues in predictive modeling remain highly relevant. Our approach, leveraging the regression fairness model DemOpts, provides a robust framework to address these challenges. As future pandemics and public health crises arise, similar issues will persist, making our contribution valuable for ensuring fairness and reliability in predictive models.

Literature Review

Deep LearningBased Forecasting Models

Deep learning models have started to become popular in time series prediction tasks. The available methods include (1) autoregressive models, such as Long Short-Term Memory or Gated Recurrent Network [23]; (2) graph-based neural networks, such as graph attention networks [24], Spatio-temporal Graph Convolutional Network [25], neighbor convolution model [26], or graph convolutional network; and (3) transformers, including Logarithmic Sparse Transformer [27], Informer [28], Autoformer [29], Frequency Enhanced Decomposed Transformer [30], Pyramidal Attention–based Transformer [31], and Patch Time Series Transformer [32]. In this paper, we specifically focus on the temporal fusion transformer (TFT) architecture [22], since it allows us to easily incorporate exogenous variables (eg, mobility data) as well as static variables (eg, demographic data) on top of the COVID-19 time series.

Bias in Mobility and COVID-19 Data

The COVID-19 epidemic was closely monitored and had extensive data available about the counts of cases, hospitalizations, and deaths, as well as fine-grained information about mobility of people, policy implementations, vaccinations, and so on. Reducing the impact of mobility data or COVID-19 case bias in COVID-19 case predictions, as we do in this paper, is of critical importance to support decision-making processes focused on resource allocation during pandemics, to reduce harm and guarantee that decisions are fair and just across racial and ethnic groups. Human mobility data has been used to characterize human behaviors in the built environment [33-37], for public safety [38,39], during epidemics and disasters [40-45], as well as to support decision-making for socioeconomic development [46-53]. During the COVID-19 pandemic, human mobility has played a central role in driving decision-making, acknowledging the impact of human movement on virus propagation [7,9,10,18,54]. Previous work has revealed sampling bias in mobility data collected via mobile apps, with Black and older individuals being underrepresented in the datasets [20], and has exposed biases in COVID-19 forecasting models [55,56]. COVID-19 underreporting bias has been discussed in the literature [57-59] and points to multiple causes, including inadequate testing across certain minority groups or a lack of consistency in reporting race and ethnicity for COVID-19 cases [19].

Fairness Metrics and Fairness Corrections

Transformer-based COVID-19 case forecast models require the use of fairness metrics for regression settings, given that the loss optimization process in gradient-based deep learning architectures uses real-number predictions instead of classes.

Agarwal et al [60], Fitzsimons et al [61], and Gursoy and Kakadiaris [17] outline the different aspects of fairness in regression settings and propose a set of fairness metrics for regression-type models. For this paper, we use the error parity metric proposed in [17]. Error parity requires error distributions to be statistically independent of racial and ethnic groups. We expand this definition and relax the statistical significance requirement to be able to also evaluate whether the proposed DemOpts method can at least reduce the differences in error distributions across racial and ethnic groups, even when they are still statistically significantly different. To correct for bias and unfair performance in deep learning models, researchers have used preprocessing [62,63] and in-processing correction approaches [64-67]. Preprocessing approaches focus on creating a better input for learning deep neural network models by removing bias from the datasets [62,63], and there have been successful efforts focused on debiasing underreporting COVID-19 datasets to estimate actual cases or deaths before they are fed into predictive models [68,69]. On the other hand, in-processing approaches to improve the fairness of deep learning models, like the one we use in this paper, focus on the model and its regularization, usually adding a bias correction term in the loss function [65,67]. In this paper, we will compare our proposed debiasing approach against 3 state-of-the-art methods for debiasing in regression settings, which are individual fairness correction [70], group fairness correction [70] (both Lagrangian-based), and sufficiency [71]. Individual and group fairness calculate penalties by determining overestimations across different groups and weighting the loss by a factor proportional to the overestimations, while sufficiency-based regularizers propose to make the loss independent of sensitive data attributes by simultaneously training a joint model and subgroup-specific networks to achieve fair predictions [71].

Methods

Proposed DemOpts

Our modeling focus is on deep learning models, which are the most frequently used approach for COVID-19 county case forecasts in the machine learning community [21]. We specifically focus on the TFT model introduced in [22] for several reasons. First, this model is state-of-the-art in interpretable time series prediction [22]. Second, this model allows for the use of static reals as input to the model (ie, attributes that do not change over the duration of the training process, such as demographic percentages or population statistics). Third, the model works well with time-dependent features, including COVID-19 cases or mobility data, whereby past data influences future statistics.

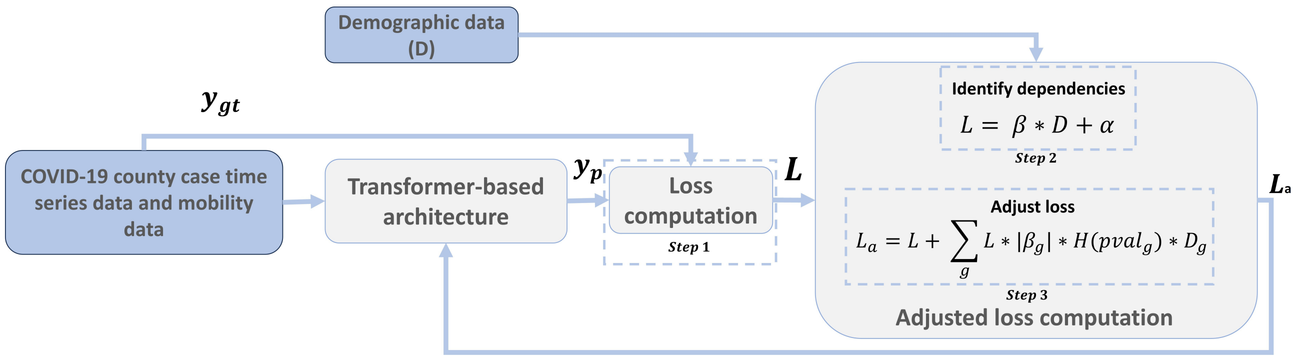
DemOpts is an in-processing algorithm that modifies the standard training procedure for deep learning models at the loss computation stage. The algorithm modifies conventional loss functions to penalize the model for any statistically significant association (P<.005) between the county prediction loss (error) and the county's racial and ethnic groups. In other words, DemOpts performs a race-based correction on the error to account for county demographic, racial, and ethnic distributions.

