Reflecting on Public Behavior With Artificial Intelligence-assisted Detection of Face Mask Wearing During the COVID-19 Pandemic

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Abstract

Background: COVID-19 has created health and socioeconomic damage worldwide, and face masks are a low-cost but effective method of preventing transmission of this disease. Artificial intelligence (AI)-assisted systems can come into play to help visualize the public's awareness of mask wearing and gain a better picture of whether there is adequate practice of protection during the outbreak. We reported the rate of face mask wearing by the general public using the artificial intelligence-assisted face mask detector, AiMASK.

Methods: This cross-sectional study was conducted between January 23 and April 22, 2021 in over 32 districts in Bangkok, Thailand. After the introduction of AiMASK, development and internal validation were performed, and average accuracy of 97.8% was found. Data were classified into a protected group (correct face mask wearing) and an unprotected group (incorrect or non-mask wearing). We analyzed the association between factors affecting the unprotected group using univariate logistic regression analysis.

Results: No significant difference was found between results from human graders and those of AiMASK using two proportion Z test ($p=0.74$). AiMASK detected a total of 1,124,524 people, the majority of whom were in the protected group (95.98%). The unprotected group consisted of 2.06% who practised incorrect mask-wearing, and the other 1.96% were those who did not wear masks. A moderate negative correlation was found between the number of COVID-19 patients and the proportion of unprotected people ($r = -0.507$, $p < 0.001$). People were 1.15 times more likely to be in the unprotected group during the holidays and in the evening than on working days and in the morning (OR=1.15, 95% CI 1.13-1.17, $p < 0.001$). Districts in the city center were 1.31 times more likely to have higher proportions of unprotected individuals than suburban districts (OR=1.31, 95% CI 1.28-1.34, $p < 0.001$).

Conclusions: AiMASK was as effective as human graders in detecting face mask wearing. The prevailing number of COVID-19 infections affected people's mask-wearing behavior, and half of the unprotected group were those who wore masks incorrectly. Public policies should communicate the importance of wearing masks consistently throughout the day and during holidays as well as providing instructions for effective mask wearing to prevent virus transmission.

1. Background

Coronavirus disease (COVID-19), caused by the infection of coronavirus 2 (SARS-CoV-2), leads to severe acute respiratory syndrome, and this new emerging disease is spreading globally. The first reported cluster was from Wuhan, China, in January 2019. (1) As of July 3, 2021, there have been over 180 million confirmed cases of COVID-19, with nearly 4 million deaths. (2) This coronavirus pandemic is affecting not only the health and well being of the population, but also socioeconomic aspects. (3–5) COVID-19 is transmitted via droplets from symptomatic and asymptomatic infected people. (6, 7) Caring for COVID-infected patients is a major concern as treatment methods and vaccines are being developed. Primary

prevention is also an important aspect of disease control; therefore, protection against virus transmission through droplets is vital. (8–10)

Wearing a face mask is one easy and effective way to protect against droplet transmissions of many diseases, including COVID-19.(11) There is ample evidence to show that face masks can reduce infection rates at a cost-effective level, (9, 12–15) and current WHO guidelines recommend wearing them to decrease transmission of the disease.(16) After the spread of coronavirus, many studies published in the literature proved that mask wearing reduces the spread of the virus. (17–20) The government has launched campaigns providing detailed information on daily mask wearing, but their effectiveness in the community has not been assessed. (21) Artificial intelligence (AI)-assisted systems can come into play to help visualize the public's awareness of mask wearing to give a better picture as to whether there is adequate practice of protection during the outbreak.

Bangkok has been reported as the city with the highest number of COVID-19 patients in Thailand. (22) The Department of Public Health, Ministry of Higher Education, Science, Research and Innovation together with Sirindhorn International Institute of Technology, Thammasat University, have created an AI-assisted face mask detector, and it has been used since January 23, 2021.

This research provides comprehensive information on the development of AI-assisted face mask detection, its results, and clinical correlations with the number of new cases in Bangkok.

2. Materials And Methods

The study protocol was approved by the institutional review boards of Rajavithi Hospital, Thailand and of Sirindhorn International Institute of Technology (SIIT), Thammasat University.

