Tohoku J. Exp. Med., 2024, **262**, 211-220

Socioeconomic Disparity in the Effect of SARS-CoV-2 on Outpatient Visits among People with Type 2 Diabetes in Taiwan

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The severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) outbreak posed impact on healthcare. This study evaluated the effect of SARS-CoV-2 outbreak on the outpatient visits of patients with type 2 diabetes and determined the most affected groups. We analyzed Taiwan's National Health Insurance data, including 1,922,702 patients diagnosed with type 2 diabetes from 2018 to 2021. Group-based trajectory modelling identified four distinct outpatient visit patterns, namely, consistently high (Group 1, 74.2%), low-to-high (Group 2, 8.1%), high-to-low (Group 3, 6.0%) and consistently low (Group 4, 11.7%) utilization. Logistic regression was used to analyze correlations between trajectory types and patients' demographics and health statuses. Group 3 members had higher odds of being male [adjusted odds ratio (aOR) = 1.04, 95% confidence interval (CI) 1.03-1.05] and earning below 20,000 New Taiwan Dollar monthly (aOR = 1.29, 95% CI 1.26-1.31) than those in Group 1. However, they were less likely to be under 80 years old (aOR = 0.70-0.97), from lower median family income regions (aOR = 0.81-0.89) or possess a Charlson Comorbidity Index score > 2 (aOR = 0.67, 95% CI 0.66-0.68). Patients with lower income in affluent areas displayed the highest likelihood of falling into Group 3. Patients with type 2 diabetes and low income from wealthy areas were vulnerable during the pandemic. This result emphasizes the need to target resources and support for this subgroup during such crises.

Keywords: claims analysis; latent class analysis; SARS-CoV-2; socioeconomic disadvantage; type 2 diabetes mellitus
Tohoku J. Exp. Med., 2024 March, **262** (3), 211-220.
doi: 10.1620/tjem.2023.J104

Introduction

Diabetes is a prevalent disease with a significant global effect (Zimmet et al. 2014). The incidence of diabetes increases worldwide, and its adverse health consequences are devastating (Gregg et al. 2016; GBD 2021 Diabetes Collaborators 2023), including myocardial infarction (Kadowaki et al. 2008; Emerging Risk Factors Collaboration et al. 2010; Doi et al. 2010), stroke (Kissela et al. 2005; Emerging Risk Factors Collaboration et al. 2010; Doi et al. 2010), renal failure (Fioretto et al. 2006; Kalantar-Zadeh et al. 2021) and high mortality (Zimmet et

Received September 28, 2023; revised and accepted December 18, 2023; J-STAGE Advance online publication December 28, 2023
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al. 2016). In 2021, there were some 529 million people living with diabetes worldwide, and the global age-standardized total diabetes prevalence was estimated at 6.1%, with the highest age-standardized rates observed in North Africa and the Middle East. In addition, there were 37.8 million total diabetes-related years of life lost (YLLs), 41.4 million years lived with disability (YLDs), and 79.2 million disability-adjusted life-years (DALYs) (GBD 2021 Diabetes Collaborators 2023). Regular outpatient follow-ups constitute a crucial component of diabetes care and significantly mitigate complications, reduce mortality rates (Chan et al. 2021, 2022) and curtail overall healthcare expenditure (Wen et al. 2021). Consequently, the importance of routine follow-up evaluations is emphasized because they play a crucial role not only in optimizing individual diabetes management but also in effectively controlling expenditures within the healthcare system.

The coronavirus disease 2019 (COVID-19) pandemic caused by the spread of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) which broke out and swept across the globe in early 2019 has profound effects across societal, economic, medical and individual dimensions (Nouri et al. 2020; Yun et al. 2022). This phenomenon raises concerns about its potential effect on care of diabetes, especially outpatient follow-ups. Recurrent lockdowns and public health measures throughout the pandemic have restricted access to routine diabetes care, limiting new diagnoses, and affecting self-management, routine follow-ups, and access to medications, as well as affecting lifestyle behaviors and emotional wellbeing globally (Khunti et al. 2022). A time-series analysis assessed outpatient department (OPD) service utilization and diabetes-related hospitalizations over a period of 44 months (i.e., 2018-2021) in Ethiopia, and noted that female sex, older age, and COVID-19 were associated with impaired OPD service. In addition, OPD visits decreased differently by geographic area as COVID-19 cases increased (Benoni et al. 2022).