The algorithm can be divided into 3 steps (refer to Figure 1, Figure 2, and "S.1 DemOpts Method" in Multimedia Appendix 1 for mathematical details).

Figure 1. Algorithm: Demographic Optimization (DemOpts). TFT: Temporal Fusion Transformer.

```
Input: Training set (X, D, Y), Learning rate (lr), Number of epochs, threshold
Output: Trained model (M)
X: COVID-19 Timeseries data for all counties
Y: COVID-19 cases in future for all counties
D: Demographic data for all counties
Initialize model parameters randomly
for epoch in range(0, epochs) do
    // sample from X, D, Y of size b
    for (X_b, D_b, Y_bt) in (X, D, Y) do
        // Forward propagation
        Y_bp = M(X_b)
        //Calculate QuantileLoss
        L_i = QuantileLoss(Y_bp, Y_bt)
        //Find association
        olsreg = OLS.fit(D_b, L_b)
        pvals, β = olsreg.pvals, olsreg.coef
        // additional penalty on loss
        for index in |pvals| do
            pval_i, β_i = pvals[index], β[index]
            // Get the corresponding demographic percentage column and all rows
            D_b,idx = D_b[:, index]
            if pval_i < threshold then                //this ensures significant association
              L_b += L_b * |β_i| * D_b,idx
            end if
        end for
      backpropagate(M, L_b)
    end for
end for
return TFT
```

Figure 2. Flow diagram for the Demographic Optimization (DemOpts) method.



Step 1: Calculate Loss

We use quantile predictions, as standard in COVID-19 forecasting literature [2,72], instead of point-value predictions. Quantile predictions are measured for 7 quantiles (0.02, 0.1, 0.25, 0.5, 0.75, 0.9, and 0.98) to gain insights into the uncertainty ranges and CIs of the COVID-19 county case predictive models. When using quantile predictions, the error is computed using quantile loss, also known as pinball loss (PBL), and defined as follows:

$$PBL_q(y_{ip}, y_i) = \begin{cases} q*(y_i - y_{ip}) & \text{if } y_i \geq y_{ip} \\ (q-1)*(y_i - y_{ip}) & \text{if } y_i < y_{ip} \end{cases}$$

For quantile q, the PBL for the prediction of a given input X_i is $PBL_q(y_{ip}, y_i)$, where y_i is the ground truth, and y_{ip} is the predicted value. The average over all quantiles can be represented as $PBL(y_{ip}, y_i) = \frac{1}{q}\sum_q PBL_q(y_{ip}, y_i)$.

Step 2: Identify Dependencies Between Prediction Errors, Race, and Ethnicity

To achieve error parity, that is, mean errors being independent of racial and ethnic population distributions, we determine the relationship between errors and race and ethnic distributions. For that purpose, DemOpts fits a regression model between the prediction losses PBL (y_{ip},y_i) across data points *i* and their corresponding county race and ethnicity distribution for each race D_i:

$$PBL(yip,yi)= \beta*Di + \alpha \text{ with } Di = [d1,d2,d3,d4, lookahead]$$

where d_i are the corresponding county demographic features extracted from the US census data (represented as the percentage of each racial and ethnic group of the county for datapoint i), and lookahead refers to the number of days into the future the COVID-19 case prediction was generated for. In matrix representation:

$$PBLYip,Yi=\beta*D+\alpha$$

Once the regression model is fit, both regression coefficients (β) and their statistical significance (*P* value) are passed on to Step 3 to modify the adjusted loss and attempt to decouple race from the errors (loss).

Step 3: Adjust the Loss

DemOpts modifies the conventional loss of deep learning models by adjusting for racial or ethnic bias in the error, that is, the loss is increased whenever a statistically significant regression coefficient for a race or ethnicity is found in Step 2 (with *P* value threshold=.005). By increasing the loss, DemOpts attempts to reduce the association between errors and race. Specifically, the loss is adjusted by the product of the original loss PBL (y_{ip},y_i), the percentage race or ethnicity D_j that holds a significant relationship with the error, and its coefficient β_j in absolute value:

$$Ladj=PBL(yip,yi)+\sum jH(pvalj)(|\beta j|*Dj*L) \text{ where}$$

$$H(x)=\{1 \quad \text{if } x<0.0050 \quad \text{if } x\geq 0.005$$

Evaluation Protocol

In this section, we present a novel evaluation protocol to assess changes in fairness for TFT forecasting models when debiasing approaches, including DemOpts, are applied. We first describe the TFT COVID-19 county case prediction model we use, and the different debiasing approaches we evaluate on that prediction model. Next, we describe the error parity metrics we use to evaluate the fairness of each prediction model, and finally, we present the approach to analyze whether DemOpts improves the error parity metrics when compared to other state-of-the-art debiasing approaches for regression settings.

Predictive Model and Debiasing Approaches

We use the TFT with the conventional PBL function (PBL is the standard metric for reporting model performance in CDC Forecast Hub [2]) as our baseline model ($TFT_{Baseline}$) to predict the number of COVID-19 county cases for a given day.

Input data to the TFT model includes past COVID-19 cases per county, mobility data from SafeGraph, and race and ethnicity data for the county. We also train and test another TFT enhanced with the DemOpts debiasing method, $TFT_{DemOpts}$, that adjusts the loss computation to attempt to eliminate or reduce the dependencies between error and race to achieve error parity. In addition, we train and test 3 more TFTs enhanced with state-of-the-art debiasing methods for regression settings, namely, individual fairness $TFT_{Individual}$ [70], group fairness TFT_{Group} [70], and the sufficiency-based regularizer $TFT_{Sufficiency}$ [71]. Individual and group fairness methods calculate penalties by determining overestimations across different groups and weighting the loss by a factor proportional to the overestimations, while the sufficiency-based regularizer trains a joint model and group-specific networks to achieve fair predictions. We replicate their methodology and adapt it to the forecasting setting by keeping TFT as the common network.

Measuring Model Fairness

We choose error parity as our fairness metric [17], with a focus on evaluating whether the distribution of predictive errors at the county level is independent of county majority race and ethnicity, that is, prediction errors are not statistically significantly different across racial and ethnic groups. To measure the fairness of each of the models $TFT_{Baseline}$, $TFT_{DemOpts}$, $TFT_{Individual}$, $TFT_{Group}$and $TFT_{Sufficiency}$, we propose a 2-step process.

