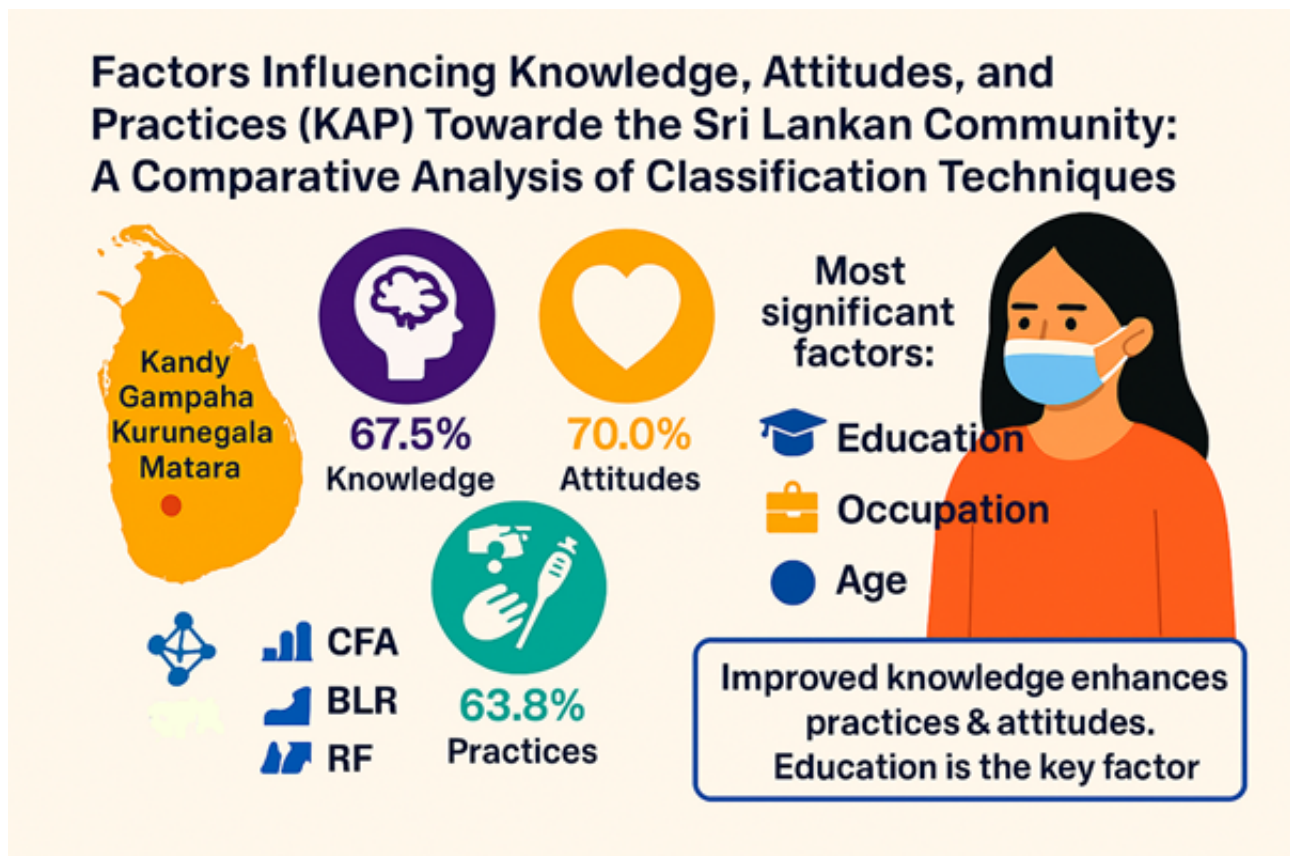


RESEARCH ARTICLE

Knowledge, Attitudes, and Practices towards COVID-19 and Their Sociodemographic Associations among Communities in Selected Districts of Sri Lanka

H.S. Jayaneththi, L.S. Nawarathna, M.E. Eremeeva and R.S. Rajakaruna

Graphical Abstract



Highlights

- 67.5% of participants demonstrated good knowledge, 63.8% good practices, and 70.0% a positive attitude towards COVID-19
- Education was significantly associated with all three KAP dimensions, followed by job, income, and age
- Confirmatory factor analysis identified key items contributing to the three KAP dimensions
- Binary logistic regression showed better overall classification performance than Random Forest
- Knowledge, attitudes, and practices were positively and significantly correlated

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Knowledge, Attitudes, and Practices towards COVID-19 and Their Sociodemographic Associations among Communities in Selected Districts of Sri Lanka

