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Diabetes mellitus as a risk factor for SARS-CoV-2 test positivity in Mexico: A propensity score matched study



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ABSTRACT

Aims: We sought to investigate whether individuals with diabetes have a higher likelihood of testing positive for SARS-CoV-2, as a proxy for infection risk, than individuals without diabetes.

Methods: We conducted a cross-sectional study of publicly available data among a Mexican population, totaling 2,314,022 adults ≥ 18 years who underwent SARS-CoV-2 testing between March 1 and December 20, 2020. We used 1:1 nearest neighborhood propensity score matching by diabetes status to account for confounding among those with and without diabetes.

Results: In the overall study population, 1,057,779 (45.7%) individuals tested positive for SARS-CoV-2 and 270,486 (11.7%) self-reported diabetes. After propensity score matching, patient characteristics were well-balanced, with 150,487 patients in the diabetes group (mean [SD] age 55.9 [12.7] years; 51.3% women) and 150,487 patients in the no diabetes group (55.5 [13.3] years; 50.3% women). The strictest matching algorithm (1:1 nearest neighbor) showed that compared to individuals without diabetes, having diabetes was associated with 9.0% higher odds of having a positive SARS-CoV-2 test (OR 1.09 [95% CI: 1.08–1.10]).

Conclusions: Presence of diabetes was associated with higher odds of testing positive for SARS-CoV-2, which could have important implications for risk mitigation efforts for people with diabetes at risk of SARS-CoV-2 infection.

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1. Introduction

Diabetes mellitus, which affects nearly a half-billion people worldwide [1], has emerged as an important risk factor for poor COVID-19 outcomes [2–4]. Over the course of the COVID-19 pandemic, numerous studies have documented an association between diabetes and higher risk of hospitalization, intensive care unit admission, and mortality among individuals with COVID-19 [4–5]. Yet whether individuals with diabetes are at a higher risk of infection with SARS-CoV-2 than individuals without diabetes remains an important, yet unanswered question in the intersection between these two pandemics. Given the high prevalence of diabetes globally [1] and the ongoing burden of COVID-19 [6], understanding whether individuals with diabetes are at a heightened risk of SARS-CoV-2 infection could inform urgently needed risk mitigation policies.

Diabetes confers increased susceptibility to a wide array of infections [7–9], including respiratory infections [7], which has been attributed to a complex interplay of host-specific factors as well as a reduced immune response to infection, particularly in the context of hyperglycemia [10–12]. While some studies have documented a higher prevalence of diabetes among patients with COVID-19 than in the general population [13], other studies have reported opposing findings [14]. Moreover, this literature has generally been limited by inclusion of only hospitalized patients with COVID-19, who may be more likely to undergo testing for SARS-CoV-2, and by a lack of adjustment for confounders that may increase the opportunity of infection among individuals with diabetes, such as low socioeconomic status [15].

In this study, we examine data from over two million individuals who underwent SARS-CoV-2 testing in Mexico to assess whether individuals with diabetes have a higher likelihood of testing positive for SARS-CoV-2, as a proxy for infection risk. We conduct propensity score matching among individuals with and without diabetes to account for possible confounders in the association between diabetes and likelihood of testing positive for SARS-CoV-2.

2. Methods

2.1. Data source and study population

We used publicly available data from the General Directorate of Epidemiology of the Mexican Ministry of Health, an open-source dataset that gathers information from individuals who have undergone testing for SARS-CoV-2 in Mexico [16]. Epidemiological surveillance of SARS-CoV-2 in Mexico is carried out using a sentinel surveillance system. This sentinel system consists of 475 health care units known as Viral Respiratory Disease Health Care Monitoring Units (USMER from its abbreviation in Spanish). The sampling strategy at these monitoring units includes 10% of suspicious cases of viral respiratory disease with mild symptoms (outpatient) and 100% of suspicious cases with severe symptoms (hospitalized). In addition, 100% of the cases that meet the definition of severe acute respiratory infection are sampled in all medical units (Not USMER) from the National Health System in the country.