Step 1: Associate Errors With County Race or Ethnicity

To carry out the fairness analysis, we need to associate the PBL error of each county with race and ethnicity labels. However, that would require access to race-stratified COVID-19 case data at the county level, which is unfortunately not available due to systemic data collection failures during the pandemic [73]. Hence, we propose to associate each county and its error with the majority race, that is, we label each county with the race or ethnicity that has the highest population percentage in that county. During the fairness analysis, we refer to majority White counties as the unprotected group and majority minority counties, such as Black or Hispanic, as the protected groups (details about the racial and ethnic groups considered in the evaluation are provided in the "Datasets" section).

In addition, we normalize each county's PBL error by county population size. The normalization by county population allows us to scale the errors appropriately, since higher-population counties will have higher case counts and thus, higher-magnitude errors. Normalizing by population fairly compares the error per unit population of one county with another:

$$NormPBLypi,yti=1000\cdot PBLyp,i,yt,ipopi$$

where y_{ti} is the ground truth, y_{pi} is the predicted value, and pop_i is the county population.

We then calculate the average normalized PBL for each racial or ethnic group:

$$AvgNormPBL(yp,yt,g)=\sum i\in cgNormPBL(ypi,yti)|cg|$$

where g represents the racial or ethnic group and c_g is the set of all counties with as the majority group. This gives us the average normalized PBL for each demographic group.

Step 2: Compute Fairness Metric

Once PBLs have been calculated for each racial and ethnic group in the United States, we can compute the error parity, that is, the fairness metric focused on evaluating whether the prediction errors are different across race and ethnicity. We propose 2 metrics to measure the error parity of COVID-19 county case predictions: hard error parity and soft error parity.

Hard Error Parity Metric

Model predictions exhibit hard error parity when no statistically significant differences exist between normalized mean case prediction errors (AvgNormPBL) across racial or ethnic groups. In other words, normalized mean PBL errors across counties of different racial and ethnic groups are similar and hence, not biased by race or ethnicity. To test for the hard error parity of a prediction model, we propose to run one-way ANOVA followed by post hoc Tukey honestly significant difference (HSD) tests between the normalized mean error distributions of all racial and ethnic groups. ANOVA tests are an adequate choice even in violation of normality for large sample sizes, and in the presence of unequal sample sizes with homogeneous variance; thus, we choose this parametric test due to its superior strength [74,75].

Rejecting the null hypothesis for ANOVA would point to significantly different mean error values across some racial or ethnic groups and to a lack of perfect hard error parity. The subsequent analysis of the post hoc Tukey HSD test would reveal the pairs of racial and ethnic groups whose mean error values are significantly different and the numerical difference. The Tukey test also highlights the pairs of racial and ethnic groups for which the mean error is not statistically significantly different, pointing to instances where hard error parity exists for that model.

Soft Error Parity Metric

Instead of measuring the statistical significance of the relationship between county race labels and county errors, we propose to use the Accuracy Equity Ratio (AER) metric [76]. AER computes the ratio between the errors of the protected and unprotected groups as follows:

AERpg=AvgNormPBLyp,yt,pgAvgNormPBLyp,yt,unpg

where subscript pg indicates counties labeled as the protected group (majority minority counties). unpg indicates counties labeled as the unprotected group (White), and AvgNormPBL is the average of the normalized PBL across counties for a given racial group g (pg or unpg).

As defined, the AER metric goes from 0 to ∞. AER values in the range [0, 1] indicate comparatively lower normalized PBL for protected groups, which means the model predictions could be biased—have higher errors—for White majority counties; while AER values larger than one indicate that the model could be biased against the protected group, that is, the prediction errors are larger for counties with majority-minority groups. Values close to 1 indicate parity in error distribution between the protected group counties and the majority White counties. We claim that a predictive model achieves soft error parity for a given protected group when the AER value is close to 1, that is, the mean predictive error between that protected group and the White race is similar.

An alternative approach to assigning majority race or ethnicity would be to explore the associations between PBL errors and the distribution of racial and ethnic groups in a county (independent of COVID-19 cases, since that data are not available). Using a quantile regression, we can explore whether DemOpts eliminates significant associations between racial or ethnic percentages and the PBL errors, or at least reduces their magnitude. This approach removes the majority race requirement, but does not allow us to perform analyses with well-established fairness metrics in the literature, such as AER. Results are provided in the Multimedia Appendix 1.

DemOpts Over State-of-the-Art

To assess whether DemOpts is a better debiasing approach than state-of-the-art methods, we need to compare the error parity metrics of the COVID-19 county case prediction model enhanced with the DemOpts method, $TFT_{DemOpts,}$ against the error parity metrics of the same prediction model enhanced with the other debiasing approaches (individual $TFT_{Individual}$, group TFT_{Group}, or sufficiency $TFT_{Isufficiency}$), as well as with the baseline COVID-19 county case prediction model without any debiasing approach, $TFT_{Baseline}$. Next, we describe how we carry out this analysis for the hard and soft error parity metrics.

Hard Error Parity

We computed the hard error parity metric for each of the COVID-19 county case prediction models, using one-way ANOVA and the post hoc Tukey HSD test. An exploration of the statistical significance of the mean error difference for each pair of racial and ethnic groups will reveal whether applying DemOpts to the COVID-19 case prediction model produces fewer instances of significant mean error differences than any of the other debiasing methods or the baseline. In other words, a decrease in the number of significantly different mean PBL errors between races would point to an achievement of hard error parity for more racial and ethnic groups than other state-of-the-art debiasing approaches or the baseline.

Soft Error Parity

To assess whether DemOpts applied to a COVID-19 case prediction model has higher soft error parity than any of the other state-of-the-art debiasing approaches, we propose to compare the AER values for each protected race and ethnic group across the 5 models: $TFT_{DemOpts}$, $TFT_{Individual}$, TFT_{Group}, $TFT_{Sufficiency}$, and $TFT_{Baseline}$. Since AER values represent the quotient between the normalized mean prediction errors of a protected race or ethnicity vs White counties, the model with AER values closer to 1 will be the approach with the highest soft error parity. To measure AER's distance to 1, we compute the distance=$|1\text{-}AER_{race}|$ for each race and ethnic group, which represents the distance to a perfect soft parity error of 1. Distances closer to zero reveal better soft error parities.

