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**MH6191 - Practicum**

**Project Report**

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| **NAME** | **MATRICULATION NUMBER** |
| Ang Shu Wei | G2302794C |

Title of the project: Asthma-related medication oversupply and carbon footprint in the Singapore General Hospital (SGH) asthma cohort

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| --- | --- |
| Table of Contents | Page |
| 1. Background | 3 |
| 1. Problem Statement    1. Primary Objective    2. Secondary Objective    3. Tertiary Objective | 4 |
| 1. Dataset | 4 |
| 1. Methods used | 5 |
| 1. Results | 6 |
| 1. Conclusion | 6 |
| 1. Limitations & Future Work | 7 |
| 1. Reflections | 7 |
| 1. Acknowledgements | 8 |

1. **Background**

In the treatment of asthma, several types of medications are commonly used - Inhaled Corticosteroids (ICS), Inhaled Corticosteroids combined with Long-Acting Beta Agonists (ICS-LABA) and Short-Acting Beta Agonists (SABA).

Although asthma inhalers might have the same medication, it can, however come in different formulations. The more common formulations are the Metered Dose Inhalers (MDIs) and Dry Powder Inhalers (DPIs). For example, you can have Symbicort MDI and Symbicort DPI which are equally effective in treating controlling asthma. Why are there different formulations of asthma inhalers then? The choice of inhaler depends on patient's preference.

Despite having the same medication to treat asthma, the carbon footprint of Symbicort MDI is much significantly higher than Symbicort DPI by approximately 40 times (Table 1) due to the due to the propellent used in the inhaler.

Therefore, asthma inhalers especially the Metered Dose Inhalers (MDIs) can be quite detrimental to the environment’s carbon footprint because they contain hydrofluorocarbons (HFCs). While HFCs are not ozone depleting, they are potent greenhouse gases1. These potent greenhouse gases can lead to the worsening of the global warming situation.

Singapore has been experiencing erratic weather such as much warmer temperatures and extreme rainfalls in recent years. This situation of worsening climate change is largely due to the emission of the greenhouse gases. Based on projections, by 2050, at least 317 nights in Singapore are expected to be warm2.

To reduce the greenhouse gases, mainly the carbon dioxide (CO2), Singapore’s government has been committed to achieving net zero emissions by 2050 and has pledge the reduction of CO2 emissions by 36% from 2005 levels to 2030 levels3.

While there has been a lot of qualitative research on how inhalers will impact the environment, there has not been much quantitative research on this topic, thus it is worthwhile to investigate this research gap.

Since MDIs emit more CO2 emissions than Dry Powder Inhalers (DPIs), there are a few strategies that Singapore government hospitals like Singapore General Hospital (SGH) can emulate what other countries have done, such as promoting the switch of inhalers to lower carbon alternatives (i.e. from MDIs to DPIs)1 and implement programmes in educating the asthma patients in the storage of inhalers. In some of the qualitative literature reviews, effectiveness of pharmacist-delivered counselling4 on patients' knowledge and beliefs about the medicines, adherence level, and asthma control can lead to reduction in medication oversupply. As such, hospitals might want to set up workshops for pharmacists to counsel such patients and improve the worsening of medication oversupply problem.

What is medication oversupply? Medication oversupply refers to the situation where patients receive more medication than is necessary for their treatment (i.e. dispensed inhalers are more than prescribed inhalers). One of the reasons for medication oversupply is non-adherence as patients take more than required for their period of treatment and this can be measured using the medication possession ratio (MPR), based on the ratio of dispensed and prescribed duration obtained from the electronic medication records. The exact prescribed duration was used instead of an arbitrary duration such as 365 days (adopted in other studies) to avoid underestimation of MPR. The formula for MPR is as follows:

Medication Possession Ratio (MPR) for each defined interval (in days):

Where dispensed/prescribed duration, if not available on the database, were derived from:

Patients can be categorized into good adherence (MPR 0.75-1.2), poor adherence (MPR <0.75) or medication oversupply (MPR >1.2).5,6 Medication oversupply occurs when the inhalers were dispensed more than the required interval to the next visit and has not been associated with improved clinical outcomes.7

In this study, we are looking at the medication oversupply group. Medication oversupply is an important problem in the healthcare systems because it can lead to poor clinical outcomes and increased healthcare utilization. Adverse events from oversupplied medications can lead to increased exacerbations and potentially frequent switches of inhalers thus increasing the healthcare costs. Besides the increased healthcare utilization, these oversupplied medications, mainly the MDIs contributes to the environmental carbon footprint. This is a research problem which we want to address and discuss in this study.