We analyzed data on the Mexican adult population (18 years or older) who presented to one of the health care units included in the sentinel surveillance system between March 1st and December 20th, 2020 and who underwent testing for SARS-CoV-2, prompted by presence of symptoms. The data were downloaded on December 20, 2020 from <https://www.gob.mx/salud/documentos/datos-abiertos-152127?idiom=es>. We included adults who had complete information on the variables of interest as described below ($N = 2,538,985$; 93.2% of the original study population). Given that there was <10% loss between the original study population and those who had complete information, we excluded the 6.8% of individuals missing one or more variables of interest.

2.2. Definition of the outcome

The outcome variable, COVID-19 case positivity, was defined based on laboratory confirmation of SARS-CoV-2 with either RT-PCR or antigen testing (Rapid Ag-T)

2.3. 3.1.1 Definition of the exposure

The exposure variable, diabetes status, was available in the database via self-reported diagnosis, which is considered a reliable measure of diagnosed diabetes in Mexico [17]. To contextualize the prevalence of diabetes reported in our study sample with that of the population-level estimate, we included the most recent national estimates reported by the National Health and Nutrition Survey conducted in Mexico (ENSANUT 2018) [18] (Appendix 1).

2.4. Covariates

Age, sex, and indigenous language spoken were available through self-report. Obesity, hypertension, cardiovascular disease (CVD), and chronic kidney disease (CKD), also available through self-report, were included in the analysis given the high prevalence of these conditions among individuals with diabetes [19]. Healthcare provider type, healthcare setting, month of presentation to care, and days between symptom onset and presentation to care were also available at the individual level. Given lack of individual-level data on socioeconomic status, which can influence one's risk of infection [15], we included two indices with information on the social context and health system capacity of the study sample. First, we included a municipality-level social deprivation index, which is considered a reliable measure of an individual's socioeconomic context in Mexico [20]. This index is constructed based on access to basic public services, housing conditions, and wage earnings in 2015 [20]. Second, we included a state-level and multivariate index of availability of human resources and hospital equipment prior to the COVID-19 pandemic, which corresponded to the state in which SARS-CoV-2 testing was conducted. This index was constructed using factor analysis [21] and followed the official guidelines for the organization and execution of the Hospital Conversion COVID-19 among the Mexican National Health System Institutions (Appendix 7) [22].

2.5. Statistical analysis

To account for differences in characteristics between individuals with and without diabetes that could confound the association between diabetes and SARS-CoV-2 test positivity, we used propensity score matching (PSM). Briefly, PSM is a robust statistical technique that reduces systematic differences between two comparison groups based on observable variables to estimate the effect of a treatment on a specific outcome [23]. In absence of an experimental design, the strength of PSM is that it allows for the robust assessment of the treatment effect (in this case the exposure) on the outcome.

We used logistic regression to create the propensity score and matched the study sample on all covariates listed above (Appendix 2). Matching was performed using the 1–1 nearest-neighbor algorithm (the most straightforward matching estimator in terms of efficiency and bias) including caliper = 0.001, non-replacement and common support. PSM was performed using the *psmatch2* command in Stata MP v15.1. Balance in covariates after matching was examined using standardized differences among common support (Appendix 3) [24]. Small absolute values (<0.05) and an average percentage absolute bias before matching of 20% and after matching of 1% indicated balance between comparing groups (Appendix 4). We also computed the Mantel-Haenszel test to assess the sensitivity of estimated average treatment effects on the treated in the presence of unobserved heterogeneity (hidden bias) [25–27] using *mhbounds* command in Stata MP v15.1 (with $\gamma(1(0.025)1.5)$, suggesting that matching estimations were insensitive to a hidden bias (Appendix 4). In order to ease interpretation, we transformed average treatment on the treated (ATT) into odds ratios. Standard errors from logistic regression were obtained through the Delta method [28] by resampling primary sampling units with 1000 bootstrap replications. A sensitivity analysis was performed by contrasting the naïve model (unmatched) with three additional algorithms: kernel, local linear regression, and radius matching (Appendix 5) [29]. We also conducted a sensitivity analysis that included a broader definition of COVID-19 case positivity, based on symptoms suggestive of COVID-19 with a positive contact (confirmed through laboratory testing), which did not alter the main analysis results (Appendix 6).