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Abstract

Coronavirus disease 2019 (COVID-19), caused by the SARS-CoV-2 virus, created a profound global health crisis that reshaped health systems worldwide. Compliance with preventive measures such as mask-wearing, hand hygiene, and vaccination is influenced by people's knowledge, attitudes, and practices (KAP) in Sri Lanka. Understanding these dimensions and the factors associated with them is vital for effective pandemic preparedness and control. This study examined the KAP of Sri Lankans towards COVID-19, explored sociodemographic predictors, and compared the performance of Binary Logistic Regression (BLR) and Random Forest (RF) algorithms in classifying KAP levels. Responses were collected from 80 adults across four districts using an online questionnaire adapted from validated tools comprising 48 items. Confirmatory Factor Analysis (CFA) was employed to preliminarily assess and refine the measurement structure, while BLR and RF were applied to assess predictors. Results showed that 67.5% of respondents demonstrated good knowledge, 63.8% good practices, and 70.0% a positive attitude towards COVID-19. Education was significantly associated with all three KAP dimensions in the univariate analyses, while age and education were associated with knowledge and attitude, and education with practice. In the multivariable BLR models, Advanced Level (A/L) education was significantly associated with higher odds of good knowledge and attitude, while no predictor was statistically significant for practice. CFA supported a reduced measurement structure in which a subset of items showed satisfactory factor loadings across the three KAP dimensions. A comparison of classification performance revealed that BLR demonstrated higher Area Under the Curve (AUC), accuracy, recall, and F1-scores than RF across all three KAP dimensions, although RF achieved higher precision for knowledge and practice. These findings underscore the critical role of education in shaping public responses and suggest that different KAP dimensions may benefit from different analytical approaches. The study offers valuable insights for policymakers and health authorities in designing targeted health education campaigns to address sociodemographic disparities and strengthen community resilience. Despite limitations of sample size and convenience sampling, the research provides a foundation for future large-scale, representative, and longitudinal studies on KAP and similar contexts.

Keywords: Confirmatory factor analysis; COVID-19; Knowledge, Attitudes, and Practices (KAP); Classification

INTRODUCTION

Coronavirus disease 2019 (COVID-19), caused by the Severe Acute Respiratory Syndrome Coronavirus 2

(SARS-CoV-2), was first detected in Wuhan, China, in December 2019 (Feng et al., 2020). The World Health Organisation declared the outbreak a global pandemic on 11 March 2020 (Cucinotta & Vanelli, 2020). Sri Lanka



reported its first confirmed case in February 2020 and rapidly implemented stringent public-health measures, including mandatory quarantine, nationwide curfews, and restrictions on public gatherings, to curb early transmission (Amaratunga et al., 2020).

By late 2021, the emergence of the Delta and Omicron variants significantly reshaped global transmission patterns and influenced public perceptions of risk and vaccine effectiveness (del Rio et al., 2021; Lambrou et al., 2022). During this period, several countries, including Sri Lanka, faced challenges such as vaccine hesitancy, misinformation regarding booster doses, and declining adherence to preventive behaviours (Lee & Chen, 2024; Perera et al., 2023; Rahman et al., 2024; Smith et al., 2022). In response, the Government of Sri Lanka (2022) introduced a National COVID-19 Response Plan emphasising community engagement, while outreach initiatives targeted rural and low-literacy populations to strengthen risk communication (Perera et al., 2023; World Bank, 2024).

Despite these efforts, a gap remains in Sri Lankan research examining Knowledge, Attitudes, and Practices (KAP) using multiple classification techniques. This gap is important because, in the absence of a definitive treatment for COVID-19, infection rates and healthcare demands can rise rapidly, and uncertainty about treatment options may lead individuals to adopt unverified or non-standard practices (Blendon et al., 2004). Globally, governments implemented border controls, social-distancing measures, and movement restrictions to slow transmission (WHO, 2020). Sri Lanka adopted similar measures, including a mandatory 14-day quarantine for international arrivals, border closures, suspension of entry visas, and isolation of suspected cases (Amaratunga et al., 2020).

Additional preventive strategies included banning public gatherings, closing educational institutions, enforcing an island-wide curfew with work-from-home arrangements, discontinuing non-essential services, promoting virtual meetings, encouraging respiratory etiquette, regulating consumer flow in markets, promoting online purchasing and doorstep delivery, limiting public-transport capacity, and restricting non-essential travel (Amaratunga et al., 2020). However, the early response also revealed several systemic limitations, such as outdated local-level population records, shortages of trained healthcare personnel, inadequate supplies of Personal Protective Equipment (PPE), inconsistencies in government circulars, and the establishment of ad hoc structures without clear legal mandates (Amaratunga et al., 2020).

Community KAP strongly shapes public adherence to preventive measures, which influences risk perception, fear, and behavioural responses during outbreaks (Azlan, et al., 2020). Evidence shows that knowledge and attitudes toward infectious diseases are closely linked to fear levels, which can hinder disease-control efforts and encourage reliance on alternative or unverified treatments (Blendon et al., 2004). Assessing KAP is therefore essential for

identifying knowledge gaps and behavioural patterns across sociodemographic groups, enabling health authorities to design targeted interventions and strengthen community resilience (Papagiannis et al., 2020). Improving public awareness remains critical for reducing pandemic risks and preventing community transmission.