The allocation of limited medical resources to SARS-COV-2 has led to a shortage of healthcare personnel and resources (Wright et al. 2020; Kendzerska et al. 2021). Rigorous SARS-COV-2 prevention measures have negatively influenced the economy, employment, public transportation and access to healthcare. The fear induced by the pandemic, the decrease in income and the limitations placed on public transportation due to epidemiological guidelines may have changed individuals' inclination and ability to pursue regular healthcare (Tao et al. 2020). Therefore, accurately determining the effect of SARS-COV-2 on regular diabetes follow-up visits and identifying the most vulnerable groups affected are of utmost importance for establishing a resilient and equitable society.

Taiwan reported its first imported case of SARS-COV-2 on January 21, 2020. From March to April 2020, a social distancing measure of 1.5 m was implemented and the public was required to wear masks in crowded places, such as public transportation, medical facilities, schools and religious places. This study aims to evaluate the effect of SARS-CoV-2 outbreak on the outpatient visits by patients with type 2 diabetes and determined the most affected groups.

Materials and Methods

The study was approved by the National Chung Kung University Governance Framework for Human Research Ethics (No. 111–332). No further written informed consent is needed for this study as all the personal identification numbers used to inter-link the data were scrambled.

Sources of data and study patients

Data from Taiwan's National Health Insurance (NHI) medical claims (2018-2021), and Taiwan Death Registry (TDR) (2018-2021) were analyzed. The NHI claims are supervised by the National Health Insurance Administration, which also performs quarterly expert reviews on random samples of medical claims to ensure the accuracy of such claims (Chen et al. 2019). In Taiwan, all live births and deaths are legally required to be registered within 10 days after birth or death. The completeness of the TDR has been evaluated and considered high (Lu et al. 2000).

We searched for outpatient NHI claims of patients with type 2 diabetes. An individual was considered to have type 2 diabetes if he/she had an ICD-10-CM diagnostic code of 'E11' in the claim in 2018-2021 and received another one or more diagnoses within the subsequent 12 months. The first and last outpatient visits during the 12-month period should be separated by at least 30 days to avoid accidental inclusion of mis-coded patients (Chen et al. 2019). A total of 3,838,192 patients with type 2 diabetes were identified. We then excluded the following patients: had no outpatient visit in the first 6 months of 2018 (n = 1,695,853); aged < 18 years (n = 3,447) or > 116 years (n = 22); and died between 2018 and 2021 (n = 216,168). The reason for including only patients who had clinical visits beginning from the first half of 2018 and remained alive throughout the entire observational period was to ensure the study patients consistently had an opportunity to get access to health care. We limited the study patients to adults because healthcare-seeking behavior by children is largely the decision of their parents (Khasanah et al. 2023). The Monthly Bulletin published by the Ministry of the Interior indicated the oldest age of 116 years in December 2021 (https://www.moi.gov.tw/english/Default.aspx). A total of 1,922,702 patients with type 2 diabetes were analyzed. The flow chart of selecting study patients is presented in Supplementary Fig. S1.

Trajectory of outpatient visit

We used Group-based Trajectory Modelling (GBTM) to determine distinctive socio-demographic features of the outpatient visit trajectory by patients with type 2 diabetes. The approach is particularly useful in discovering heterogeneous subpopulations. Both Growth Mixture Modelling (GMM) and Group-Based Trajectory Modelling (GBTM) are applicable to categorical, continuous, and count data. Indeed, GBTM is a simplified version of GMM (Nagin and Odgers 2010). Additionally, both GMM and GBTM have the same advantages regarding handling missing data and allowing for correlated residuals. Unlike GMM, on the other hand, GBTM estimates fewer parameters and can thus run faster with fewer errors. Consequently, the results may be easier to interpret because the model is less complex (Jung and Wickrama 2008; Frankfurt et al. 2016).

We calculated the proportion of patients who made outpatient visits over each 3-month segment, known as a quarter, from the first quarter of 2018 through the final quarter of 2021, yielding a total of 16 quarters. We chose a 3-month interval to calculate the prevalence of outpatient visits, reflecting the NHI regulation that allows the majority of chronic disease prescriptions to be refilled every 3 months.

GBTM was performed with the PROC TRAJ macro with SAS statistical software. This method assumes that the population is composed of a mixture of distinct groups defined by their trajectories, and each group of patients follows similar patterns of developmental trajectories. The Bayesian information criterion (BIC) associated with models of various group numbers of trajectory fitted by intercept-only, linear, quadratic, or cubic terms (up to a third-order polynomial) was calculated to determine the final model with the best fit (Jones et al. 2001). The optimal trajectory group number was derived using the following formula: 2 (ΔBIC) > 2 (Jones et al. 2001; van Leeuwen et al. 2011). Supplementary Table S1 demonstrates that a group number of 4 with a cubic polynomial function (i.e., trajectories) shows the best fit of our data.