3. Results

3.1. Study sample characteristics by SARS-CoV2 test result

The characteristics of the study sample according to SARS-CoV-2 test result are presented in Table 1. A total of 2,314,022 individuals underwent testing for SARS-CoV-2 between March 1 and December 20, 2020, of whom 45.7% had a positive test. A total of 11.7% (95% CI: 11.6–11.7) of individuals self-reported diabetes. Compared to individuals who tested negative, individuals with a positive SARS-CoV-2 test were more likely to be male than female (50.3% vs. 49.7%), older, speak an indigenous language (0.8% vs.

0.7%), and have diabetes, obesity, hypertension, CVD, CKD, and COPD.

3.2. Study population characteristics before and after propensity score matching

The final study population after 1:1 propensity score matching included 507,114 individuals who underwent SARS-CoV-2 testing (Table 2). Before matching, a higher proportion of individuals with diabetes were older, spoke an indigenous language (1.1% vs. 0.7%), self-reported obesity (25.7% vs. 13.4%), hypertension (53.4% vs. 10.7%), CVD (5.2% vs. 1.1%), CKD (7.1% vs. 0.8%), COPD (3.6% vs. 0.7%), and asthma (2.9% vs. 2.7%) compared to patients without diabetes. A higher proportion of patients with diabetes were hospitalized (34.5% vs. 9.3%), admitted to the intensive care unit (1.0% vs. 0.3%), and mechanically ventilated (1.2% vs. 0.3%), compared to patients without diabetes. After propensity score matching, the two exposure groups (with and without self-reported diabetes) achieved adequate balance on measured covariates (Table 2).

3.3. Effect of having diabetes on testing positive for SARS-CoV-2 before and after propensity score matching

The odds of testing positive for SARS-CoV-2 are presented in Table 3. Before matching, the adjusted OR and 95% CI were 1.14 [1.13–1.15]. After 1:1 nearest neighbor propensity score matching, the adjusted OR attenuated to 1.09 [1.08–1.10]. Non-parametric matching algorithms confirmed the robustness of the association between diabetes and higher risk of testing positive for SARS-CoV-2 than patients without diabetes (ATT presented in Appendix 5).

4. Discussion

In this study of over two million individuals who underwent testing for SARS-CoV-2 in Mexico, we showed through rigorous propensity score matching that the odds of testing positive for SARS-CoV-2 were 9% higher among individuals with diabetes compared with individuals without diabetes. Although much has been documented in the U.S. and elsewhere on the role of diabetes as a risk factor for severe SARS-CoV-2 infection (2,4,5), our study expands the current literature by showing that individuals with diabetes have higher odds of testing positive for SARS-CoV-2 than individuals without diabetes. These findings suggest that individuals with diabetes may have a higher infection risk of SARS-CoV-2 than individuals without diabetes. Given the high prevalence of diabetes in Mexico (15.2%; 12.8 million adults) [1] and the high case burden of COVID-19 (2.2 million cases and 194,490 deaths as of March 2021) [6], our findings could inform health policies for risk mitigation efforts in Mexico and in other contexts with a high concurrent burden of diabetes and COVID-19.

The association between diabetes and higher susceptibility to a broad range of infections has been well documented in previous matched-cohort studies [7–9]. However, less is known about the association between presence of diabetes and risk of infection with coronaviruses. Studies from the

Table 1 – Characteristics of 2,314,022 individuals tested for SARS-CoV-2 in Mexico between March 1 and December 20, 2020.