Although several international studies have examined KAP in general populations or specific groups (Al Demour et al., 2021; Amaratunga et al., 2020; Sujarwoto et al., 2022), few have focused specifically on Sri Lanka. A Sri Lanka-specific analysis is necessary because the country's pandemic response, sociocultural context, and health-system structure differ significantly from those of other settings. For example, Sri Lanka adopted a stringent 'Zero-COVID' strategy during the early phase of the pandemic, supported by a strong primary healthcare network and extensive public-health infrastructure (Rannan-Eliya et al., 2024). These contextual factors, combined with variations in public trust, risk communication, and access to services, suggest that KAP patterns may differ from those observed elsewhere. Recent assessments also indicate that Sri Lankans exhibit distinct perceptions regarding long-term COVID-19 complications and health-system responsiveness, underscoring the need for context-specific evidence (World Bank, 2024).

Analytically, classification techniques are increasingly used to identify factors associated with KAP, with evidence showing that multiple classifiers outperform single-method approaches by capturing diverse data structures and improving predictive accuracy (Saeed et al., 2022). Comparing classifiers allows researchers to determine the most suitable model for each KAP dimension, thereby enhancing the reliability and interpretability of findings.

The objectives of this study were to assess KAP levels during the early pandemic period in Sri Lanka, identify sociodemographic factors associated with KAP, compare the performance of Binary Logistic Regression (BLR) and Random Forest (RF) models in classifying KAP outcomes, and preliminarily evaluate and refine the measurement structure of the KAP constructs using Confirmatory Factor Analysis (CFA). This study focuses on selected sociodemographic characteristics collected through the survey, namely district, gender, age, education, occupation, income, and religion, to examine their associations with knowledge, attitudes, and practices (KAP) towards COVID-19. Although other demographic, socioeconomic, and behavioural factors may also be associated with KAP, these were beyond the scope of the present study.

MATERIALS AND METHODS

Questionnaire development and approval

A cross-sectional online survey was developed to assess Knowledge, Attitudes, and Practices (KAP) towards COVID-19 among the Sri Lankan community. The 48-item questionnaire was adapted from validated sources,

including the World Health Organisation (WHO) Rapid Behavioural Assessment Toolkit (WHO, 2020), the KAP survey for Greek healthcare workers (Papagiannis et al., 2020), and the Hajj/Umrah prevention questionnaire (Goni et al., 2020). The final instrument comprised 8 sociodemographic items, 20 knowledge items, 14 practice items, and 7 attitude items (Appendix 1: full questionnaire provided as Supplemental Material).

Sociodemographic items were short-answer questions. Knowledge items included multiple-choice and Yes/No/Not sure responses. Practice items were multiple-choice questions, while attitude items were rated on a 5-point Likert scale (Norman, 2010). All items were translated into Sinhala and back-translated to ensure semantic equivalence. Content validity was assessed by a panel of three experts in public health and biostatistics, achieving a Content Validity Index (CVI) ≥ 0.80 . A pilot test with 15 community members confirmed item clarity and an average completion time of approximately 12 minutes.

Seven sociodemographic characteristics were considered: district, gender, age, level of education, occupation, level of income, and religion. These variables were selected based on the information collected through the survey and the predefined scope of the study. Other potentially relevant demographic, socioeconomic, and behavioural factors were not included because they were outside the predefined scope of the study. Although all seven characteristics were collected, district was assessed only in the descriptive and univariate analyses and was not included as a predictor in the multivariable BLR and RF models because of the highly uneven distribution across districts and the very small number of respondents from Matara ($n = 3$), which could lead to unstable estimates.

Ethical approval was obtained from the Postgraduate Institute of Science, University of Peradeniya (Ref: PGIS/2020/07). Informed consent was obtained electronically from all participants, and data were anonymised before analysis.

Questionnaire administration and data collection

Data collection was conducted online during August–September 2020 across four districts: Kandy, Gampaha, Kurunegala, and Matara, selected to represent the Central, Western, Northwestern, and Southern provinces. Districts were chosen based on COVID-19 case burdens during the first wave and feasibility under movement restrictions. Eligible participants were adults aged 18 years or older who had resided in one of the selected districts for at least six months and were fluent in Sinhala or English. Healthcare professionals and individuals previously involved in KAP studies were excluded to ensure representation of the general community.