After the model was selected, the following diagnostic criteria were examined to judge model adequacy: (1) average posterior probability of assignment > 0.7; (2) odds of correct classification > 5; (3) estimated group probabilities that did not deviate from the proportions of group assignments; and (4) tight confidence intervals for group membership probabilities (Nagin and Odgers 2010; Kuo et al. 2020). Based on the four-group model with a cubic polynomial function and a stable standard error of the estimates, various indicators of model adequacy were acceptable: the average of the posterior probabilities of group membership for individuals assigned to the four groups was 0.94, and the odds of correct classification was 42.0. The average probability for each group was very close to the proportion of group assignments.

Socio-demographic variables and covariates

The socio-demographic variables included individual-level and aggregate-level characteristics. Age at the first-time outpatient visit for type 2 diabetes during the study period was analyzed. Monthly income was obtained from the beneficiary records of NHI claims and used to determine the paid insurance premium (Hsing and Ioannidis 2015). The insurance premium typically reflects the socioeconomic status of individuals. We grouped the city district/township of each patient's residential area or the location of their employment into three urbanization statuses (urban, satellite and rural) in accordance with a modified classification scheme (Lu et al. 2020). Information on the median family income for each of the 368 cities and townships in 2018 was retrieved from the Government Open Data, supervised by Taiwan National Development Council (http://data.gov.tw/node/17983).

Certain covariates included in the analysis were age, sex and Charlson Comorbidity Index (CCI). Information of patients' age and sex was also obtained from the beneficiary records of NHI claims, whereas the CCI was calculated from the diagnosed codes in the NHI claims. Considering that the frequency and consistency of patient visits might correlate with their disease severity, we calculated the CCI score for each study participant based on the NHI medical records claimed in a 3-year period prior to the first-time outpatient visit in 2018. The CCI is a widely used tool to predict 10-year mortality risk based on the presence of 17 different comorbid conditions. Each condition is assigned a score that reflects its associated risk of mortality, and the scores are totaled, with higher sums indicating higher mortality risk (Charlson et al. 1987).

Statistical analysis

To illustrate the distributions of the selected continuous variables, including monthly income, median family income for the township of residence, and CCI, we presented and analyzed them according to percentiles. For monthly income and median family income for the township of residence, three categories were used: < 25th, 25th-75th, and > 75th percentile. For CCI, two categories were created: < 50th and > 50th percentile. We also illustrated the distribution of age by categorizing it into non-older adults (< 60 years), young older adults (60-69 years), middle older adults (70-79 years), and olde older adults (> 80 years). ANOVA or Chi-squared test was used to evaluate the distributions of socio-demographic variables among patients with various trajectories. An unconditional polynomial logistic regression model was applied to estimate the crude and adjusted odds ratios (aORs) and the corresponding 95% confidence intervals (CIs) of a specific type of trajectory in relation to selected socio-demographic variables and covariates.

We were particularly interested in the socio-demographic characteristics of patients assigned to Group 3 (i.e., high-to-low utilization), who had high utilization before the outbreak but turned to utilize less in 2020 and 2021. As such, we performed stratified analyses according to participant's personal income level and the level of wealth indicated by family median income level of the residential city district/township.

All statistical analyses were performed using SAS statistical software (SAS System for Windows, Version 9.4, SAS Institute Inc., Cary, NC, USA) A p-value of < 0.05 was considered statistically significant.

Results

Trajectories of outpatient visits by the study participants

Supplementary Fig. S3 shows the observed and predicted trajectories of outpatient visits by all patients with type 2 diabetes in Taiwan before and during the SARS-CoV-2 pandemic. A slightly declining trend in outpatient visits was found during the 4-year study period.

The total number of patients were as follows: 1,432,960 patients in Group 1 (G1; *persistently high utilization*); 154,304 in Group 2 (G2; *low-to-high utilization*); 112,309 in Group 3 (G3; *high-to-low utilization*); and 223,129 in Group 4 (G4; *persistently low utilization*). Fig. 1 and Supplementary Fig. S2 show the observed (raw) and predicted (smoothed) group-specific trajectories of outpatient visits by patients with type 2 diabetes, respectively.