AI-assisted face mask wearing (AiMASK)

Data was gathered with the AiMASK system, developed using advanced object detection technology (Scaled-YOLOv4). The initial developmental phase utilized training sets and testing sets of images obtained from closed-circuit televisions (CCTVs) around the city. Images were categorized into 4 groups: correct mask-wearing, incorrect mask-wearing, non-mask-wearing, and ungradable. The total images used in the training set was 10,775, with 3,910 images labeled as correct mask-wearing, 2,175 deemed incorrect mask-wearing, 1,460 images being of non-mask-wearing individuals, and a further 3,230 images marked as ungradable. (Table 1)

The correct mask-wearing group consisted of people whose face masks covering their mouth, nose, and chin simultaneously, while the incorrect mask-wearing group was composed of people who wore a face mask that did not cover their mouth, nose, and chin at the same time. The non-mask-wearing group was made up of those whose face mask was not detected. Ungradable images were those identified of humans whose faces could not be detected, such as views of the back of someone's head or of people wearing helmets.

After training was completed successfully, internal validation was performed using the testing set of images which were categorized into the four groups as follows: 368 correct mask-wearing; 280 incorrect mask-wearing; 168 non-mask-wearing; and 290 ungradable. The average accuracy of AiMASK was 97.8% (95%CI; 96.55–98.69%), and AiMASK accuracy percentages in each group were 98.91%, 96.42%, and 97.67% for the correct mask-wearing, incorrect mask-wearing, and non mask-wearing groups respectively. (Table1)

Table 1
Overall performance of AiMASK on training and testing datasets

	Total (N = 11,867)	Training set (N = 10,775)	Testing set (N = 1,092)			
			Sample Images	AiMASK	Accuracy	CI 95%
Correct mask-wearing	3,558	3,190	368	364	98.91%	97.24– 99.70%
Incorrect mask-wearing	2,455	2,175	280	270	96.42%	93.53– 98.27%
Non-mask-wearing	1,632	1,460	172	168	97.67%	94.15– 99.36%
Ungradable	3,502	3,230	272	290		

AiMASK data collection

Having been verified internally and externally, AiMASK was used to gather information for this study. Data classified as ungradable were manually allocated into the correct group. The non-mask-wearing and incorrect mask-wearing groups were confirmed manually as well.

AiMASK analyzed recorded videos from the same CCTVs from which that the training images were gathered. Files from CCTVs in various areas in every district around Bangkok were sent to AiMASK for evaluation. Each file collected had a duration of one hour, and all data were updated on the AiMASK website daily. (<https://aimask.aiat.or.th/>)

AiMASK detected images from public areas over 32 districts of Bangkok's 50 districts collected between January 23, 2021, and April 22, 2021 (90 days). Videos were taken from two separate timeframes, one during the morning (7am-8am), and one during the evening (5pm-6pm). We subcategorized days into working days and holidays, with working days defined as Monday to Friday, and holidays defined as weekends and public holidays. We also subcategorized data by type of place from which images were gathered into 7 categories: market entrances; inside the markets; public transportation (bus stops and sky

trains); malls and convenience store entrances; building entrances; footbridges; and along the sidewalk. The 32 districts were subdivided into 2 groups: the city center and suburban districts.

The numbers of COVID-19 patients were taken from the daily official reports from Bangkok Metropolitan Data Center which reveals new cases over a 24-hour period. New clusters of COVID-19 in this research comprised 2 big events announced by the Department of Disease Control under the Ministry of Public Health. The first cluster was reported on March 14, 2021, from Bang Kae, and the second cluster was in Thonglor on April 5, 2021. Patients who tested positive were reported according to their current residential district.

Outcome measures

Data were categorized into two groups for analysis: the protected group, which was the correct mask-wearing group; and the unprotected group, consisting of people from both the incorrect mask-wearing and non-mask-wearing groups. The primary outcome was the proportion of the protected and unprotected groups together with correlations with the reported number of COVID-19 infections. The secondary outcome was identification of factors showing correlations with the varying proportions of the unprotected group.

Statistical Analysis

Descriptive statistics were used to report the total number of people analyzed by AiMASK and the proportion of mask wearing. Continuous data were reported using mean, median, and standard deviation (SD). External validation of AiMASK was analyzed by two proportion Z-test. The correlation between the number of COVID-19 infections and the relative size of the unprotected group was calculated by Pearson's correlation coefficient. A "very high" correlation was defined as a correlation coefficient of 0.90–1.00, a "high" correlation was a value of 0.70–0.89, a "moderate" correlation was defined as a correlation coefficient of 0.50–0.69, and a "low" correlation was a value of 0.30–0.49. Little or no correlation was considered to be a correlation coefficient ≤ 0.29 .