1. **Problem Statement and objectives**

The below objectives are important because through understanding the extent of the problem and the causes due to medication oversupply, we can improve clinical practice and decrease the carbon footprint caused by the inhalers. From clinical practice perspective, medication oversupply problem can be solved through improved patient education and communication. From the environmental perspective, since MDIs produce much more carbon footprint this can have potential policy implications whereby hospitals can encourage patients to switch to lower carbon footprint alternatives like DPIs.

* 1. **Primary objective:** To understand the extent of medication oversupply (in terms of CO2 and medication cost) in asthma using the SGH cohort
  2. **Secondary objective**: To evaluate the patient-related and disease-related factors associated with medication oversupply.
  3. **Tertiary objective**: To examine any associations between the groups of patients (Inhaler switch / Inhaler switch (same drug, different device)/ No inhaler switch)and the frequency of Switches / Emergency Department (ED) Visits / Intensive Care Unit (ICU) admissions and Exacerbations.

1. **Dataset**

This is a retrospective cohort study whereby asthma patients were treated in Singapore's largest healthcare cluster from 2015 to 2019. These patient records can be retrieved from the SingHealth COPD and Asthma Data Mart (SCDM)8, an integrated real-world data database from the largest public health system in Singapore. There are 2 datasets – looking at the visits data of all patients (visits data) and at the patients’ data (cohort data). Patients with missing data on covariates and visits with missing dispensed or prescribed data were excluded from the study analysis. There are around 63,000+ visits in the visits data. In the cohort data, there are 8023 unique patients.

Before we can delve into the medication oversupply, we came up with the carbon footprint of the inhalers (Table 1) after confirming the brand’s strength and inhaler type through various publications9,10,11. In addition, we collaborated with the pharmacists to get the cost of each inhaler as well. Although there some costs of the inhalers are missing, we took the cost of a similar one to approximate it instead so that we can have a complete picture of the carbon footprint and the cost of inhalers of each patient. After which, we matched the cost and carbon footprint of each visit of the patient. We had to clean up the names of the inhalers so that the matching can be done smoothly.

As the names of the medication of the inhalers found in the dataset are not harmonized with the names of the carbon footprint of the inhalers, we did clean up the names to harmonize them before merging the carbon footprint data with the visits data.

As we need to find out how many switches each patient had, we need to ensure that the dispensed date of the inhaler is in the correct date format so that the visits of each patient can be ordered from the first visit to the last visit, and we can see in which visit did the switch in inhaler occur (if any).

1. **Methods Used**

We performed descriptive statistics (no. of inhalers, medication cost of inhalers and carbon footprint emitted from inhalers) of a multi-ethnic cohort of asthmatic patients seen in the largest public healthcare cluster in Singapore between 2015 and 2019 (Table 2). We also did the same to those patients with Medication Possession Ratio (MPR) > 1.2 (Table 3) where they are coined as medication oversupply group6.

One of the reasons for medication oversupply could be due to excessive SABA prescribing whereby a patient has been prescribed more than or equal to 3 SABA canisters in a year12. We coined this group of patients to be SABA Excessive Group. For these 2 groups, we calculated the average medication cost ($) per visit and average CO2/kg per visit respectively. And we performed logistic regression on this group to see how the changes of medication cost and carbon footprint affects the probability of SABA Excessive group.

To see the extent of medication oversupply, we also performed linear regression analysis on the no. of SABA canisters in a year on medication cost as well as carbon footprint respectively to see for each additional canister of SABA how does it affect the medication cost and carbon footprint.

Initially, the simple regression results for average carbon footprint per visit and no. of SABA canisters dispensed in a year is only with a R2 of 0.084 (Figure 3) while the simple regression results for average medication cost per visit and no. of SABA canisters dispensed in a year is slightly higher with a R2 of 0.19 (Figure 4). After analysing the respective scatterplots in relationship to the no. of SABA canisters dispensed in a year, we decided to remove some outliers (removing visits where average medication cost is less than $50 when the no. of SABA canisters dispensed is more than 20 and removing visits where average carbon footprint is less than 20 when the no. of SABA canisters dispensed is more than 20 too). After which the simple regression results have improved from R2 of 0.084 to 0.667 (Figure 5) for average carbon footprint per visit and improved from R2 of 0.19 to 0.507 (Figure 6) for average medication cost per visit.