The required sample size was estimated using the standard formula for estimating a population proportion,

$$\frac{z_{1-\frac{\alpha}{2}}^2 p(1-p)}{d^2}, \text{ where } p \text{ denotes the assumed prevalence}$$

and d is the desired margin of error. A conservative prevalence of $p = 0.5$ was assumed, with a margin of error of $d = 0.1$. At a 95% confidence level, using $Z_{1-\alpha/2} = 1.961$, the calculated sample size was 96.04, which was rounded up to 97. At a 90% confidence level, using $Z_{1-\alpha/2} = 1.645$, the calculated sample size was 67.65, which was rounded up to 68. Due to practical constraints associated with online data collection, 80 complete responses were obtained. Under the standard population-proportion formula, the final sample of 80 exceeded the calculated sample size of 68, corresponding to a nominal 90% confidence level and a 10% margin of error. Since the study used non-probability convenience sampling, this calculation should be regarded as a planning reference rather than as evidence of population-representative precision. The calculation was not intended to establish the adequacy of the sample for CFA or multivariable modelling, for which the relatively small sample remains an important limitation. This population proportion calculation was used to determine the minimum number of survey respondents required for the intended estimation of population proportions. The limitations associated with the sample size for these analyses are therefore considered separately.

A non-probability convenience sampling approach was used. Survey invitations were disseminated through district-level community groups, local social media pages, and university networks. Because this was a non-probability sampling approach, the resulting sample may not be representative of the wider Sri Lankan adult population, and the findings should therefore not be interpreted as nationally representative estimates. Weekly reminders were issued until the target of 80 completed responses was reached. Two trained public health graduates administered the online survey following a one-day training session on ethical conduct, informed consent procedures, data privacy, and troubleshooting.

Questionnaire analysis

Internal consistency of the KAP domains was assessed using Cronbach's alpha, with values above 0.80 considered acceptable for reliability (Taber, 2018). Descriptive statistics (frequencies and percentages) were generated for all variables. Spearman's rank correlation was used to examine interrelationships among KAP scores.

The Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity were used as preliminary assessments of the factorability of the item correlation structure (Bartlett, 1954; Kaiser, 1974; Shrestha, 2021). These tests were not used as criteria for validating the CFA model. CFA was subsequently conducted to evaluate the predefined measurement structure of the KAP constructs. Given the ordinal response format and evidence of non-normality, the Diagonally Weighted Least Squares (DWLS) estimator was used (Flora & Curran, 2004; Li, 2016). Three candidate measurement models were evaluated sequentially.

Model 1 represented the initial specified measurement model. Subsequent models were obtained through the sequential removal of items that demonstrated relatively low standardised factor loadings and/or inadequate representation of their respective predefined KAP constructs. No correlated residuals or correlated error terms were introduced during model refinement. Item-retention decisions considered both statistical performance and the conceptual relevance of each item to the corresponding KAP construct.

Model adequacy was evaluated using the Chi-square statistic, Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardised Root Mean Squared Residual (SRMR) (Hu & Bentler, 1999). Standardised factor loadings were examined to assess the contribution of individual items to their respective constructs. Construct reliability was evaluated using composite reliability (CR), while convergent validity was assessed using the standardised factor loadings and average variance extracted (AVE). Discriminant validity was assessed using the Heterotrait–Monotrait ratio (HTMT), with values below the recommended threshold of 0.90 indicating adequate discriminant validity (Henseler et al., 2015).

Because the present study used a single sample for model development and evaluation, external validation of the final CFA model was not undertaken. The association of the demographic factors with the estimates of knowledge, practices, and attitude level was evaluated using Spearman's Rank Correlation coefficient, and the significance of the associations was tested at a 5% significance level.

Analysis of questionnaire outcomes

KAP outcomes were categorised as 'good' or 'poor' based on Bloom's cut-off criteria (Akalu et al., 2020). Chi-square tests were used to assess univariate associations between sociodemographic variables and KAP categories. The selected sociodemographic variables were specified a priori based on their relevance to KAP research and public health considerations. Gender, age, level of education, occupation, level of income, and religion were retained in the BLR models irrespective of their individual statistical significance to obtain adjusted estimates and maintain a consistent model specification across the three KAP outcomes. Binary logistic regression (BLR) models were fitted separately for knowledge, practice, and attitude, with each dimension coded as a binary outcome (Hosmer et al., 2013). The three KAP dimensions were modelled separately because each was treated as a distinct binary outcome, allowing outcome-specific associations with the selected sociodemographic predictors to be estimated and interpreted. Although the KAP dimensions were positively correlated, separate outcome-specific models were used rather than a joint multivariate model. The implications of this approach are considered in the Discussion. For the BLR models, the likelihood-ratio test was used to assess whether the included predictors, considered jointly, significantly

improved the model relative to the corresponding intercept-only model. Goodness of fit was assessed separately using the Hosmer–Lemeshow goodness-of-fit test and deviance-based diagnostics. Model discrimination was assessed using the area under the receiver operating characteristic curve (AUC), while classification performance was evaluated using accuracy, precision, recall, and F1-score (Tharwat, 2020).

Because accuracy may not fully reflect the balance between false-positive and false-negative classifications, the F1-score was also reported as a summary measure that balances precision and recall. The F1-score is the harmonic mean of precision and recall and was calculated as

$$F1 = 2 \frac{(\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})}$$

Precision represents the proportion of positive predictions that were correctly classified, whereas recall represents the proportion of actual positive cases that were correctly identified. Furthermore, the importance of factors affecting knowledge, practice, and attitude levels was assessed using the Mean Decrease Gini index (Breiman, 2001). All analyses were conducted in R version 4.2.1 at a 5% significance level (R Core Team, 2022).