N (%)	Total 2,314,022 (100.0) % or mean and 95% CI	SARS-CoV-2 Negative 1,256,243 (54.3)	SARS-CoV-2 Positive 1,057,779 (45.7)
Sex			
Female	52.3 [52.3–52.4]	54.5 [54.4–54.6]	49.7 [49.6–49.8]
18–35	38.0 [37.9–38.1]	41.9 [41.8–41.9]	33.4 [33.3–33.5]
36–50	33.3 [33.2–33.3]	33.1 [33.0–33.2]	33.5 [33.4–33.6]
51–65	20.4 [20.3–20.4]	18.4 [18.3–18.5]	22.7 [22.7–22.8]
65-over	8.3 [8.3–8.4]	6.6 [6.6–6.7]	10.4 [10.3–10.4]
Indigenous language spoken	0.7 [0.7–0.7]	0.7 [0.6–0.7]	0.8 [0.8–0.8]
Obesity	14.9 [14.8–14.9]	13.0 [13.0–13.1]	17.0 [17.0–17.1]
Hypertension	15.6 [15.6–15.7]	13.3 [13.3–13.4]	18.4 [18.3–18.5]
Cardiovascular disease	1.6 [1.6–1.6]	1.5 [1.5–1.6]	1.7 [1.6–1.7]
Chronic kidney disease	1.6 [1.5–1.6]	1.5 [1.5–1.5]	1.7 [1.6–1.7]
COPD	1.1 [1.0–1.1]	1.0 [0.9–1.0]	1.2 [1.2–1.2]
Asthma	2.7 [2.7–2.7]	2.9 [2.9–3.0]	2.5 [2.4–2.5]
Municipality social deprivation index	–1.4 [–1.4––1.4]	–1.4 [–1.4––1.4]	–1.4 [–1.4––1.4]
Healthcare setting			
Ambulatory	87.0 [86.9–87.0]	92.2 [92.2–92.3]	80.7 [80.7–80.8]
Hospitalized	12.3 [12.2–12.3]	7.8 [7.7–7.8]	17.6 [17.6–17.7]
ICU admission	0.3 [0.3–0.3]	0	0.8 [0.7–0.8]
Mechanical ventilation	0.4 [0.4–0.4]	0	0.9 [0.8–0.9]
Health care provider type			
Ministry of Health	66.2 [66.1–66.3]	72.0 [71.9–72.1]	59.3 [59.2–59.4]
Social Security	33.8 [33.7–33.8]	28.0 [27.9–28.1]	40.7 [40.6–40.8]
Human resources and hospital equipment*			
Lowest	19.0 [18.9–19.0]	16.0 [15.9–16.1]	22.5 [22.4–22.6]
Low	15.8 [15.8–15.9]	16.6 [16.6–16.7]	14.9 [14.8–15.0]
Middle	21.1 [21.0–21.1]	20.0 [20.0–20.1]	22.3 [22.2–22.3]
High	12.5 [12.4–12.5]	12.3 [12.2–12.3]	12.7 [12.7–12.8]
Highest	31.6 [31.6–31.7]	35.0 [35.0–35.1]	27.6 [27.5–27.7]
Month of presentation to care			
March–April	3.8 [3.8–3.8]	4.7 [4.6–4.7]	2.8 [2.7–2.8]
May	7.7 [7.7–7.8]	7.6 [7.5–7.6]	7.9 [7.9–8.0]
June	11.8 [11.7–11.8]	10.7 [10.6–10.7]	13.1 [13.0–13.1]
July	14.4 [14.4–14.5]	13.1 [13.0–13.1]	16.1 [16.0–16.1]
August	13.6 [13.6–13.7]	13.8 [13.7–13.9]	13.4 [13.3–13.5]
September	12.6 [12.5–12.6]	13.8 [13.8–13.9]	11.1 [11.0–11.1]
October	15.1 [15.0–15.1]	16.1 [16.0–16.1]	13.9 [13.8–14.0]
November	15.1 [15.1–15.2]	14.6 [14.6–14.7]	15.7 [15.6–15.8]
December	5.9 [5.8–5.9]	5.7 [5.6–5.7]	6.1 [6.1–6.1]
Days from symptom onset to presentation to care			
0–3	54.9 [54.8–54.9]	61.4 [61.3–61.5]	47.1 [47.0–47.2]
4–7	34.3 [34.2–34.3]	30.1 [30.0–30.2]	39.3 [39.2–39.3]
8-over	10.9 [10.8–10.9]	8.5 [8.5–8.6]	13.6 [13.6–13.7]

*Human resources and hospital equipment index represents state-level health system resources available in 2018.

two prior coronavirus related outbreaks, namely the Severe Acute Respiratory Syndrome (SARS, first reported in 2003) [30], and the Middle East Respiratory Syndrome (MERS, first reported in 2012) [31], documented heightened illness severity among individuals with diabetes [32–33]. Although the high prevalence of diabetes among patients hospitalized with these infections raised concern about a higher risk of infection, these studies were limited to data on hospitalized patients only. In the current and far deadlier coronavirus pandemic, several studies using population-level data have been conducted on the prevalence of SARS-CoV-2 among individuals with diabetes showing conflicting findings. An analysis of U.S. data found that individuals with laboratory-confirmed SARS-CoV-2 had a higher prevalence of diabetes compared to adults in the general U.S. population (31.2% vs. 12.7%)

[13], whereas a meta-analysis of six studies conducted in China showed that the prevalence of diabetes among individuals with COVID-19 was similar to the background prevalence of diabetes in China [14].