Characteristics of the study participants with various trajectories

Table 1 displays the socio-demographic characteristics of patients with type 2 diabetes, categorized based on their outpatient visit patterns during the study period. Patients in Groups 3 and 4 had lower utilization and were generally younger. Group 4 stood out with a higher proportion of female patients. The distribution of monthly income was similar among the three other groups. Patients in Group 2 were characterized by low-to-high utilization and had a higher prevalence of lower income. These patients also showed distinct distribution of urbanization levels and median family income in their residential areas, with a higher prevalence of urban living and residing in regions with higher median family income.

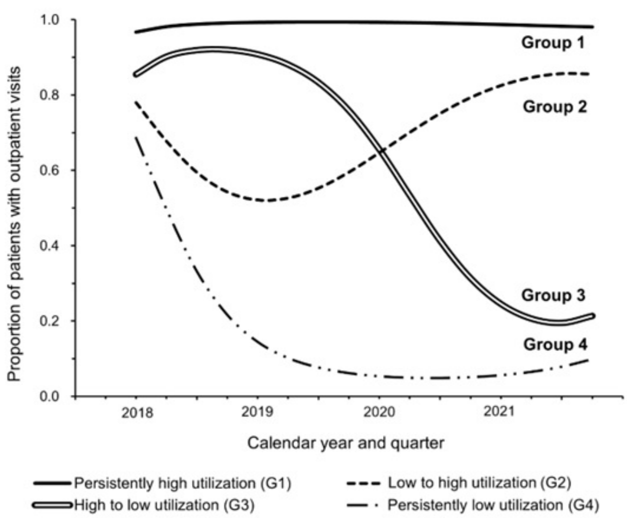

Fig. 1. Group-specific predicted trajectory of outpatient visits by patients with type 2 diabetes.
Group 1 (G1), Persistently high utilization; Group 2 (G2), Low to high utilization; Group 3 (G3), High to low utilization; Group 4 (G4), Persistently low utilization.

Associations between sociodemographic variables and various trajectories

Regarding the association between specific factors and group assignments, baseline younger ages (< 80 years) demonstrated a significant positive association with being assigned to Group 2 and a significant negative association with being assigned to Group 3. Sex played a role, with men having a higher likelihood of being in Group 3 (aOR = 1.04, 95% CI, 1.03-1.05) but a lower likelihood of being in Group 4 (aOR = 0.80, 95% CI, 0.79-0.81). Lower monthly income (< 20,000 New Taiwan Dollars, NTD) was significantly associated with increased odds of being assigned to Groups 2, 3 and 4. Furthermore, living in satellite areas showed a small but significant increase in the odds of belonging to Groups 2, 3 and 4 by a magnitude of 5%-9%. Rural living was also associated with significantly increased odds of being in Groups 2 and 3 by 6% and 5%, respectively. Median family income level in the living area also played a role in group assignments, with lower levels (< 620,000 NTD) being associated with increased odds of being in Groups 2 (aOR = 1.05, 95% CI, 1.03-1.07) and 4 (aOR = 1.03, 95% CI, 1.01-1.05) and significantly reduced odds of belonging to Group 3 (aOR = 0.81, 95% CI, 0.79-0.83). Compared with patients with a CCI score ≤ 2, those with a score > 2 were less likely to be in Groups 2 (aOR = 0.52, 95% CI, 0.51-0.52), 3 (aOR = 0.67, 95% CI, 0.66-0.68) and 4 (aOR = 0.19, 95% CI, 0.19-0.20) (Table 2).

Table 3 presents the findings on the significant interaction (p-value = 0.0241) between higher monthly income and lower family income in the residential region. In comparison with patients with higher personal monthly income and lower family income in the residential region, those with lower personal income only exhibited a significantly elevated aOR of 1.26 (95% CI, 1.23-1.29) for being assigned to Group 3. Patients with higher family income in the residential regions only also showed an increased aOR of 1.12 (95% CI, 1.10-1.14) for belonging to Group 3. When patients had lower personal monthly income and higher family income in a residential region, the aOR further increased to 1.41 (95% CI, 1.38-1.44) for Group 3, indicating an interactive effect of the two factors.

Discussion

This study highlights the socio-demographic differences among type 2 diabetes patients with various outpatient visit trajectories and sheds light on factors associated with group assignments. Group-specific predicted trajectory analysis revealed that 74.2% of patients maintained regular medical visits during the pandemic (Group 1), but approximately 6.0% transitioned from high healthcare utilization to low healthcare utilization (Group 3). Patients in Group 3 had lower personal monthly income, resided in higher income areas, older age, a higher proportion of males and lower CCI scores. Understanding these associa-

Table 1. Comparisons of characteristics between study participants with various trajectories of outpatient visits for type 2 diabetes in 2018-2021.