RESULTS

Sociodemographic characteristics of participants

The sociodemographic characteristics of the study participants are summarised in Table 1. The eighty respondents were from four districts, with the highest number of 45 participants from Kandy (56.2%), and the lowest number of three participants (3.8%) from the Matara district. The female and male respondents were similarly represented (z -score = 0.6325, p = 0.5287) and accounted for 52.5% and 47.5% of participants, respectively. The majority of respondents were in the age group of 31–60 (51.3%), and 50% of participants held a degree or higher level of education. The majority of the respondents (73.8%) had an income level ranging from LKR 10,000 to LKR 50,000. The highest percentage of respondents (83.8%) identified as Buddhists, and the remainder (16.2%) belonged to other religions, including Hinduism, Christianity, and Islam.

The overall Cronbach's alpha was obtained as 0.802, which indicated that the internal consistency of the questions used to evaluate KAP had met a reliable level. The internal consistency of the questions used to assess each dimension was identified as moderate, adequate, and relatively high (0.624, 0.661, 0.707).

The study sample was characterised by a concentration of respondents within specific sociodemographic groups. In particular, the majority of participants were aged 31–60 years (51.3%), held a degree or higher educational qualification (50.0%), and were students or employed in the government or private sector (63.8%).

Table 1: Sociodemographic characteristics of respondents

Sociodemographic characteristic		Total (n = 80)	
		Count	Percentage (%)
District	Kandy	45	56.2
	Gampaha	16	20.0
	Kurunegala	16	20.0
	Matara	3	3.8
Gender	Female	42	52.5
	Male	38	47.5
Age (years)	18-30	33	41.2
	31-60	41	51.3
	Over 60	6	7.5
Level of Education	Primary or Lower	5	6.2
	O/L	15	18.8
	A/L	20	25.0
	Degree or Higher	40	50.0
Occupation	Student	31	38.8
	Government or Private Sector	20	25.0
	Business	15	18.7
	Other	14	17.5
Level of income	Below LKR 10,000	5	6.2
	LKR 10,000 – 50,000	59	73.8
	Over LKR 50,000	16	20.0
Religion	Buddhist	67	83.8
	Other	13	16.2

Note. O/L = Ordinary Level Examination, A/L = Advanced Level Examination, LKR = Sri Lankan rupees

Respondents were predominantly from the Kandy district (56.2%) and identified as Buddhist (83.8%), reflecting the geographic and cultural composition of the recruitment networks used. Apart from gender, which was approximately equally distributed, other demographic characteristics were not proportionally representative of the broader Sri Lankan population. The distribution of respondents across the four districts was highly unequal, with Kandy contributing more than half of the respondents and Matara contributing only three respondents.

Relationship and composition of knowledge, attitudes, and practices

The relationships between knowledge and practices, knowledge and attitude, and attitude and practices scores were moderately positive, as Spearman's rank correlations were 0.489, 0.469, and 0.633. Moreover, it was observed that the association among each pair was significant ($p < 0.05$). Although the three KAP dimensions were positively correlated, they were treated as distinct outcome constructs

in the subsequent classification analyses. The objective of these analyses was to evaluate the associations of the selected sociodemographic characteristics with each KAP dimension separately and to compare the predictive performance of BLR and RF for each outcome. The univariate factors' effect on KAP revealed that the age ($p < 0.05$) and level of education ($p < 0.05$) of the respondents showed a significant association towards the knowledge of COVID-19, while there was a significant association between the level of education ($p < 0.05$) and practice on COVID-19 (Table 2). Moreover, it was noted that the respondents' age ($p < 0.05$) and level of education ($p < 0.05$) were significantly associated with their attitude towards COVID-19.

Table 3 shows the composition of knowledge, practice, and attitude (KAP) responses according to binary levels. It was identified that 32.5% (26) of the total respondents had a poor knowledge level, and 67.5% (54) had a good knowledge level of COVID-19. 36.2% (29) and 63.8% (51) belonged to the 'poor' and 'good' categories when

considering the practices of COVID-19. The attitude towards COVID-19 was categorised as 'poor' and 'good', while 30.0% (24) were included in the 'poor' category, and 70.0% (56) belonged to the 'good' category.

Confirmatory factor analysis for knowledge, attitudes, and practices

The KMO measure and Bartlett's test of sphericity were used as preliminary assessments of factorability. The initial KMO value was 0.49. After removing items identified as having relatively low factor loadings during the preliminary assessment, the KMO value increased to 0.63, indicating improved sampling adequacy. Bartlett's test of sphericity was statistically significant ($\chi^2 = 868.2$, $df = 378$, $p < 0.05$), indicating that the item correlation matrix was not an identity matrix. These results were used only as preliminary evidence that the item correlation structure was suitable for factor analysis and were not used to establish the adequacy of the CFA model. The CFA models were subsequently evaluated using the specified model-fit and measurement-quality criteria.