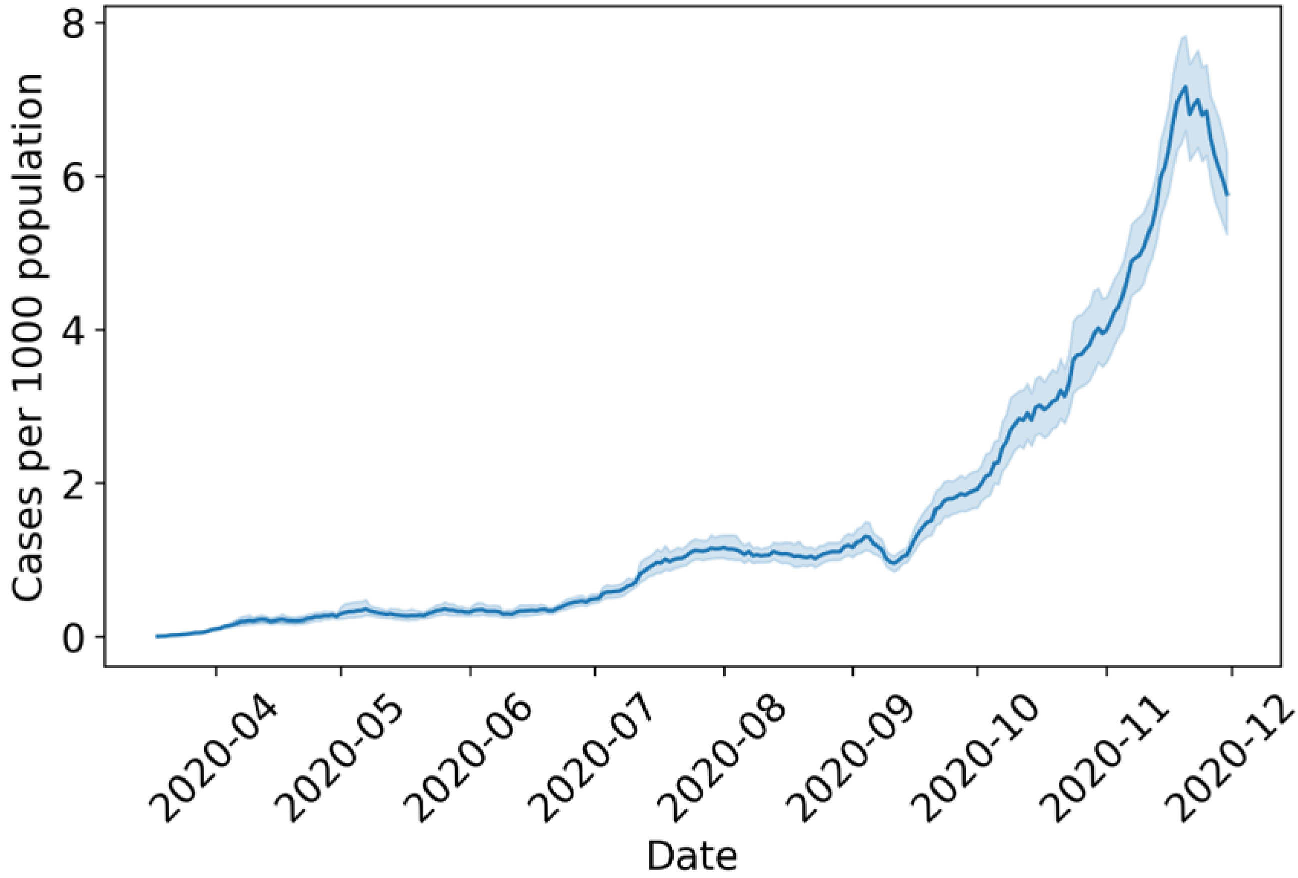
Datasets

In this section, we discuss the datasets we use in the DemOpts evaluation in the "Results" section. We train COVID-19 county case prediction models for the United States using COVID-19 case data, as well as mobility and demographic data. Mobility data has been used by previous work to inform case predictions via human mobility behaviors, under the assumption that the way people move might have an impact on the spreading of the epidemic. On the other hand, demographic data, either raw from the census or combined in different types of vulnerability indices, has also been shown to help predict COVID-19 prevalence, given the fact that COVID-19 has heavily affected vulnerable populations [59].

COVID-19 Case Data

We use the COVID-19 case data compiled by the NYT at the county level [12]. We account for delayed reporting by using the 7-day daily rolling average of COVID-19 cases (computed as the average of its current value and 6 previous days) instead of raw counts. Figure 3 charts the daily COVID-19 reported cases throughout the data collection period.

Figure 3. COVID-19 reported case counts per 1000 population across the United States.