To evaluate the patient-related and disease-related factors associated with medication oversupply, we performed multivariate logistic regression analysis on the patient-related and disease-related factors with the reference group ‘MPR <= 1.2’. Patient related factors included are age groups, gender, race, BMI groups. Disease-related factors include Allergic Conjunctivitis, Allergic Rhinitis, Chronic Pulmonary Diseases (COPD), Hypertension, Pneumonia, Asthma Counselling, and GINA Step.

Before looking at the correlation between the switch of inhalers with other variables such as the no. of switches or no. of visits done in the cohort data, we need to calculate the total no. of switch of inhalers done by each patient, tagging of whether the switch is from MDI or DPI or vice versa, and then arrange the dates from the oldest to the most recent one in the visits data first. This is done so that we can see on which visit did the switch occur then label that visit with the visit number. For example, on the 3rd visit, the first switch occurs, there is a 3 on the ‘switch visit’ column. Once we have completed the information in the visits data, we sliced the visits to get these 3 groups of patients - Inhaler switch *(same drug, same device)* / Inhaler switch *(same drug, different device)* / No inhaler switch to form the new cohort data. For those with switch of inhalers, we will take the visit which has the first switch. Once the new cohort data is formed, we can perform correlation tests.

1. **Results**

By looking at the temporal trends of the number of inhalers used (Figure 1), **SABA is the most dispensed inhaler followed by ICS-LABA MDI**. And **ICS-LABA is increasing across the years**.

We also looked at the temporal trends of those patients with Medication Possession Ratio (MPR) > 1.2 (Figure 2). **The average medication cost and carbon footprint of each patient in the medication oversupply group is higher than the non-medication oversupply group (i.e. MPR <= 1.2)**. For example, the average cost of ICS-LABA MDI in the oversupply group is $437.67 which is more than $335.38 in the non-medication oversupply group. This is the same for the carbon footprint whereby the carbon footprint for ICS-LABA MDI in the oversupply group is 136.38 kg as compared to 103.03 kg in the non-medication oversupply group. **The average medication cost per person is the highest for ICS-LABA at $437.67 and $335.38 respectively for medication oversupply group and non-medication oversupply group.**

From the 2 groups**, there is a significantly higher carbon footprint and medication cost for those in SABA Excessive Group** (Table 4). For each one-unit increase in the Average CO2, the odds of SABA Excessive Group occurring are 1.018 times higher (Table 5). For each one-unit increase in the Average medication cost, the odds of SABA Excessive Group occurring are 1.005 times higher (Table 6).

An increase in 1 SABA canister dispensed in a year leads to 0.8631 CO2 / kg increase in emissions (Table 8). Similarly, an increase in 1 SABA canister dispensed in a year leads to $2.67 increase in medication cost (Table 9). **This shows that an increase in 1 SABA canister leads to greater medication cost as well as greater carbon footprint.**

From the multivariate logistic regression (Figure 7), **Chinese is more likely to be associated with Oversupply group as compared to MPR<=1.2 group. Patients with GINA step 1 is more likely to have medication Oversupply as well.**

There is an increasing correlation from those without inhaler switch, inhaler switch, to those with inhaler switch (same drug, different device) when we look at the correlation between the ED Visits and ICU admissions and the correlation between Switches and Exacerbations (Figure 12). **This shows that those with inhaler switch (same drug, different device) is more associated with ED Visits and ICU admissions.**

1. **Conclusion**

ICS-LABA MDI contributes the greatest to carbon footprint. Over the years, SABA use did not decline (despite guideline recommendations) and ICS-LABA MDI use increased (possibly due to guideline recommendations for earlier ICS-LABA use). Average carbon footprint for ICS-LABA DPI is the lowest. However, they are one of the most expensive inhalers.

It might pose challenges for Singapore hospitals to encourage patients to switch from ICS-LABA MDIs to ICS-LABA DPIs due to the higher cost of switching. Alternative is to switch from branded to generic forms (symbicort to duoresp).