Next, each of the selected items was tested for normality. The results obtained using Shapiro-Wilk's test indicated that none of the items followed a normal distribution ($p < 0.05$). Three candidate measurement models were evaluated sequentially based on the specified item structure and the statistical performance of the candidate models. Model

01 represented the initial measurement model. Model 02 was obtained by removing items with relatively low standardised factor loadings, using 0.40 as the minimum loading criterion. Model 03 was subsequently obtained by applying a more stringent factor-loading criterion of 0.50 to the remaining items and explicitly addressing discriminant validity. Specifically, items contributing to HTMT values above the 0.90 threshold were considered for removal, together with their factor loadings and conceptual relevance to the predefined constructs. Item-retention decisions considered both the statistical performance of the items and their conceptual relevance to the predefined knowledge, practice, and attitude constructs. No correlated residuals or correlated error terms were introduced during the model-refinement process. Each candidate model was evaluated using the fit indices reported in Table 4.

The final Model 03 contained 15 observed indicators in total, comprising six indicators for knowledge, four indicators for practices, and five indicators for attitudes. The knowledge indicators included how COVID-19 enters the human body (ER), vulnerable people (VP), cure for COVID-19 (CC), droplets can move about 1 m through the air (DRA), people without symptoms can spread the disease (SCS), and loss of taste or smell (TS). The reduction in the number of indicators was based on the observed factor loadings and was intended to obtain a more parsimonious measurement structure.

Table 2: Association between sociodemographic factors and knowledge, practices, and attitudes (KAP)

Dimension	Knowledge		Practice		Attitude	
	Chi-Sq	p-value	Chi-Sq	p-value	Chi-Sq	p-value
District	6.312	0.097	3.245	0.355	3.737	0.291
Gender	0.005	0.943	0.000	1.000	0.193	0.660
Age	10.167	0.006*	2.540	0.281	7.746	0.021*
Level of Education	12.953	0.005*	11.197	0.011*	10.079	0.018*
Occupation	7.334	0.062	2.608	0.456	6.221	0.101
Level of Income	3.155	0.207	3.532	0.171	1.339	0.512
Religion	0.681	0.409	0.018	0.893	1.120	0.290

Note. Chi-sq = Chi-square test statistic, * indicates statistical significance at $p < 0.05$.

Table 3: Composition of the binary levels of knowledge, practices, and attitudes (KAP) levels

Dimension	Knowledge		Practice		Attitude	
	Count	Percentage	Count	Percentage	Count	Percentage
Good	54	67.5	51	63.8	56	70.0
Poor	26	32.5	29	36.2	24	30.0

Table 4: Fit indices for the three candidate CFA measurement models

Model	Chi-square	CFI	TLI	RMSEA	SRMR
Model 01	465.22	0.953	0.949	0.064	0.182
Model 02	360.24	0.962	0.959	0.065	0.174
Model 03	129.54	0.987	0.984	0.053	0.127

Note. CFI = Comparative Fit Index, TLI = Tucker–Lewis Index, RMSEA = Root Mean Square Error of Approximation, SRMR = Standardised Root Mean Squared Residual.

The three candidate CFA models were evaluated using the chi-square statistic, CFI, TLI, RMSEA, and SRMR (Table 4). Model 03 provided the most favourable overall fit among the candidate models, with CFI = 0.987, TLI = 0.984, and RMSEA = 0.053. However, the SRMR remained relatively high at 0.127, indicating that not all fit indices supported satisfactory model fit. Model 03 was retained as the final measurement model because it provided the most favourable overall fit among the candidate models while retaining a theoretically meaningful and parsimonious set of indicators.

The reliability and validity of the final measurement model were further assessed using composite reliability (CR), average variance extracted (AVE), and discriminant validity. The CR values for knowledge, practices, and attitudes were 0.659, 0.746, and 0.758, respectively. Reliability was stronger for practices and attitudes, whereas the knowledge construct showed comparatively lower internal consistency. The corresponding AVE values were 0.389, 0.502, and 0.609. Thus, the conventional AVE criterion for convergent validity was met for practices and attitudes but not for knowledge; therefore, convergent validity of the knowledge construct should be interpreted cautiously. Discriminant validity was assessed using the HTMT criterion, with values of 0.651, 0.898, and 0.866. Although these values were below 0.90, the value of 0.898 was close to the threshold and therefore warrants cautious interpretation. The final Model 03 retained six indicators for knowledge, four indicators for practices, and five indicators for attitudes, as shown in Table 5.