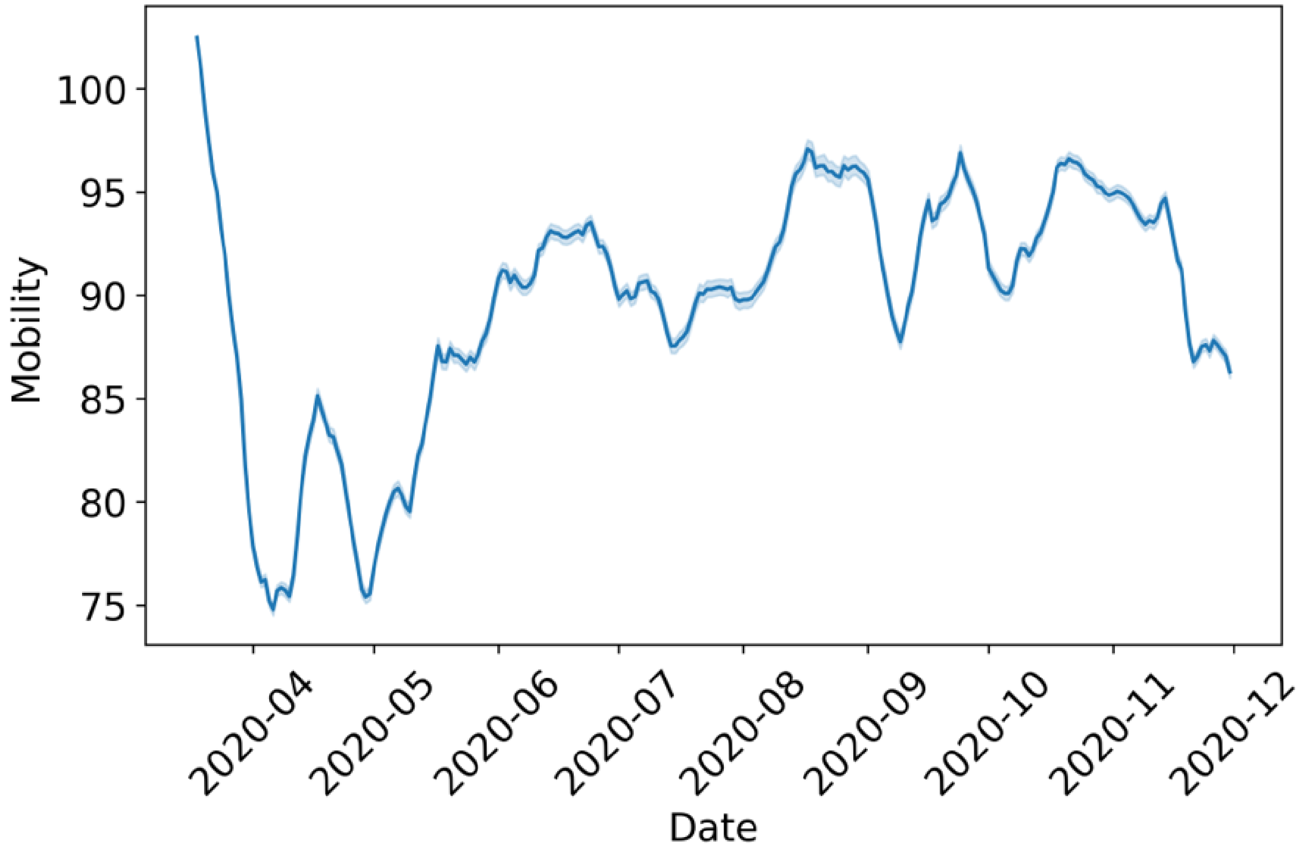


Mobility Data

SafeGraph open-sourced the mobility patterns of smartphone app users at the onset of the pandemic. These data points are curated by tracking the movements of millions of pseudonymized users via mobile app Software Development Kits (SafeGraph). Based on the data available, we use the daily origin-destination (OD) county-to-county flows [77]. OD flows represent the volume of trips between pairs of counties across the United States for each day. For OD flows, we only use SafeGraph inflow (ie, mobility into the county). The inflow mobility is measured as changes in volumes of flows with respect to a baseline of normal behavior computed by SafeGraph using mobility data from February 17, 2020, to March 7, 2020.

Previous work has shown sampling bias in mobility datasets, revealing that not all races and ethnicities are equally represented due to variations in smartphone penetration rates [20,78]. It has also been shown that sampling bias in mobility data can negatively impact downstream tasks such as COVID-19 forecasting [56]. While the addition of mobility data could potentially help improve prediction accuracy and support better decision-making, it also introduces bias. Our empirical analysis of DemOpts aims to understand whether the debiasing method proposed in this paper can improve the fairness of COVID-19 county case predictive models when mobility data is used as input to the predictive model. Figure 4 shows the aggregate mobility data across the country. We see an initial drop in mobility in April (2020 - 04), which corresponds to the first lockdown period. We then observed an increase in mobility a month later, which partially stabilizes after April.

Figure 4. Mobility for all ethnic and racial groups.



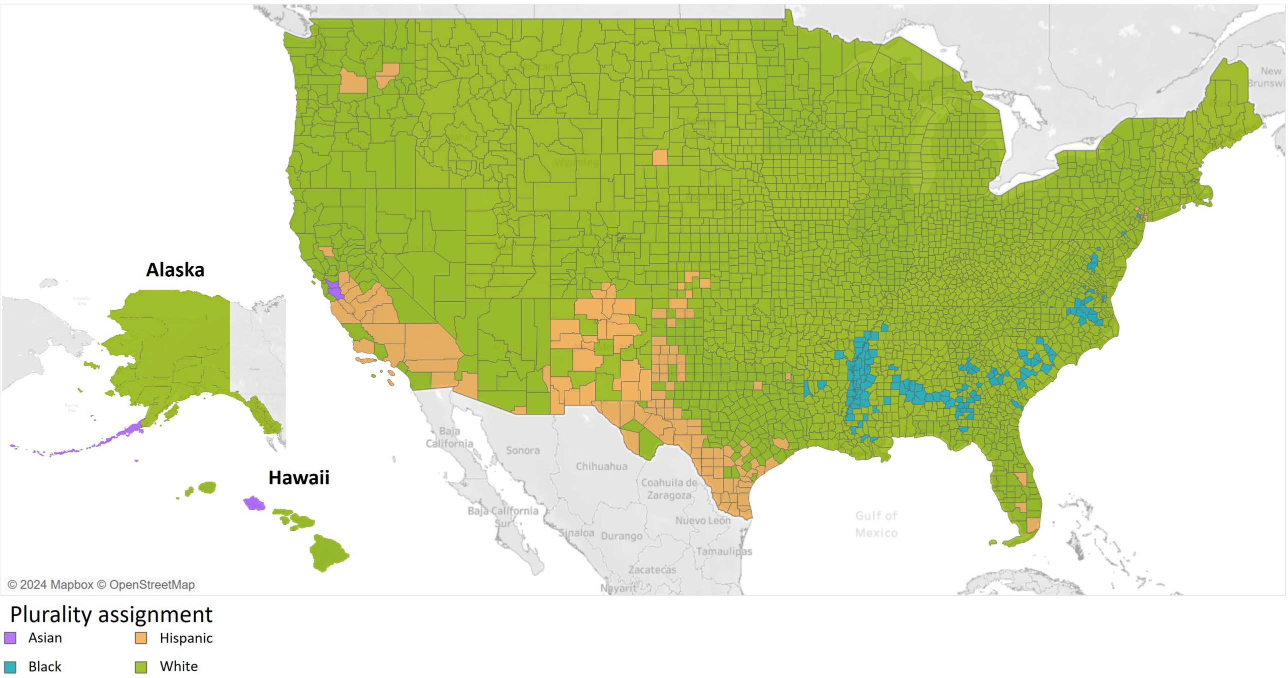
Race and Ethnicity Data

We retrieve the race and ethnicity data from each county in the United States from the 2019 5-year American Community Survey. This survey collects data annually from all 50 states, Puerto Rico, and Washington, DC. As described in Step 1 of the evaluation protocol, we associate each county and its errors with the majority race (ie, we label each county with the race or ethnicity that has the highest population percentage in that county). Following this procedure identifies 4 racial and ethnic groups for the majority of counties: Asian, Black, Hispanic, and White. Table 1 shows the distribution of US counties into these 4 racial and ethnic groups, and Figure 5 show color-coded maps with the majority racial or ethnic group for each county.

Table . Majority label counts.

Majority label	Count, n (%)
Asian	6 (0.194)
Black	127 (4.118)
Hispanic	126 (4.085)
White	2825 (91.601)

Figure 5. Counties and majority-based label. (Mapbox and OpenStreetMap were used to create this map [79,80,81].)