Our findings have several policy implications. First, given the high prevalence of diabetes globally (463 million adults) [1], and the disproportionate burden of diabetes in low- and middle-income countries (LMICs), risk mitigation strategies should continue to be emphasized for this high-risk population. Second, strategies for the timely and equitable distribution and administration of COVID-19 vaccines, which have been primarily allocated to high-income countries [34], should consider the high concurrent burden of diabetes and COVID-19 in LMICs and improve allocation efforts to reach those at highest risk living in lower resource contexts. Third,

Table 2 – Study population characteristics before and after propensity score matching of the cohort who underwent SARS-CoV-2 testing, according to diabetes status.

N (%)	Before matching (N=2,314,022)			After matching (N=507,114)		
	No Diabetes (A) 2,043,525 (88.3) % or mean and 95% CI	Diabetes (B) 270,497 (11.7)	Abs. Diff. (%) (B-A)/A	No Diabetes (A) 253,557 (50.0) % or mean and 95% CI	Diabetes (B) 253,557 (50.0)	Abs. Diff. (%) (B-A)/A
Female	52.5 [52.4–52.6]	51.1 [51.0–51.3]	2.6	50.3 [50.1–50.5]	51.2 [51.1–51.4]	1.9
Age (years)						
18-35	42.3 [42.2–42.3]	5.8 [5.7–5.9]	86.3	5.6 [5.5–5.7]	6.2 [6.1–6.3]	9.5
36-50	34.2 [34.1–34.3]	26.2 [26.0–26.3]	23.5	27.5 [27.3–27.7]	27.8 [27.6–27.9]	1.0
51-65	17.4 [17.4–17.5]	42.7 [42.5–42.9]	144.9	43.0 [42.8–43.2]	42.3 [42.2–42.5]	1.5
65-over	6.1 [6.1–6.1]	25.3 [25.2–25.5]	315.7	23.9 [23.7–24.1]	23.7 [23.6–23.9]	0.8
Indigenous language	0.7 [0.7–0.7]	1.1 [1.0–1.1]	59.6	1.0 [1.0–1.1]	1.0 [1.0–1.1]	3.6
Obesity	13.4 [13.4–13.5]	25.7 [25.5–25.9]	91.7	25.4 [25.3–25.6]	25.2 [25.1–25.4]	0.7
Hypertension	10.7 [10.6–10.7]	53.4 [53.2–53.6]	401.7	50.1 [49.9–50.3]	50.4 [50.2–50.6]	0.5
Cardiovascular disease	1.1 [1.1–1.1]	5.2 [5.1–5.3]	369.1	4.1 [4.1–4.2]	4.6 [4.6–4.7]	12.1
Chronic kidney disease	0.8 [0.8–0.8]	7.1 [7.0–7.2]	753.1	3.7 [3.7–3.8]	4.4 [4.3–4.5]	18.6
COPD	0.7 [0.7–0.7]	3.6 [3.5–3.6]	388.5	3.0 [2.9–3.1]	3.2 [3.1–3.3]	6.9
Asthma	2.7 [2.7–2.7]	2.9 [2.9–3.0]	8.5	2.8 [2.7–2.8]	3.0 [2.9–3.0]	6.0
Municipality social deprivation index	-1.4 [-1.4–-1.4]	-1.4 [-1.4–-1.4]	3.3	-1.4 [-1.4–-1.4]	-1.4 [-1.4–-1.4]	0.5
Healthcare setting						