The covariances among the latent variables showed a positive relationship with each other. The covariance among knowledge and practice was identified as 0.617, among knowledge and attitude as 0.847 and among practice and attitude as 0.874, and they were significant ($p < 0.05$) for all pairwise comparisons. The path diagram of the CFA model was obtained to visualise the relationship of factors with latent variables, and the relationships among the latent variables are shown in Figure 1.

Cronbach's alpha was re-evaluated using the items retained based on the CFA results. For the knowledge dimension, Cronbach's alpha was 0.617, compared with 0.624 for the initial set of items. For the practice dimension, Cronbach's alpha increased from 0.661 to 0.707 after omitting the items not retained in the CFA model. For the attitude dimension, Cronbach's alpha increased from 0.707 to 0.739, with all

items retained as they showed statistically significant factor loadings at the 5% level. Subsequently, the knowledge, practice, and attitude scores were re-estimated using the fitted CFA model (Table 6).

Age, level of education, and occupation were significantly associated with the estimated knowledge, practices, and attitude scores. Moreover, the level of education was moderately positively associated with knowledge score, while age and occupation were moderately negatively associated with knowledge score. It was further noted that the level of education was positively associated with practices and attitude scores, having a weak relationship. Besides that, age and occupation level were negatively associated with practices and attitude scores.

Binary Logistic Regression models for knowledge, attitudes, and practices

The estimated coefficients of BLR models fitted for the factors affecting knowledge level, practice level, and attitude level on COVID-19 are represented in Table 7.

Specifically, the odds of having a high level of knowledge were 13.42 times higher for respondents with an A/L education when compared to the baseline O/L group. For the level of practice on COVID-19, the fitted model indicated that none of the demographic variables, gender, age, education, occupation, income, or religion, demonstrated a statistically significant association at the 5% significance level. The BLR model for knowledge identified a statistically significant association between education at A/L level and good knowledge compared with O/L education (AOR = 13.42, 95% CI: 1.07–167.97, $p = 0.044$). Thus, respondents with A/L education had higher adjusted odds of having good knowledge than those with O/L education. None of the demographic variables included in the practice model showed a statistically significant association with good practice at the 5% significance level. In the attitude model, respondents with A/L education had higher adjusted odds of having a good attitude compared with those with O/L education (AOR = 316.52, 95% CI: 1.79–5.59 $\times 10^4$, $p = 0.029$). In contrast, respondents with an income of LKR 10,000–50,000 had lower adjusted odds of having a good attitude than those with an income below LKR 10,000 (AOR = 0.01, 95% CI: 0.00–0.73, $p = 0.036$).

The Area Under the Curve (AUC) values for the fitted BLR models for knowledge, practice, and attitude were 0.891, 0.837, and 0.876, respectively, indicating good

Table 5: Standardised factor loadings of confirmatory factor analysis (CFA) model for knowledge, practices, and attitudes (KAP)

	Standardised Loadings	Standard Error	p-value
Knowledge			
How COVID-19 enters the human body	0.567	0.119	<0.001*
Vulnerable People	0.598	0.117	<0.001*
Cure for COVID-19	0.638	0.118	<0.001*
Droplets can move about 1m through the air	0.638	0.118	<0.001*
People without symptoms can spread the disease	0.709	0.095	<0.001*
Loss of taste or smell	0.591	0.118	<0.001*
Practice			
Frequency of mask wearing	0.801	0.064	<0.001*
Frequency of handwashing	0.712	0.086	<0.001*
Hand sanitiser use	0.698	0.064	<0.001*
Practices after lockdown	0.610	0.068	<0.001*
Attitude			
Importance of avoiding crowded places	0.726	0.071	<0.001*
Importance of washing hands	0.933	0.051	<0.001*
Importance of wearing masks in public places	0.843	0.071	<0.001*
Following Ministry of Health guidelines	0.776	0.083	<0.001*
Perception of government control	0.577	0.075	<0.001*

Note. * Indicates statistical significance at $p < 0.05$

discriminatory ability (Table 8). The likelihood-ratio tests were used to compare each fitted model with its corresponding intercept-only model. The statistically significant results indicated that the selected predictors, considered jointly, significantly improved the models relative to the intercept-only models for knowledge ($p = 0.009$), practice ($p = 0.037$), and attitude ($p = 0.028$). The Hosmer–Lemeshow goodness-of-fit tests did not provide evidence of lack of fit for the knowledge, practice, or attitude models ($p = 0.142$, 0.940 , and 0.323 , respectively). The corresponding deviance statistics were 42.929, 50.271, and 43.757. When the fitted models were applied to the test data, the classification accuracy was 0.609 for knowledge, practice, and attitude. These results indicate that predictive performance on the test data was lower than the corresponding in-sample classification accuracy.

Random Forest Classification for knowledge, attitudes, and practices

The most important factor for knowledge and practice was level of education, whereas religion had the highest Mean Decrease Gini value for attitude (Table 9). Gender was the least important factor for knowledge and practice, while occupation was the least important factor for attitude

(Table 9). The least important factor was gender, as the lowest value was obtained for gender for knowledge and practice, while occupation was the least important factor for attitude.