Characteristics	Total		Group 1 Persistently high utilization		Group 2 Low-to-high utilization		Group 3 High-to-low utilization		Group 4 Persistently low utilization		*p*-value
	n	%	n	%	n	%	n	%	n	%	
Total	1,922,702	100	1,432,960	100	154,304	100	112,309	100	223,129	100	
Age (years)											
< 60	672,082	34.96	449,989	31.40	67,706	43.88	42,982	38.27	111,405	49.93	< 0.0001
60-69	645,569	33.58	499,932	34.89	50,227	32.55	34,000	30.27	61,410	27.52	
70-79	413,111	21.49	332,846	23.23	25,833	16.74	21,628	19.26	32,804	14.70	
> 80	191,940	9.98	150,193	10.48	10,538	6.83	13,699	12.20	17,510	7.85	
Mean ± SD	63.99 ± 12.63		65.09 ± 11.91		61,26 ± 12.69		63.52 ± 13.74		59.05 ± 14.85		
Sex[a]											
Male	975,274	50.72	729,289	50.89	81,405	52.76	58,865	52.41	105,715	47.38	< 0.0001
Female	947,425	49.28	703,671	49.11	72,899	47.24	53,444	47.59	117,411	52.62	
Monthly income (NTD)											
< 20,000[b]	394,398	20.51	288,667	20.14	32,186	20.86	27,284	24.29	46,261	20.73	< 0.0001
20,000-39,999	1,015,743	52.83	765,590	53.43	79,836	51.74	55,089	49.05	115,228	51.64	
≥ 40,000	512,561	26.66	378,703	26.43	42,282	27.40	29,936	26.66	61,640	27.63	
Urbanization of residence											
Urban	827,096	43.02	618,508	43.16	63,528	41.17	50,882	45.31	94,178	42.21	< 0.0001
Satellite	610,795	31.77	448,417	31.29	52,129	33.78	36,150	32.19	74,099	33.21	
Rural	484,811	25.22	366,035	25.54	38,647	25.05	25,277	22.51	54,852	24.58	
Median family income for the township of residence (NTD)											
< 620,000	486,357	25.30	364,564	25.44	39,870	25.84	25,000	22.26	56,923	25.51	< 0.0001
620,000-819,999	941,293	48.96	700,283	48.87	76,683	49.70	54,604	48.62	109,723	49.17	
> 820,000	495,052	25.75	368,113	25.69	37,751	24.47	32,705	29.12	56,483	25.31	
CCI											
CCI ≤ 2	1,095,121	56.96	730,311	50.97	105,822	68.58	68,702	61.17	190,286	85.28	< 0.0001
CCI > 2	827,581	43.04	702,649	49.03	48,482	31.42	43,607	38.83	32,843	14.72	

NTD, New Taiwan Dollars; 1 US dollar ≈ 30 NTD; CCI, Charlson Comorbidity Index.
[a]Participants in the persistently low utilization group have missing information on sex.
[b]Including those who were not actively employed.

tions can provide valuable insights for healthcare professionals in tailoring interventions and supporting patients with different utilization patterns.

Our study showed an association between lower personal monthly income and reduced regular diabetic outpatient follow-ups during the pandemic, which echoed the prior findings that the pandemic caused by SARS-CoV-2 has disproportionately affected certain socially deprived groups, such as some minority ethnic populations (Martin et al. 2020), people living in a suboptimal home environment (e.g., an overcrowded space) or have little access to medical coverage (Barboza et al. 2021). The relationship between lower socioeconomic status and decline in clinical visit during the pandemic could be due to various reasons. Strict societal SARS-COV-2 control measures that limited economic activities may disproportionately affect individuals with low income because they often have fewer savings or financial reserves than their wealthier counterparts, leading to immediate and severe effects (Memmott et al. 2021). Additionally, healthcare facilities are considered high-risk areas for SARS-COV-2 infection. In Taiwan, between 2019 and March 2023, those infected with SARS-COV-2 were required to quarantine. Consequently, quarantine measures led to inability to engage in work, resulting in a loss of income. This situation substantially affected low-income individuals, likely leading to a decreased willingness to seek medical care. Moreover, economic hardships often prompt a reordering of healthcare priorities and financial allocations. The scenario leads to a higher likelihood of low-income individuals in reducing regular follow-ups for chronic diseases during the SARS-COV-2 pandemic. Therefore, financial assistance to low-income groups during the SARS-COV-2 pandemic may be critical in maintaining regular follow-ups for managing diabetes.