The categorical variable group were compared using the Chi-Square test. Data were analyzed using univariate analysis with 95% confidence interval (CI), and $p < 0.05$ was considered statistically significant. All analyses were performed with SPSS 16.0 for Windows (SPSS Inc., Chicago, IL, USA).

3. Results

External validation of AiMASK

After internal validation was completed, we randomly selected 32 (one-hour) CCTV files from each of the 32 districts and compared the results of the human graders with those of AiMASK. Human graders counted 3,681 people, with 3,623 in the correct mask-wearing group, 47 in the incorrect mask-wearing group, and 11 in the non-mask wearing group. AiMASK detected 3,682 people, 12 of whom were classified as ungradable, while 3,619 people were counted as correct mask-wearing, 42 people as

incorrect mask-wearing, and 9 people were classified in the non-mask-wearing group. The proportion of individuals in the correct mask-wearing group counted by human graders was 0.984 (3623/3681), while that of AiMASK was 0.983 (3619/3682). No significant difference was found between human graders and AiMASK from two proportion Z-test ($p = 0.74$). (Table 2)

Table 2
External validation of AiMASK

	Human	AiMASK
Total number of people	3,681	3,682
Correct mask-wearing	3,623	3,619
Incorrect mask-wearing	47	42
Non-mask-wearing	11	9
Ungradable	0	12

Overall data

During the 90 days of the study, 1,124,524 people were analyzed from 32 different places distributed throughout every district of Bangkok, Thailand. The protected group accounted for the largest proportion at 1,079,276 (95.98 %) of the participants, followed by the unprotected group at 45,248 (4.02%, with the incorrect mask wearing and the non-mask-wearing groups constituting 2.06% and 1.96% respectively). The protected group constituted more than 90% of participants at every timepoint. The average number of places analyzed per day was 24.87 ± 5.34 , and the average number of people detected per day was $12,494 \pm 3044.63$.

During the same 90-day timeframe, the total number of new COVID-19 patients was 6,312. The median number of new daily cases was 15.5 (range 0-446). Two weeks before the Bang Kae cluster, the size of the unprotected group increased to 5.31%. During the same two weeks before the first cluster, an average of 4.2 cases were reported per day. The highest percentage of people in the unprotected group was 8.38% on March 14, 2021, the same day the Bang Kae cluster was announced. A day later, the size of the unprotected group decreased to 4.74%.

Twenty-three days after the Bang Kae cluster, another one was announced that was found in in the Thonglor area (April 5, 2021). On that day, the unprotected group accounted for 3.51% of the observed individuals. One day after the Thong Lor cluster, the unprotected group decreased to just 2.90% of the total. Ever since this second cluster, the proportion of the people in the unprotected group has varied between 2.18% and 3.84%. After the Thong Lor cluster, the mean number of cases reported per day was 272.9.

A negative correlation was found between the number of new COVID-19 patients and the size of the unprotected group ($r = -0.507$, $p < 0.001$). Overall, there was a moderate negative correlation between the amount of new COVID-19 patients and the proportion of people in the unprotected group. A decrease in new COVID-19 patients correlated with an increase in the size of the unprotected group. (Fig. 1)

Face mask wearing divided by place

The percentage of unprotected individuals in all 7 types of places showed statistically significant differences ($p < 0.001$). Of the 7 places, building entrances had the highest proportion of unprotected people at 5.85%, followed by on the sidewalk at 4.80%, and malls and convenience store entrances at 3.39%. The lowest percentage of unprotected individuals was found inside markets at 2.64%. The Odds Ratio (OR) of building entrances was 2.30 (95% CI 2.20–2.41, $p < 0.001$), while the OR of the sidewalk was 1.88 (95% CI 1.80–1.96, $p < 0.001$) compared with inside markets. (Table 3)

Face mask wearing divided by date and time

The percentage of unprotected people during the holidays (4.06%) was higher than on working days (3.40%). Sundays and Saturdays had the highest rates of unprotected individuals at 4.98% and 3.99% respectively, while Mondays had the lowest rate at 3.23% of the 5 working days. The percentage of unprotected people gradually increased as the week progressed, reaching its highest point on Friday at 3.55%.