1. **Limitations & Future Work**

As this project hinges a lot on the definition of medication oversupply (MPR > 1.2) and a major limitation of MPR was that it does not indicate actual medication use and tends to overestimate the actual adherence.13 This was evident from the paradoxical association between optimal MPR and SABA overdispensation which was likely due to patients collecting excessive SABA canisters rather than actual SABA overuse. The intrinsic limitation of MPR also led to the overestimated proportions of patients with good adherence when a shorter study duration was used; the 1-year MPR of a frequent defaulter would be greater than the corresponding 5-year MPR due to a smaller denominator used.

Not all cost of the inhalers can be found, thus for the completeness of the study, we took the cost of the inhaler with the same brand although the dosage might be different, thus this might not reflect the true medication cost of each visit/ patient.

In future, it would be exciting to explore those patients with frequent exacerbations / ED visits but did not switch inhaler.

1. **Reflections**

This project has presented me various challenges and opportunities to deal with real world dataset and using the dataset and trying to solve the real-world problems – which in this case is to understand the extent of the carbon footprint in the hospital context and how we can solve this carbon footprint problem that asthma inhalers produce.

Challenges:

1. Steep learning curve: As this topic of asthma and its inhalers is relatively new to me, it is a steep learning curve for me to understand this project before embarking on it. Besides self-learning on asthma inhalers through online materials, I am grateful to be given the opportunity to connect with pharmacists who were able to give me a crash course on asthma inhalers which speeds up my understanding.
2. Time management: To juggle between my full-time job and the tasks set out to do for the project is challenging. The dataset only resides in a few computers due to strict access to patients’ data which only can be accessed during working hours. As such, I can only work on the dataset during working hours in between of my current working time. Also, all the codes must be typed out since there are no internet connectivity on such computers. To be more productive, I always prepare my codes in advance so that I can write quickly, run them, and troubleshoot (if needed). Once the codes are done, I will check my results before proceeding to the next task. I even set up weekly plans to ensure that I am on track with completing my objectives.

Opportunities:

1. To be able to collaborate with multidisciplinary team (data management team, pharmacists, clinicians) and be part of a meaningful project: By collaborating with different stakeholders, I can learn a lot from different perspectives and try out various methods that the team proposes when the results of the data are not too ideal.
2. To have a great mentorship experience: Although I am the one executing the project, the one who is driving this project is Dr Toh Mingren. He has been mentoring me throughout the project. We have weekly check-ins to present the results to him so that he can advise if those results make sense. Mentorship should not be one-way but a reciprocal relationship. The key is communication. Learn to be always in contact with Dr Toh so that we both are on the same page.
3. To have a great bonding experience and memorable friendships along this journey: I am grateful to be able to meet helpful, like-minded colleagues and team members who are motivated to make this project a success. I am glad that this path is not taken alone.
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**Appendices**