In addition to socioeconomic status, certain structure factors and health literacy could pose influences on health-

Table 2. Crude and covariate adjusted odds ratios of the specific trajectory of outpatient visits by patients with type 2 diabetes.

Characteristics	Group 2 Low-to-high utilization		Group 3 High-to-low utilization		Group 4 Persistently low utilization	
	Crude OR (95% CI)	Adjusted OR[a] (95% CI)	Crude OR (95% CI)	Adjusted OR[a] (95% CI)	Crude OR (95% CI)	Adjusted OR[a] (95% CI)
Age (years)						
< 60	2.14 (2.10-2.19)	1.83 (1.79-1.87)	1.05 (1.03-1.07)	0.97 (0.95-0.99)	2.12 (2.09-2.16)	1.57 (1.54-1.60)
60-69	1.43 (1.40-1.46)	1.29 (1.26-1.32)	0.75 (0.73-0.76)	0.71 (0.70-0.73)	1.05 (1.04-1.07)	0.85 (0.84-0.87)
70-79	1.11 (1.08-1.13)	1.05 (1.03-1.08)	0.71 (0.70-0.73)	0.70 (0.68-0.71)	0.85 (0.83-0.86)	0.77 (0.75-0.78)
> 80	Reference	Reference	Reference	Reference	Reference	Reference
Sex						
Male	1.08 (1.07-1.09)	1.01 (1.00-1.02)	1.06 (1.05-1.08)	1.04 (1.03-1.05)	0.87 (0.86-0.88)	0.80 (0.79-0.81)
Female	Reference	Reference	Reference	Reference	Reference	Reference
Monthly income (NTD)						
< 20,000[b]	1.00 (0.98-1.01)	1.19 (1.17-1.21)	1.20 (1.18-1.22)	1.29 (1.26-1.31)	0.99 (0.97-1.00)	1.24 (1.23-1.26)
20,000-39,999	0.93 (0.92-0.95)	1.01 (0.99-1.02)	0.91 (0.90-0.92)	0.98 (0.97-0.99)	0.93 (0.92-0.93)	1.02 (1.01-1.03)
≥ 40,000	Reference	Reference	Reference	Reference	Reference	Reference
Urbanization of residence						
Urban	Reference	Reference	Reference	Reference	Reference	Reference
Satellite	1.13 (1.12-1.15)	1.09 (1.08-1.11)	0.98 (0.97-0.99)	1.05 (1.03-1.06)	1.09 (1.07-1.10)	1.05 (1.03-1.06)
Rural	1.03 (1.01-1.04)	1.06 (1.04-1.07)	0.84 (0.83-0.85)	0.99 (0.97-1.01)	0.98 (0.97-1.00)	1.05 (1.03-1.06)
Median family income for the township of residence (NT)						
< 620,000	1.07 (1.05-1.08)	1.05 (1.03-1.07)	0.77 (0.76-0.79)	0.81 (0.79-0.83)	1.02 (1.01-1.03)	1.03 (1.01-1.05)
620,000-819,999	1.07 (1.05-1.08)	1.04 (1.03-1.06)	0.88 (0.87-0.89)	0.89 (0.88-0.91)	1.02 (1.01-1.03)	1.02 (1.01-1.04)
> 820,000	Reference	Reference	Reference	Reference	Reference	Reference
CCI						
CCI ≤ 2	Reference	Reference	Reference	Reference	Reference	Reference
CCI > 2	0.48 (0.47-0.48)	0.52 (0.51-0.52)	0.66 (0.65-0.69)	0.67 (0.66-0.68)	0.18 (0.18-0.19)	0.19 (0.19-0.20)

NTD, New Taiwan Dollars; 1 US dollar ≈ 30 NTD; OR, odds ratio; CI, confidence interval; CCI, Charlson Comorbidity Index.
[a]Based on the multinomial regression model, which simultaneously includes age, sex, urbanization, insurance premium and income.
[b]Including those who were not actively employed.

Table 3. Interaction of personal monthly income and median family income in a residential region on follow-ups in Group 3, which showed a decline in diabetes outpatient visits during the pandemic.