The proportion of people in the unprotected group was significantly lower in the morning than in the evening (3.27% and 3.74% respectively, $p < 0.001$). Among the unprotected group, incorrect mask-wearing was more prevalent than non-mask-wearing both in the evening and in the morning.

Sunday evening had the highest rate of unprotected people at 5%. On holidays and in the evening, people were 1.15 times more likely to be unprotected than on working days and in the morning (OR = 1.15, 95% CI 1.13–1.17, $p < 0.001$). (Table 3)

Face mask in different districts

The 5 districts with the highest proportions of unprotected people were Yannawa (19.4%), Klong San (9.37%), Sathorn (9.18%), Bang Kholaem (7.62%), and Bang Rak (7.55%). All these 5 districts are situated in the center of Bangkok and are adjacent to each other. (Fig. 2). Districts in the city center were 1.31 times more likely to have higher rates of unprotected people than suburban districts (OR = 1.31, 95% CI 1.28–1.34, $p < 0.001$). (Table 3).

The 5 districts with the highest number of COVID-19 patients were Bang Kae (534 patients), Pasicharoen (358), Bang Khun Thian (280), Bangkokhen (231), and Chatuchak (219). No correlation was found between reported COVID-19 cases and unprotected people divided into each district.

Table 3

Univariate analysis of the unprotected group divided into type of public place, date, time, and districts.

Variables	Total (%) N = 1,124,524	%Unprotected (%Incorrect, %Non mask)	OR	CI 95%	p-value
Type of place					
Building entrances	75,284 (6.70)	5.85 (3.12,2.73)	2.30	2.20–2.41	< 0.001
Along the sidewalk	102,560 (9.12)	4.80 (2.76,2.04)	1.88	1.80–1.96	< 0.001
Mall and convenience store entrances	202,840 (18.04)	3.39 (1.96,1.43)	1.29	1.24–1.35	< 0.001
Market entrances	254,400 (22.62)	3.21 (1.73,1.48)	1.23	1.18–1.28	< 0.001
Public transportation (bus stops and sky train)	118,007 (10.50)	3.06 (1.54,1.52)	1.17	1.11–1.22	< 0.001
Footbridges	280,067 (24.90)	3.00 (1.92,1.08)	1.15	1.10–1.19	< 0.001
Inside markets	91,366 (8.14)	2.64 (1.54,1.10)	Ref		
Date					
Holidays	383,464 (34.10)	4.06 (2.26,1.80)	1.15	1.13–1.17	< 0.001
Working days	741,060 (65.90)	3.40 (1.88,1.52)	Ref		
Time					
Evenings	613,625 (54.57)	3.74 (2.16,1.58)	1.15	1.13–1.18	< 0.001
Mornings	510,899 (45.43)	3.27 (1.80,1.47)	Ref		
District					
City center	511,273 (45.47)	4.14 (2.32,1.82)	1.31	1.28–1.34	< 0.001
Suburban	613,251 (54.53)	3.19 (1.83,1.36)	Ref		

4. Discussion

AI-assisted face mask wearing (AiMASK)

Constant face mask detection is required in order to gather information about the public's compliance with recommendations regarding wearing face masks. While previous studies have used manual methods to acquire this information, AiMASK-assisted face mask detection methods have allowed us to monitor a large number of people in a short period of time with high accuracy. AiMASK's accuracy has been assessed using actual images captured from CCTVs through external validation processes. This study is the first to use AI-assisted face mask detection in real world settings. Previous studies from Egypt and China also developed a machine-learning device to detect face masks, but they only performed internal validation, with reported accuracy ranging from between 98–100%. (23, 24)

Overall data

The overall rate of mask-wearing in Bangkok was 95.98%. At the beginning of the year 2021 (January 22 to February 28), the percentage of unprotected people was 2.95%, during which the number of new COVID-19 patients was at around 8.7 cases per day. Two weeks before the first cluster was announced, the proportion of unprotected individuals increased to 5.31%, reaching its maximum at 8.38%. The increase in the unprotected group was due to the lower number of new infections per day, averaging at 4.2 cases, the low number of new cases resulting in people letting their guard down.