**Table 1:** **Carbon footprint and cost of each inhaler.**



**Table 2: All MPR (visits data)**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Number of units (canister, tablet)** | | | | | |
| Year | ICS MDI | ICS DPI | ICS-LABA MDI | ICS-LABA DPI | SABA |
| 2015 | 7,630 | 2,269 | 6,270 | 4,503 | 14,256 |
| 2016 | 7,627 | 2,222 | 8,281 | 6,167 | 15,551 |
| 2017 | 7,478 | 1,918 | 9,445 | 7,030 | 16,651 |
| 2018 | 7,074 | 1,707 | 10,593 | 7,438 | 16,613 |
| 2019 | 6,853 | 1,514 | 11,746 | 8,592 | 15,936 |
| 2015-2019 | 36,635 | 9,630 | 46,335 | 33,730 | 79,007 |
| **Total costs, $ (and per person)** | | | | | |
| Year | ICS MDI | ICS DPI | ICS-LABA MDI | ICS-LABA DPI | SABA |
| 2015 | $83,102 ($45.59) | $105,758 ($197.67) | $368,111 ($318.44) | $275,841 ($329.17) | $71,280 ($17.47) |
| 2016 | $86,665 ($45.85) | $103,567 ($195.78) | $492,973 ($334.67) | $380,880 ($350.40) | $77,755 ($17.69) |
| 2017 | $91,170 ($48.27) | $89,398 ($188.91) | $560,995 ($334.25) | $431,880 ($358.70) | $83,255 ($18.09) |
| 2018 | $97,531 ($52.52) | $79,563 ($186.77) | $624,134 ($329.18) | $452,557 ($323.02) | $83,065 ($17.70) |
| 2019 | $97,723 ($55.46) | $70,568 ($199.91) | $707,993 ($352.24) | $530,311 ($343.03) | $79,680 ($17.00) |
| 2015-2019 | $456,191 ($49.47) | $448,854 ($193.63) | $2,754,206 ($335.38) | $2,071,469 ($340.92) | $395,035 ($17.59) |
| **Total CO2/ kg footprint (and per patient)** | | | | | |
| Year | ICS MDI | ICS DPI | ICS-LABA MDI | ICS-LABA DPI | SABA |
| 2015 | 68,143 kg (37.38) | 740 (1.38) | 114,476 (99.03) | 3,377 (4.03) | 59,875 (14.67) |
| 2016 | 68,641 kg (36.32) | 705 (1.33) | 151,229 (102.67) | 4,630 (4.26) | 65,314 (14.86) |
| 2017 | 68,406 (36.21) | 634 (1.33) | 172,433 (102.82) | 5,278 (4.38) | 69,934 (15.19) |
| 2018 | 66,333 (35.72) | 603 (1.42) | 193,389 (102.00) | 5,591 (3.99) | 69,775 (14.87) |
| 2019 | 64,623 (35.68) | 503 (1.42) | 214,575 (106.75) | 6,453 (4.17) | 66,931 (14.28) |
| 2015-2019 | 335,146 (35.45) | 3,185 (1.37) | 846,102 (103.03) | 25,329 (4.16) | 331,829 (14.78) |

**Table 3**: **MPR > 1.2 (visits data)**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Number of units (canister, tablet)** | | | | | |
| Year | ICS MDI | ICS DPI | ICS-LABA MDI | ICS-LABA DPI | SABA |
| 2015 | 2,829 | 810 | 652 | 416 | 3,155 |
| 2016 | 2,807 | 724 | 933 | 706 | 3,490 |
| 2017 | 26,08 | 631 | 1,081 | 850 | 3,678 |
| 2018 | 2,515 | 583 | 1,280 | 989 | 3,743 |
| 2019 | 2,553 | 480 | 1,710 | 1,462 | 3,944 |
| 2015-2019 | 13,312 | 3,228 | 5,656 | 4,423 | 18,010 |
| **Total costs, $ (and per person)** | | | | | |
| Year | ICS MDI | ICS DPI | ICS-LABA MDI | ICS-LABA DPI | SABA |
| 2015 | $30,218 ($53.86) | $37,754 ($240.47) | $37,766 ($429.16) | $26,048 ($400.74) | $15,775 ($18.11) |
| 2016 | $30,592 ($52.93) | $33,746 ($219.13) | $53,895 ($441.76) | $44,956 ($468.29) | $17,450 ($18.63) |
| 2017 | $30,421 ($53.64) | $29,411 ($216.26) | $63,625 ($461.05) | $52,965 ($472.90) | $18,390 ($18.67) |
| 2018 | $33,527 ($59.13) | $27,174 ($204.32) | $75,322 ($440.48) | $61,658 ($395.24) | $18,715 ($17.85) |
| 2019 | $35,390 ($60.70) | $22,373 ($223.73) | $100,705 ($423.13) | $94,161 ($364.97) | $19,720 ($18.10) |
| 2015-2019 | $160,148 ($56.07) | $150,458 ($221.26) | $331,313 ($437.67) | $279,788 ($407.26) | $90,050 ($18.27) |
| **Total CO2/ kg footprint (and per patient)** | | | | | |
| Year | ICS MDI | ICS DPI | ICS-LABA MDI | ICS-LABA DPI | SABA |
| 2015 | 24,857 (44.31) | 216 (1.38) | 11,890 (135.11) | 312 (4.80) | 13,251 (15.21) |
| 2016 | 24,732 (42.79) | 164 (1.06) | 17,011 (139.43) | 530 (5.52) | 14,658 (15.69) |
| 2017 | 23,193 (40.90) | 170 (1.25) | 19,718 (142.88) | 638 (5.70) | 15,448 (15.68) |
| 2018 | 22,948 (40.47) | 180 (1.35) | 23,358 (136.60) | 744 (4.77) | 15,721 (15.00) |
| 2019 | 23,466 (40.25) | 124 (1.24) | 31,259 (131.34) | 1,097 (4.25) | 16,565 (15.21) |
| 2015-2019 | 119,196 (41.74) | 854 (1.26) | 103,236 (136.38) | 3,321 (4.83) | 7,5643 (15.35) |