Characteristics		Group 1 Persistently high utilization		Group 3 High-to-low utilization		Crude OR (95% CI)	Adjusted OR (95% CI)
		n	%	*n*	%		
Personal monthly income (Median = 24,000 NTD)	Median family income in a residential region (Median = 697,000 NTD)	1,432,960	100	112,309	100		
≥ 24,000	≥ 697,000	506,723	35.36	40,273	35.86	1.16 (1.14-1.18)	1.12 (1.10-1.14)[a,b]
≥ 24,000	< 697,000	555,899	38.79	38,098	33.92	Reference	Reference
< 24,000	≥ 697,000	210,497	14.69	20,272	18.05	1.41 (1.38-1.43)	1.41 (1.38-1.44)[a,b]
< 24,000	< 697,000	159,841	11.15	13,666	12.17	1.25 (1.22-1.27)	1.26 (1.23-1.29)[a,b]

NTD, New Taiwan Dollars; 1 US dollar ≈ 30 NTD; OR, odds ratio; CI, confidence interval.
[a]Based on the logistic regression model, which simultaneously includes age, sex, urbanization and Charlson's Comorbidity Index.
[b]*p*-value and for the interaction between personal monthly income and median family income in a region is 0.0241.

care accessibility. Chaiban et al. (2022) conducted phone interviews with users of the International Committee of the Red Cross' Physical Rehabilitation Program and revealed that economic challenges, including rising costs of essentials, transportation issues, and limited income, were prominent. Structural obstacles, such as transportation availability and service quality, along with cultural factors like marginalization, were also identified. Personal barriers like inadequate psychosocial support and COVID-19-related fears heightened their vulnerability. Socio-culture reasons were also found to influence time-to-vaccination during the pandemic. Benoni et al. (2023) included adults vaccinated against SARS-CoV-2 receiving at least one dose in the Verona Province, Italy between December 27, 2020 and December 31, 2021, and found the average time-to-vaccination was 41.8 days (standard deviation, SD; 43.5) in the Italian population, and much longer at 71.6 days (SD 49.1) in the migrant one. A recent review included 21, 17 and 32 studies that evaluated health literacy related to COVID-19, SARS and MERS, respectively. This review noted certain sociodemographic determinants of lower health literacy including lower education, younger age, and male sex (Seng et al. 2023).

Our research demonstrates that residing in high-income regions during the SARS-COV-2 outbreak has a counterintuitive negative effect on regular diabetes follow-ups. High-income areas generally offer better infrastructure, more comprehensive public transportation systems, a more extensive healthcare system and a wider array of healthcare options, such as clinics, medium-sized hospitals and medical centers. However, during the pandemic, living in high-income regions led to a decrease in regular diabetes appointments. Possible explanations might be that the relatively higher cost of living in these regions leads to increased economic pressure during the pandemic. Furthermore, high-income areas are often located in urban regions, which offer more public transportation options, such as subways, metros or bus systems. Hence, residents in these high-income areas have more opportunities to use public transport (Taylor et al. 2009; Litman 2015). However, the effect of pandemic controls on public transport is more pronounced (Chang et al. 2021; Rasca et al. 2021; Qi et al. 2023). This insight is of great importance to policymakers. While much attention is paid to low-income districts, potential negative effects on high-income areas are also an issue that deserves serious consideration.

During the pandemic, while many regions experienced reduced clinical visits, the patients in Group 2 increased their outpatient visits. Despite global trends (Tu et al. 2022) showing fewer clinical visits during pandemic, Pendrith et al. (2022) highlighted a surge in visits among certain non-communicable disease patients. This Canadian study evidenced a rise in internal medicine clinic visits during the pandemic due to increased follow-up visits, outweighing decreased new consultations (Pendrith et al. 2022). This surge was credited to widespread virtual care usage. Variations in virtual care uptake were seen by clinic and diagnosis; congestive heart failure, hypertension, and asthma visits rose by 20%, while atrial fibrillation decreased by 20%. Notably, diabetes visits surged the most, by 59% (Pendrith et al. 2022).

Prior studies suggested older patients were less inclined toward virtual care and technology adoption (Levine et al. 2016; Ferguson et al. 2021; Kochar et al. 2021). Our data indicated Group 2 patients, compared to consistent outpatient seekers during the pandemic, were younger (61.26 vs. 65.09 years) with fewer comorbidities. However, the exact reasons behind an increase in clinical visit during the pandemic remain unclear due to limited availability of research data. Multiple patient, provider, and system factors might contribute to the variability in clinical visits during the pandemic.