Immediately after the first cluster was announced, the size of the unprotected group started to decline gradually. Not long after the first, the announcement of the second cluster brought about a further decrease in the size of the unprotected group, which dropped to 2.61%. When the number of patients increase rapidly, people tend to exercise more care to protect themselves. The government has emphasized the importance of social distancing and self-protection ever since the pandemic began in Thailand in 2020. Even when the situation was improving, the public health department still encouraged everyone to keep their distance and to not drop their guard. Data provided by AiMASK showed that measures taken have not been effective enough to maintain adequate prevention. Awareness has been raised by the announcement of new outbreaks, and the longer the duration of sustained increases in new COVID-19 patients, the more the proportion of unprotected people decreases, with high correlations. This illustrates that when the public see that the situation is not showing signs of improving, they are more aware of the high risk of contracting the virus.

Interestingly, the unprotected group consisted more of incorrect mask-wearing people than of non-mask-wearing ones. The reason for improper usage of face masks might be carelessness or lack of knowledge; either way, measures should be taken to ensure not only mask usage but also correct mask usage. During the first COVID-19 outbreak in Thailand, availability of face masks was a problem, resulting in people not wearing masks; however, this was no longer a problem at the time this study was conducted.

Global comparison

A study of the rate of mask-wearing in public in Poland, which observed 2,353 people over 3 days, found that 65–75% of people wore masks.(25) Other studies used series of photographs to estimate rates of mask wearing from 3–5 April 2020, and they found rates in Cambodia, Peru, India, Mexico, and USA of 97%, 86%, 41%, 25%, and 21% respectively.(26, 27) Facemask wearing in France, Iran, and Hong Kong was reported at 56.4%, 45.6%, and 87% respectively. (28–30) A study in India reported that 64.9% of health-care workers in a tertiary care hospital wore face masks.(31)

A comparison of the rate of face mask wearing with the number of COVID-19 patients per 1 million population shows that the USA, Poland, Peru, Mexico, and India had high percentages of patients with lower rates of mask wearing; in contrast, Thailand and Cambodia have relatively higher rates of mask wearing and lower proportions of patients with COVID-19. We believe that effective face mask wearing, which reduces virus transmission in the community, is partly reflected through the numbers of COVID-19 patients, with countries with higher rates of compliance tending to have lower rates of COVID-19 infections. (Table 4)

Table 4

A comparison among different countries of the rates of wearing masks, the number of COVID-19 cases per one million population, and the ranking of number of COVID-19 cases per one million. (Last update July 3rd, 2021) (2)

Country	Rate of wearing mask	Number of cases per one million	Ranking of number of cases per one million
Cambodia (26)	97%	3,144	156
Thailand (This study)	96%	3,961	151
Peru (26)	86%	61,631	61
Poland (25)	65–75%	76,186	39
France (29)	56%	88,365	25
Iran (28)	46%	38,100	81
India (26)	41%	21,896	108
Mexico (26)	25%	19,428	112
USA (26)	21%	103,862	15

Face mask wearing divided by place

From our observation, the locations with the lowest unprotected rate was inside markets (2.64%). Since the start of the COVID-19 spread in Thailand, before the Bang Kae market cluster, another market cluster was reported in Samut Sakhon in December 2020. Markets became regarded as high-risk places for the

SARS-COV-2 virus, leading people to believe that they had a greater chance of contracting the virus if they went to the market, leading to their taking on self-protective measures such as wearing masks. In reality, although markets have a high density of people occupying a limited amount of space, conditions which lead to rapid spread, other places such as malls and closed spaces also present a high risk of virus infection. Anywhere occupied by people carries a risk of virus spread, whether low or high, and it is important to emphasize this to the community.

Face mask wearing divided by date and time

Higher rates of unprotected behaviour were found during the holidays, with Sunday evening showing the highest percentage, while the lowest rates were observed on Mondays, and this could be due to the desire for relaxation after a long week of working. People want to get dressed up, take nice photos, eat good food, and chat. Before the pandemic, wearing masks was not habitual; now, it is now mandatory on public transportation and in the workplace. Gradual adoption of this new habit might be the reason why on days when people are not strictly required to wear masks, they prefer not to.