Model Training

For evaluation purposes, we use COVID-19 case and SafeGraph mobility data from March 18, 2020, to November 30, 2020, for the training (207 days) and testing (49 days) of the TFT COVID-19 county case prediction models. The forecast task is the prediction of the number of COVID-19 cases for a given county from day X+1 to X+50, that is, the following 2 months (long-term forecasting with lookahead values from 1 to 50). Specifically, we train and test (1) the $TFT_{Baseline}$, a TFT prediction model without a debiasing method; (2) the $TFT_{Individual}$, TFT_{Group}, and $TFT_{Sufficiency}$, TFT prediction models with state-of-the-art debiasing methods; and (3) $TFT_{DemOpts}$, a TFT prediction model enhanced with our proposed debiasing method. All 5 models are trained and tested for the same temporal range, and all are implemented using the PyTorch Forecasting library [82]. We limit the period of analysis to a time before COVID-19 vaccines were available, given that after that event, research has revealed a less clear relationship between mobility data and postvaccines COVID-19 case volumes [83]. We use the prediction errors (PBL) per racial and ethnic group to analyze and compare the hard and soft error parity of all trained models.

Ethical Considerations

We used openly available datasets for mobility data (SafeGraph), COVID-19 case count (NYT), and demographic data (American Communities Survey). There was no human participant recruitment in this study, and thus we did not require institutional review board approval. All the datasets were aggregated at the county level and do not pose the risk of deanonymization.

Results

Hard Error Parity Results

ANOVA tests of the normalized mean PBL error distributions across racial and ethnic groups for each debiasing approach were all significant, pointing to a dependency between race and the normalized prediction errors.

Table 2 shows the *F* statistic and test significance for each of the prediction models with and without debiasing approaches. The significant ANOVA tests reveal that perfect hard error parity is not achieved by any of the debiasing methods. In other words, for some racial and ethnic groups, there exist statistically significant differences between their mean PBL prediction errors of different racial and ethnic groups; this effect occurs for the $TFT_{Baseline}$ model as well as across all the other predictive models enhanced with a debiasing approach.

Nevertheless, post hoc Tukey HSD tests revealed interesting, nuanced results, showing significant differences in errors only between specific pairs of racial and ethnic groups. Table 3 shows the post hoc Tukey HSD test results for each COVID-19 case predictive model: the baseline, the baseline enhanced with 1 of the 3 state-of-the-art debiasing approaches, and the baseline enhanced with our proposed method (DemOpts). Each row represents the output of the post hoc test, that is, the difference between the normalized mean PBL error of Group 1 and Group 2 ($NormPBL_{Group1}$ - $NormPBL_{Group2}$). If the difference is positive, it means that the normalized mean predictive error is higher for Group 1; if the difference is negative, the normalized PBL error is higher for Group 2 (superscript b indicates statistically significant differences).

The first relevant observation when examining the table is that the baseline model, focused on predicting COVID-19 county cases with no debiasing approach is highly biased, with statistically significant differences between the mean normalized errors across all pairs of races, except for the comparison between Asian and Black counties as well as Hispanic and White counties, for which there is no statistically significant difference. These results reveal that there is no racial or ethnic group that achieves hard error parity and motivate our exploration of whether state-of-the-art debiasing methods or our proposed DemOpts can improve the hard error parity results of the baseline model.

Table . ANOVA *F* test statistics comparing mean prediction errors.

Fairness method	F statistic (*df*)
Baseline	1195.398[a] (3080)
Group	1455.528[a] (3080)
Individual	1469.698[a] (3080)
Sufficiency	1195.651[a] (3080)
DemOpts[b]	668.769[a] (3080)

[a]*P*<.001.

[b]DemOpts: Demographic Optimization.

Table . Hard error parity analysis. Each value represents the difference between the mean normalized pinball loss for each pair of racial and ethnic groups and indicates whether the difference is statistically significant.

Groups 1 and 2	Baseline	Group	Individual	Sufficiency	DemOpts[a]
Asian					
Black	−0.11	−0.20	−0.12	−0.11	1.32
Hispanic	−2.30[b]	−2.65[b]	−2.50[b]	−2.29[b]	−0.77[c]
White	−2.06[b]	−2.51[b]	−2.51[b]	−2.06[b]	−0.96[c]
Black					
Hispanic	−2.18[b]	−2.45[b]	−2.38[b]	−2.17[b]	−2.09[b]
White	−1.94[b]	−2.31[b]	−2.39[b]	−1.94[b]	−2.29[b]
Hispanic					
White	0.23	0.14	−0.01	0.23	−0.19

[a]DemOpts: Demographic Optimization.

[b]*P*<.001.

[c]These values denote no significant difference between the prediction errors of Asian and White counties and of Asian and Hispanic counties.

When examining Table 3, we can observe that predictive models enhanced with the individual, group, or sufficiency debiasing methods do not improve the hard error parity over the baseline. On the one hand, similarly to the baseline model, the state-of-the-art debiasing methods ($TFT_{Individual}$, TFT_{Group}, and $TFT_{Sufficiency}$) achieve hard error parity between Asian and Black counties and between Hispanic and White counties, that is, the mean error difference between these counties is not significant, pointing to a fair distribution of errors. On the other hand, for each pair of racial and ethnic groups whose prediction error distributions are significantly different for the baseline (rows with asterisks in the Baseline column), they remain significantly different for the individual, group, and sufficiency debiasing methods (rows with superscript b in the individual, group, and sufficiency columns).

When examining the significant mean PBL differences between racial and ethnic groups for the baseline and the state of the art debiasing models, we observe that all coefficients have similar values, signaling similar significant mean PBL differences between racial and ethnic groups (with values between 1.942 and 2.659 error cases per 1000 population). The sign of the coefficients reveals higher mean PBL errors for Hispanic and White counties when compared to Asian or Black counties, and higher mean PBL errors for White counties when compared to Hispanic counties across all models. For example, Hispanic and White counties have mean prediction errors 2.302 and 2.064 cases higher, respectively, when compared to Asian counties and while using the baseline model; and Hispanic and White counties have errors 2.457 and 2.313 cases higher, respectively, when compared to Black counties using the baseline model enhanced with the Group debiasing approach.