The selection bias in this nationwide study is minimized considering that it includes more than 1.9 million diabetic patients and that the Taiwan's healthcare coverage exceeds 99.9%, including all levels of medical institutions. In addition to including basic patient information, this study also encompasses individual income and family income status of their residential area, allowing for the analysis of the interaction between personal and locational socioeconomic factors amidst the effect of SARS-COV-2. Given the association between regular follow-ups and the severity of the disease, this study incorporates CCI for further adjustment for potential confounding factors by disease severity.

Despite the above strengths, we acknowledged the following limitations in our study. First, information bias could occur due to the utilization of claimed data. To mitigate this bias, we set the inclusion criteria for patients as having two outpatient diabetes diagnoses within a year and two consultations of more than a month apart. These criteria can reduce accidental mislabeling or pre-emptive annotations made for fund claiming before official reporting. This selection method has been verified and can effectively confirm whether patients truly have diabetes in the Taiwan health insurance database (Ku et al. 2021).

Second, many important confounding factors might influence whether patients will adhere to regular follow-ups. This study could not access laboratory data and thus does not include blood sugar levels or HbA1c levels, which might be related to adherence to follow-ups. However, to consider disease severity, we incorporated the CCI score to partially adjust for the effect of potentially severe complications. Nonetheless, CCI scores may not totally reflect an individual's health status, for example, people in Group 3 who showed a decreased hospital visit might not only due to the pandemic but also because of their poor physical conditions which is unfortunately not available to this study. Third, our study analyzed changes in regular diabetes appointments in Taiwan from 2019 to 2022. Given that Taiwan has a robust national health insurance system and did not experience severe community transmission during this period, we were able to examine the possible effects of early strict containment measures on diabetes management. Nonetheless, SARS-COV-2 is a global challenge, with potential differences in the effects on regular follow-ups for diabetes across different systems, cultures and countries. Thus, caution should be exercised when extrapolating findings across diverse regions.

Because older adults with type 2 diabetes tended to have higher risk of mortality during the study period, especially after the start of pandemic, exclusion of these vulnerable patients from trajectory classifications might entail certain degrees of bias. To address this potential problem, we performed re-analyses of the data by including those who died during the study period. Supplementary Fig. S4 shows that a total of 5 trajectories were best identified, which is slightly different from what was obtained from data that excluded deceased patients.

A total of 2,138,870 patients with type 2 diabetes who made ≥ 1 clinical visit in the first two quarters of 2018, and 216,168 (10.1%) died during follow-up. Supplementary Table S2 shows the results from cross-analysis comparing between the trajectory classifications with (i.e., Group 1 to Group 5) and without (persistently high utilization, low-to-high utilization, high-to-low utilization, and persistently low utilization) inclusion of the participants who died during follow-up. The results show a substantial overlap of participants between "Group 1" and "persistently high utilization" group as well as between Group 2 and "high-to-low" group. Such high agreement was mainly due to low cumulative mortality (1.8-2.0%) in these two groups. Group 3, which also showed a decline in clinical visit during the pandemic, had the highest cumulative mortality (50.0%) during the follow-up, and 48.8% of the participants belonged to the "high-to-low" group. Both Groups 4 and 5 also experienced high cumulative mortality and demonstrated a rapid decline in clinical visit after the start of follow-up. This was particularly true for the Group 5.

Upon analyzing nationwide clinical records of 1.9 million patients with type 2 diabetes, our study revealed that under the SARS-COV-2 pandemic, the most vulnerable groups who were likely to show a decrease in regular visits for diabetes care were patients with very old ages, had lower comorbidity and were male. Patients with lower personal monthly income and living in high-income regions were also at elevated likelihood of declining diabetes follow-ups during the pandemic. During large-scale pandemics, such as SARS-COV-2, identifying such vulnerable groups and providing appropriate assistance are essential to safeguard the health consequences of patients with type 2 diabetes and other medical conditions.

Acknowledgments

Technical advice and assistance were received from Mr. Huang Hao-Gang in retrieving and managing various National Health Insurance claim datasets. This project was supported by grants from the Ministry of Science and Technology in Taiwan (MOST 111-2321-B-006-009-; NSTC 112-2314-B-006-067-MY3). The funder had no role in the design and conduct of the study; collection, management, analysis and interpretation of the data; preparation, review or approval of the manuscript; and decision to submit the manuscript for publication.

Conflict of Interest

The authors declare no conflict of interest.

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Supplementary Files

Please find supplementary file(s);
https://doi.org/10.1620/tjem.2023.J104