Ambulatory	90.1 [90.1–90.2]	63.3 [63.1–63.5]	29.7	67.9 [67.7–68.0]	67.1 [66.9–67.3]	1.1
Hospitalized	9.3 [9.3–9.4]	34.5 [34.3–34.6]	269.0	30.2 [30.0–30.4]	30.8 [30.6–31.0]	1.9
ICU admission	0.3 [0.2–0.3]	1.0 [1.0–1.1]	307.6	0.9 [0.9–0.9]	1.0 [0.9–1.0]	7.5
Mechanical ventilation	0.3 [0.3–0.3]	1.2 [1.2–1.2]	314.0	1.0 [1.0–1.1]	1.1 [1.1–1.2]	10.1
Health care provider: Ministry of Health	32.3 [32.4–32.5]	43.7 [43.5–43.9]	34.5	41.3 [41.1–41.5]	41.6 [41.4–41.8]	0.7
Human resources and hospital equipment*						
Lowest	18.6 [18.6–18.7]	21.6 [21.4–21.7]	15.8	21.1 [21.0–21.3]	21.2 [21.1–21.4]	0.5
Low	15.9 [15.8–15.9]	15.3 [15.2–15.5]	3.5	15.0 [14.9–15.1]	15.3 [15.1–15.4]	1.8
Middle	20.9 [20.8–21.0]	22.2 [22.1–22.4]	6.4	22.3 [22.2–22.5]	22.2 [22.1–22.4]	0.5
High	12.5 [12.5–12.6]	12.2 [12.1–12.3]	2.6	11.6 [11.5–11.7]	12.0 [11.9–12.1]	3.4
Highest	32.0 [32.0–32.1]	28.6 [28.5–28.8]	10.7	29.9 [29.8–30.1]	29.3 [29.1–29.4]	2.2
Month of presentation to care						
March-April	3.7 [3.7–3.7]	4.4 [4.3–4.5]	18.7	4.4 [4.3–4.4]	4.4 [4.3–4.5]	0.5
May	7.7 [7.6–7.7]	8.1 [8.0–8.2]	5.9	8.1 [8.0–8.2]	8.1 [8.0–8.2]	0.1
June	11.7 [11.7–11.8]	12.0 [11.9–12.1]	2.4	12.0 [11.8–12.1]	12.0 [11.9–12.1]	0.3
July	14.3 [14.3–14.4]	15.4 [15.3–15.6]	7.9	15.6 [15.5–15.8]	15.4 [15.3–15.6]	1.3
August	13.6 [13.5–13.6]	14.2 [14.0–14.3]	4.5	14.3 [14.1–14.4]	14.1 [14.0–14.3]	0.9
September	12.7 [12.6–12.7]	11.8 [11.7–11.9]	6.6	11.8 [11.7–11.9]	11.9 [11.7–12.0]	0.5
October	15.2 [15.2–15.3]	14.0 [13.9–14.2]	7.8	14.1 [13.9–14.2]	14.1 [14.0–14.2]	0.3
November	15.2 [15.2–15.3]	14.4 [14.3–14.6]	5.1	14.4 [14.3–14.6]	14.5 [14.3–14.6]	0.0
December	5.9 [5.9–5.9]	5.5 [5.4–5.6]	6.5	5.4 [5.3–5.5]	5.6 [5.5–5.6]	3.2
Days from symptom onset to presentation to care						
0-3	55.8 [55.7–55.8]	48.2 [48.0–48.4]	13.5	47.0 [46.8–47.2]	48.3 [48.1–48.4]	2.6
4-7	33.9 [33.8–34.0]	37.2 [37.0–37.4]	9.7	38.0 [37.8–38.2]	37.2 [37.0–37.4]	2.0
8-over	10.4 [10.3–10.4]	14.6 [14.5–14.7]	41.1	15.0 [14.8–15.1]	14.5 [14.4–14.6]	3.1

Table 3 – Effect of having diabetes on the odds of testing positive for SARS-CoV-2 before and after propensity score matching.

	Before matching (N = 2,314,022)		After matching (N = 507,114) [†]
	Crude estimates	Adjusted estimates	
OR and 95% CI	1.63 [1.61–1.64] ^{***}	1.14 [1.13–1.15] ^{***}	1.09 [1.08–1.10] ^{***}

^{***} Signifies that $P < 0.001$.