Moving on to DemOpts, the table shows that our proposed approach is the only debiasing method that achieves hard error parity in more cases than the baseline, effectively removing some of the associations between race and ethnicity and the normalized mean error distribution (PBL). Specifically, DemOpts removes the significant difference between the prediction errors of Asian and White counties and of Asian and

Hispanic counties (refer to values with supercript c in Table 3), effectively achieving hard error parity for Asian counties, that is, the mean PBL in Asian counties is always similar to the mean error in counties of all the other racial and ethnic groups. These improvements occur additionally to hard error parity already seen in $TFT_{Baseline}$ (hard error parity between Asian and Black counties and between Hispanic and White counties), which are also present in the other 3 debiasing methods. In other words, DemOpts improves the hard error parity of case predictions for 2 additional racial and ethnic pairs compared with any of the other debiasing methods.

Finally, when looking specifically at the hard error parity between protected (Asian, Black, and Hispanic) and unprotected groups (White), DemOpts achieves hard error parity for Asian and Hispanic groups; that is, their mean prediction errors are not significantly different from those of White counties, while the baseline and the other 3 debiasing methods only achieve hard error parity for the Hispanic group when compared to White counties. These findings with respect to White counties motivate the evaluation of the soft error parity of the different models to determine, for example, whether DemOpts achieves the best soft error parity for the Black group (since hard error parity was not achieved), or to see if DemOpts has better soft error parity than other debiasing methods for Asian or Hispanic groups. Next, we explore the soft error parity metric for the TFT baseline and for all TFT models enhanced with debiasing approaches.

Soft Error Parity Results

Table 4 shows the distance to the perfect soft error parity for each of the debiasing approaches across all protected racial and ethnic groups. As we can observe, DemOpts has the smallest values—closest distances to perfect soft error parity—for Asian and Black counties, while the individual debiasing method almost achieves perfect soft error parity for the Hispanic counties. In other words, DemOpts is the debiasing approach that produces the most similar errors between Asian and White counties and between Black and White counties, thereby achieving the largest reduction in predictive bias. On the other hand, the Individual debiasing method achieves errors for Hispanic counties that are closest to the White group. In addition, it is important to highlight that the Group and Sufficiency debiasing methods achieve soft error parities that are close to the $TFT_{Baseline}$, which is not enhanced with any debiasing method.

Table . Soft error parity analysis. Each value represents the distance ($|1\text{-}AER_{race}|$) for each protected group and debiasing method. $TFT_{DemOpts}$ achieves the highest soft error parity for 2 of the 3 protected races under study.

Group	Baseline	Group	Individual	Sufficiency	DemOpts[a]
Asian	0.811	0.842	0.850	0.811	0.454[b]
Black	0.764	0.774	0.807	0.764	0.681[b]
Hispanic	0.093	0.048	0.003[b]	0.093	0.12

[a]DemOpts: Demographic Optimization.

[b]Smallest error parity for the particular group

Overall, these results reveal that DemOpts is the debiasing approach that improves the soft error parity of case prediction models, with errors for Asian and Black counties being the closest to errors in White counties. When accounting for additional factors, DemOpts outperforms the other methods by reducing the racial associations of model error.

In Table S1 in Multimedia Appendix 1, we provide and discuss the results for the quantile regression analysis in detail. Overall, the results confirm our findings with majority race labels, with DemOpts consistently outperforming other methods, showing the smallest coefficient magnitude for associations between the percentage of Asian, Black, and Hispanic populations and model error.

Discussion

Principal Findings

Through our comparison of model performance for COVID-19 case prediction across counties of differing racial demographics, we showed that DemOpts outperforms other baselines for debiasing predictions. In our analysis of hard error parity, we found that DemOpts was the only debiasing method to eliminate statistically significant relationships between prediction error and racial demographics when compared with the baseline. While some significant associations remained, DemOpts achieved hard error parity for Asian vs White counties and Asian vs Hispanic counties. In the soft error parity analysis, DemOps substantially outperformed the baselines for Asian and Black counties, with a 69.4% reduction and 23% reduction, respectively, compared with the next closest method.

Why is DemOpts Better?

The results showed that DemOpts is the only debiasing approach to achieve both hard and soft error parity for all 3 racial minority groups when compared with White counties.

In an attempt to understand why DemOpts succeeds in increasing both hard and soft error parity in the context of COVID-19 county case predictions, and compared with other debiasing methods, we computed the average PBL for each racial and ethnic group and for each predictive model enhanced, or not, with a debiasing method (refer to Table 5). We observed that DemOpts achieves better hard and soft error parity metrics because it considerably increases the errors for Asian and Black counties with respect to the baseline, until the differences with Hispanic and White are made not statistically significant (hard error parity) or closer to the White mean errors (soft error parity). Comparing Tables 4 and 5, we observed that DemOpts achieves considerably higher fairness for the Hispanic group (when compared to White) than for the Asian and Black groups (0.12 vs 0.454 and 0.681 in Table 4). As a result, the average PBL error for the Hispanic group (3.59 in Table 5) is considerably higher than the Asian and Black racial groups (1.7 and 1, respectively). We hypothesize that the differences in average errors and performance across racial and ethnic groups could be due to differences in the bias present in the training data, that is, mobility data or COVID-19 case counts could be more biased for Asian or Black groups, thus making it harder to achieve fair predictions when compared to White, and, in turn, due to the fairness-accuracy trade-off, making them more accurate (lower errors).