**Figure 1: Temporal trends of the inhalers dispensed across the 5-year period.**

**Figure 2: Comparison of the average cost and average carbon footprint per patient across the 5-year period.**

**Table 4: Average carbon footprint and medication cost per visit in the two groups (patients in SABA Excessive group and patients with < 3 SABA in a year)**

|  |  |  |
| --- | --- | --- |
| **SABA.Can.Year.Excessive** | **Avg CO2 /kg per visit** | **Avg medication cost ($) per visit** |
| No | 77.4 | 17.3 |
| Yes | 101 | 21.5 |

**Table 5: Logistic regression to classify the two groups (patients in SABA Excessive group and patients with < 3 SABA in a year) against the average carbon footprint.**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Term** | **β estimate** | **Standard error** | **OR** | **P value** |
| Intercept (β0) | -0.886778 | 0.036716 | 0.411 | <0.001 |
| Average carbon footprint | 0.017932 | 0.001473 | 1.018 | <0.001 |

**Table 6: Logistic regression to classify the two groups (patients in SABA Excessive group and patients with < 3 SABA in a year) against the average medication cost.**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Term** | **β estimate** | **Standard error** | **OR** | **P value** |
| Intercept (β0) | -1.0092714 | 0.0388816 | 0.364 | <0.001 |
| Average medication cost | 0.0056859 | 0.0003732 | 1.005 | <0.001 |

**Table 7: Average carbon footprint and average medication cost per visit by no. of SABA canisters dispensed in a year**

|  |  |  |  |
| --- | --- | --- | --- |
| Total no. of SABA canisters dispensed in a year | No. of visits | Avg CO2  per visit | Avg medication cost  per visit |
| 1 | 1569 | 15.8 | 74.1 |
| 2 | 4464 | 17.4 | 76.3 |
| 3 | 4245 | 18.7 | 84.9 |
| 4 | 3184 | 20.3 | 92.1 |
| 5 | 2560 | 19.8 | 93.1 |
| 6 | 2010 | 20.3 | 107 |
| 7 | 1365 | 23.1 | 101 |
| 8 | 864 | 24.4 | 118 |
| 9 | 792 | 25.1 | 114 |
| 10 | 740 | 27.3 | 137 |
| 11 | 418 | 26.6 | 115 |
| 12 | 396 | 22.6 | 107 |
| 13 | 260 | 21.5 | 116 |
| 14 | 196 | 25.4 | 118 |
| 15 | 135 | 29.5 | 134 |
| 16 | 128 | 25 | 101 |
| 17 | 153 | 27 | 137 |
| 18 | 126 | 39.5 | 133 |
| 19 | 152 | 34.9 | 140 |
| 20 | 80 | 42.4 | 161 |
| 21 | 84 | 12.3 | 47 |
| 22 | 22 | 28.6 | 42.1 |
| 23 | 115 | 10 | 92.1 |
| 25 | 25 | 14.3 | 98.8 |
| 26 | 52 | 28.4 | 126 |
| 27 | 27 | 14.4 | 99.4 |
| 28 | 28 | 28.4 | 105 |
| 30 | 60 | 35.1 | 130 |
| 33 | 33 | 43.8 | 199 |
| 35 | 70 | 18.4 | 25.8 |
| 36 | 36 | 63.7 | 236 |

A graph of carbon footprint

Description automatically generated A graph with black dots and green line

Description automatically generated

*R2 = 0.19*

*P = 0.113*

*R2 = 0.084*

*P = 0.0138*

|  |  |
| --- | --- |
| **Figure 3: Linear regression results - Average CO2 by total no. of canister of SABA in a year (before removing outliers)** | **Figure 4: Linear regression results - Average medication cost by total no. of canister of SABA in a year (before removing outliers)** |