[†] Matching was performed using 1:1 nearest neighbor algorithm with a value for maximum distance of controls (caliper) of 0.001. Bias-corrected 95% confidence interval from logit regression were obtained through the Delta method with 1000 bootstrap replication.

while awaiting immunization delivery and administration for individuals with diabetes, the care of patients with diabetes should continue to be adapted to optimize care continuity while mitigating the risk of SARS-CoV-2 exposure, such as through the use of telemedicine and mobile health platforms [35].

Our results should be interpreted with the following limitations in mind. First, while the question of greatest interest is whether individuals with diabetes are at higher risk of SARS-CoV-2 infection, our study findings are limited to SARS-CoV-2 test positivity as a proxy for infection risk. However, this analysis was strengthened by the use of propensity score matching to account for possible confounders in the association between diabetes and SARS-CoV-2 test positivity. Second, although our study design did not specifically account for surveillance bias (i.e. people with diabetes would be more likely to undergo testing), given that all individuals in the study underwent SARS-CoV-2 testing based on presence of symptoms suggestive of SARS-CoV-2, surveillance bias due to diabetes status is less likely. Nonetheless, given that individuals with diabetes are more likely to develop severe symptoms from SARS-CoV-2 [2–4], our analysis could have been subject to ascertainment bias given that individuals with diabetes may have been more likely to present to care, and hence undergo testing, as a result of a higher likelihood of symptomatic disease. However, the prevalence of diabetes among individuals who underwent SARS-CoV-2 testing of 11.7% is only slightly higher than the national prevalence of diagnosed diabetes reported in 2018 (10.3%) [18] (Appendix 1), which argues against overrepresentation of people with diabetes in the study population. Another important potential source of bias that our analysis may have been subject to is that of having limited the study population to those who found a nearest neighbor match. If individuals with diabetes and comorbidities (i.e. frail, elderly) were excluded due to not finding a match, this could have led to a lower overall prevalence of diabetes and comorbidities and to the underestimation in the reported odds of testing positive for SARS-CoV-2 among individuals with diabetes. Third, while self-reported diabetes is generally considered a reliable measure of diagnosed diabetes [36], our estimates do not include undiagnosed diabetes, which accounts for an estimated 30% of cases of diabetes in Mexico [37]. Additionally, we could not differentiate between type 1 and type 2 diabetes but given that the study population included was 18 years or older, there is a higher likelihood that the majority of cases correspond to type 2 diabetes.

Several other limitations exist with regards to the data used in this study. First, the data source used for this study was derived from a sentinel surveillance model, which repre-

sents only a population that presented to care and cannot be generalized to individuals who may have been infected with SARS-CoV-2 but did not present to any healthcare facility. Moreover, the study population underwent testing for SARS-CoV-2 a single time with either RT-PCR or rapid antigen testing, which have variable sensitivity and specificity and could have under or overestimated the true burden of SARS-CoV-2 [38]. Finally, despite the use of a rigorous method that reduces potential biases in the effect of having diabetes on SARS-CoV-2 positivity occurrence due to observed factors [39], the original sample size and its inferential power were reduced, and it is possible that the consistency of our results was affected by the existence of unobserved characteristics in the examined relationship. While we conducted several sensitivity analyses to confirm the robustness of the reported association, the estimates presented should be considered as a conservative estimation on the effect of diabetes on SARS-CoV-2 positivity.

In this study, we show that community-dwelling individuals with diabetes have higher odds of testing positive for SARS-CoV-2 when compared with individuals without diabetes. These findings have important implications for risk mitigation efforts and vaccine allocation for people with diabetes, particularly in low resource contexts with a high concurrent burden of diabetes and SARS-CoV-2.

Author contributions

JAS, ESM and VJW co-conceived the study. ESM and JAS led the analysis, which was carried out by ESM. JAS, VJW, and ESM wrote the first draft of the manuscript and all authors provided critical inputs on multiple iterations. All authors have approved the final version. ESM is the guarantor of the work, as such, had full access to all the data in the study and takes responsibility for the integrity of the data and the accuracy of the data analysis.

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Declaration of Competing Interest

DJW reports serving on a data monitoring committee for Novo Nordisk. JBM reports serving as an Academic Associate

for Quest Diagnostics. All other authors declare no competing interests.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.diabres.2021.108953>.

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