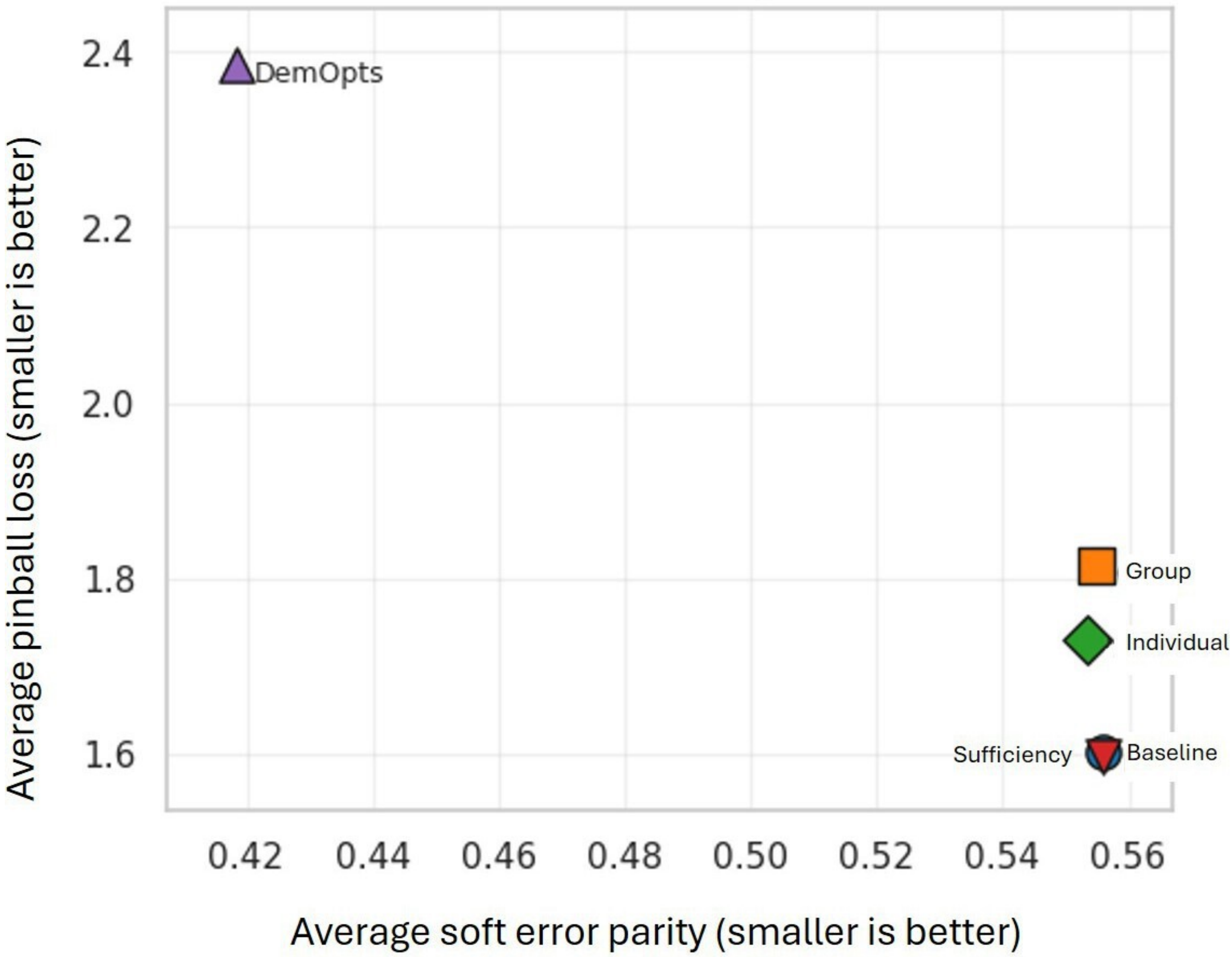
Table . Group-wise pinball loss for each model. Demographic Optimization (DemOpts) has higher average pinball loss compared to the other models. The fairness-accuracy tradeoff leads to slightly larger pinball loss values for DemOpts compared to other methods.

Group	Baseline	Group	Individual	Sufficiency	DemOpts[a]
Asian	0.482	0.472	0.444	0.479	1.741
Black	0.600	0.674	0.570	0.598	1.015
Hispanic	2.784	3.131	2.951	2.776	3.597
White	2.546	2.987	2.961	2.540	3.192

[a]DemOpts: Demographic Optimization.

These results show that DemOpts' optimization could not decrease prediction errors while trying to improve fairness, showing a fairness-accuracy trade-off that has been reported previously in the literature [84]. To further clarify this finding, Figure 6 shows both the average PBL and soft parity across all the models considered in this paper. As shown, DemOpts has the lowest soft error parity, but the highest PBL (top-left corner in the plot), while the other models decrease the PBL by sacrificing fairness (higher error parity in the bottom-right corner).

Figure 6. Fairness-accuracy tradeoff. Model error (average pinball loss) vs average soft error parity (|1-AER|) for each model.



Limitations

While DemOpts outperforms other state-of-the-art approaches in debiasing COVID-19 predictions, there are some limitations to DemOpts and our evaluation. First, DemOpts is unable to remove all statistical associations for the hard parity analysis, potentially because doing so would impose further reductions in model performance. For the soft parity analysis, the individual fairness approach is best for Hispanic counties, but the difference in parity levels is small. Regarding evaluation, our focus is exclusively on COVID-19 county case prediction—while evaluation on other datasets and prediction tasks would be helpful for future work, our current evaluation provides sufficient evidence to show its applicability to other contexts. In addition, we compare DemOpts to baselines only on error parity metrics. Other fairness metrics may apply to the COVID-19 context and should be evaluated in future work, but we focus on error parity because DemOpts is specifically designed to mitigate it. Finally, we only compare DemOpts and baseline debiasing approaches within TFT models—future work should compare with other commonly used models for COVID-19 case prediction.

Regardless, our novel debiasing approach shows that hard and soft error parity across protected and unprotected racial and ethnic groups can improve relative to other state-of-the-art approaches.

Finally, it is important to clarify that although in this paper, DemOpts focuses on bias mitigation in COVID-19 forecasting, it could also be applied to other health forecasting tasks where sampling bias in data collection can lead to bias in downstream tasks, for example, forecasting flu cases. These forecasts, when done at the county level and when using mobility data to model human spread, could benefit from the DemOpts method by reducing the effect of mobility bias or case count bias on other infectious diseases.

Conclusion

Researchers have worked tirelessly on the creation of accurate COVID-19 case prediction models to support resource allocation and decision-making. However, sampling and underreporting biases in the data used to train these models have resulted in worse prediction performance for certain protected attributes, pointing to a lack of COVID-19 predictive fairness that could affect decision-making. In this paper, we show that state-of-the-art architectures in COVID-19 case predictions (TFT models) incur unfair prediction error distributions, and we design a novel debiasing approach and evaluation method to increase the fairness of predictions in the context of COVID-19 county case forecasts. DemOpts modifies the loss function in deep learning models to reduce the dependencies between error distributions and racial and ethnic labels. Our results show that DemOpts improves both the hard and soft error parity of COVID-19 county case predictions when compared with state-of-the-art debiasing methods.

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Data Availability

We use open source data: (1) SafeGraph mobility, (2) New York Times COVID-19 case count, and demographic information from the American Communities Survey (ACS).

Conflicts of Interest

None declared.

Multimedia Appendix 1
Details on the differentiability and regression analysis of fairness method errors.
[PDF File, 257 KB - ojphi_v18i1e78235_app1.pdf]

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Abbreviations

AER: Accuracy Equity Ratio
CDC: Centers for Disease Control and Prevention
HSD: honestly significant difference
NYT: New York Times
OD: origin-destination
PBL: pinball loss
TFT: temporal fusion transformer

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