**A graph of carbon footprint

Description automatically generated A graph showing a line graph

Description automatically generated with medium confidence**

*R2 = 0.507*

*P < 0.001*

*R2 = 0.667*

*P < 0.001*

|  |  |
| --- | --- |
| **Figure 5: Linear regression results - Average CO2 by total no. of canister of SABA in a year (after removing outliers)** | **Figure 6: Linear regression results - Average medication cost by total no. of canister of SABA in a year (after removing outliers)** |

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 8: Simple linear regression analysis of average CO2 (Y) and no. of canister of SABA in a year (X)**  Multiple R2 = 0.6671   |  |  |  | | --- | --- | --- | | Covariates | Regression Coefficients | P | | Intercept | 15.3135 | <0.001 | | SABA.Can.Year | 0.8631 | <0.001 | | **Table 9: Simple linear regression analysis of average medication cost (Y) and no. of canister of SABA in a year (X)**  Multiple R2 = 0.5077   |  |  |  | | --- | --- | --- | | Covariates | Regression Coefficients | P | | Intercept | 80.0695 | <0.001 | | SABA.Can.Year | 2.6754 | <0.001 | |

**Table 10: Multivariate logistic regression to classify the two groups (patients with MPR<= 1.2 and patients with MPR > 1.2) against the patient-related and disease-related factors.**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Term** | **β estimate** | **Standard error** | **OR** | **P value** |
| Intercept (β0) | -0.89970 | 0.14432 | 0.40 | <0.001 |
| Age group 18 - <34 (β1) | 0.20600 | 0.14279 | 1.23 | 0.14911 |
| Age group 34 - <54 (β2) | 0.09130 | 0.12304 | 1.10 | 0.45808 |
| Age group 54 - <80 (β3) | 0.08101 | 0.10698 | 1.08 | 0.44888 |
| Gender Male (β4) | 0.10492 | 0.05689 | 1.11 | 0.06515 |
| Race Indian (β5) | -0.25121 | 0.08519 | 0.77 | <0.005 |
| Race Malay (β6) | -0.18888 | 0.07186 | 0.82 | <0.01 |
| Race Others (β7) | -0.26035 | 0.10687 | 0.77 | <0.05 |
| BMI Category Obese (>30) (β8) | 0.04557 | 0.08057 | 1.05 | 0.57168 |
| BMI Category Overweight (25 - <30) (β9) | 0.07870 | 0.07144 | 1.08 | 0.27059 |
| BMI Category Underweight (<18.5) (β10) | 0.43856 | 0.08253 | 1.55 | <0.001 |
| Allergic Conjunctivitis YES (β11) | 0.08700 | 0.08674 | 1.09 | 0.31586 |
| Allergic Rhinitis YES (β12) | -0.03463 | 0.06463 | 0.96 | 0.59206 |
| COPD YES (β13) | -0.23618 | 0.13073 | 0.78 | 0.07082 |
| Hyptertension YES (β14) | 0.17818 | 0.07617 | 1.19 | <0.05 |
| Pneunomia YES (β15) | -0.07619 | 0.09136 | 0.92 | 0.40431 |
| Asthma Counselling YES (β16) | -0.07066 | 0.06748 | 0.93 | 0.29507 |
| GINA.Step.New2 (β17) | -0.03084 | 0.06791 | 0.96 | 0.64973 |
| GINA.Step.New3 (β18) | -0.81520 | 0.07673 | 0.44 | <0.001 |
| GINA.Step.New4 (β19) | -1.59838 | 0.09598 | 0.20 | <0.001 |
| GINA.Step.New5 (β20) | -11.79894 | 186.28458 | 0.0000075 | 0.94950 |

**A white grid with black dots

Description automatically generated**

**Figure 7: Plot of the multivariate logistic regression to classify the two groups (patients with MPR<= 1.2 and patients with MPR > 1.2) against the patient-related and disease-related factors.**

**Figure 8: Total no. of switches across the different groups of patients**

**Figure 9: Total no. of ICU admissions across the different groups of patients**

**Figure 10: Total no. of Exacerbations across the different groups of patients**

**Figure 11: Total no. of ED Visits across the different groups of patients**

**Figure 12: Correlation between the groups of patients associated with the ED Visits/ ICU admissions/ Switches / Exacerbations**