There was a higher percentage of people in the unprotected group in the evenings than in the morning, showing that people have a tendency to relax protective measures more often in the evening than during the day. In the morning people get ready to go to work where they are required to wear masks, but in the evening after a long day at work, they travel back home where they do not need to. Since they are going straight home or going for dinner to places where masks are not worn, they might choose to leave the office without wearing one. Iran and Hong Kong reported that the rate of mask wearing in the morning was significantly higher than in the evening. (28, 32)

Knowing that during holidays and evenings people are prone to be under-protected, measures should be taken to emphasize the need to maintain mask wearing throughout the day and week. Offices and schools can help encourage people to check their protection before leaving and entering their premises. Strategies to boost the economy by promoting holidays might not be the best idea during this ongoing pandemic.

Face mask in different districts

The 5 districts containing the highest number of people in the unprotected group are all adjacent to each other and situated in central business areas. A study from France also reported the presence of independent associations between correct mask position with rural areas. (29) In contrast, the 5 districts with the highest number of COVID-19 patients were not those with the largest unprotected group. No correlation was found between reported cases and unprotected group according to districts, and this may be because the cases found in each district were reported according to where the people resided rather than where they contracted the virus.

Strengths and Limitations

This study is the first to use AI machines to detect mask wearing in public populations and had the largest number of participants in the world. The rates of mask wearing are counted by validated machines which are more reliable than the observations or questionnaires used in previous studies. (28, 29, 31, 33–35) We provided data over a period of 90 days which included both time frames of low contraction rates and high spread. We obtained data from various places across different districts and sub categorized this data according to distinct times of day and days of the week. Not only did we gather information on the percentage of people who wore a mask, but we also identified those who wore it incorrectly, which is tantamount to not wearing one.

In the hopes of providing a foundation for health care policies, we provided quantitative evidence of percentages of patients correctly and incorrectly wearing masks, and correlations with increased numbers of covid infections. Highlighting areas of higher rates of non-compliance with protective measures could possibly raise awareness of the issue in those places and lead to new improved strategies aimed at decreasing the risk of incorrectly worn masks. The fact that a number of people still wear masks incorrectly means that the information currently available is not adequate to raise the public's awareness of the danger of infection. This data is very important for policy makers, not only for COVID-19, but also for other future cases of droplet-borne respiratory tract infections.

One limitation of this study was that information was collected from a single city, Bangkok, which might not be representative of the total rates of mask wearing in Thailand. Another limitation is that the study did not address demographic data and the reasons for the lack of protection, such as whether people were careless, lacked knowledge, or had difficulties gaining access to masks. Lastly, our current AI machine could not differentiate the different types of masks used such as N95, cloth, and medical masks.

5. Conclusion

AI-assisted face mask detection illustrates the current rates of mask wearing which we believe reflects the public's awareness. Higher tendencies towards no protection were found in the evenings, during holidays, and in city centers. Though the overall rate of mask wearing in Bangkok is relatively high (95.98%), data has shown that lower rates of COVID-19 lead to increased numbers in the unprotected group, and whether this is a large or small percentage, it is still unprotected and presents the possibility of transmission, eventually leading to recurrent outbreaks. This study provides data which reinforces the generally-accepted fact that mask wearing is necessary to lower the risk of virus transmission. Policies focusing on current shortfalls will help maintain a high rate of protection.

Abbreviations

AiMASK: Artificial intelligence-assisted face mask

COVID-19: Corona virus disease 2019

Declarations

Ethics approval and consent to participate

The data collection method was observational, and there were no human participants in this study, so that it was unnecessary to obtain informed consent according to the regulations. The Ethics Committee of Rajavithi Hospital approved the protocol (Number 64139)

Consent for publication

Not applicable

Availability of data and materials

The dataset used and/or analyzed during the current study are available from the corresponding author on reasonable request

Competing interests

Not applicable

Funding

Not applicable

Authors' contributions

KS and TT were principle investigators of the study and drafted the manuscript. PR, PS and NK were advisors of the study. NS performed the statistical analysis. All authors read and approved the final version of the manuscript.

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Figures

Figure 1

Correlation between the unprotected group and reported new COVID-19 patients

Figure 2

Map of Bangkok highlighting the top five districts with the highest numbers in the unprotected group 1. Yannawa (19.4%), 2. Klong San (9.37%), 3. Sathorn (9.18%), 4. Bang Kholaem (7.62%), 5. Bang Rak (7.55%)