The RF discrimination statistics are also reported in Table 10. The AUC values for the RF models fitted for knowledge, practice, and attitude were 0.697, 0.643, and 0.681, respectively, indicating moderate discriminatory ability. The corresponding classification accuracies were 0.789, 0.737, and 0.789 for knowledge, practice, and attitude, respectively. These results indicate that the RF models provided moderate discrimination and acceptable classification performance in the study sample.

Comparison among BLR and RF models obtained for KAP

Table 10 shows the model comparison statistics used to compare the models.

The recall and F1-score values further demonstrated differences in classification performance between the two approaches. BLR achieved F1-scores of 0.883, 0.821, and 0.894 for knowledge, practice, and attitude, respectively,

compared with 0.571, 0.444, and 0.539 for RF. Although RF showed higher precision for knowledge and practice, its lower recall resulted in lower F1-scores across all three outcomes. Overall, BLR provided a better balance between precision and recall in the present sample.

Comparison of the BLR and RF models showed that BLR generally outperformed RF across the reported evaluation metrics for the Knowledge, Practice, and Attitude domains. BLR achieved higher AUC values of 0.891, 0.837, and 0.876, respectively, compared with 0.697, 0.643, and 0.681 for RF. BLR also achieved higher accuracy and F1-scores across all three outcomes. Although RF showed higher precision for knowledge and practice, its lower recall

resulted in lower F1-scores. Overall, BLR showed better classification performance than RF in the present sample.

DISCUSSION

This study examined the KAP of Sri Lankans towards COVID-19 through an online questionnaire and determined that the majority of respondents demonstrated good knowledge, good practices, and a positive attitude towards COVID-19. The sample was predominantly composed of middle-aged adults, individuals with tertiary-level education, and participants engaged in formal employment, with a substantial proportion residing in the Kandy district. While gender distribution was balanced,

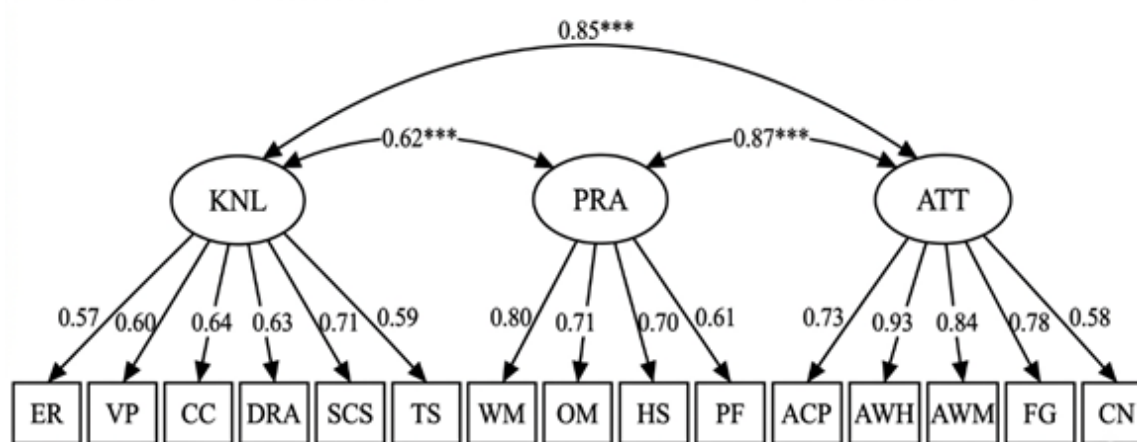


Figure 1: Path diagram of the confirmatory factor analysis (CFA) model for knowledge, practices, and attitudes (KAP). KNL = knowledge, PRA = practices, ATT = attitudes, ER = how COVID-19 enters the human body, VP = vulnerable people, CC = cure for COVID-19, DRA = droplets can move about 1 m through the air, SCS = people without symptoms can spread the disease, TS = loss of taste or smell, WM = frequency of mask wearing, OM = frequency of handwashing, HS = hand sanitizer use, PF = practices after lockdown, ACP = importance of avoiding crowded places, AWH = importance of washing hands, AWM = importance of wearing masks in public places, FG = following Ministry of Health guidelines, CN = perception of government control. Values on single-headed arrows are standardised factor loadings, and values on curved double-headed arrows are latent-variable covariances. *** indicates $p < 0.001$

Table 6: Association of sociodemographic factors with estimated latent knowledge, practices, and attitudes (KAP) variables

Dimension	Knowledge		Practice		Attitude	
	Corr	p-value	Corr	p-value	Corr	p-value
Gender	0.062	0.686	0.009	0.909	0.052	0.761
Age	-0.484	<0.001*	-0.317	0.014*	-0.431	<0.001*
Level of Education	0.448	<0.001*	0.276	<0.013*	0.351	<0.001*
Occupation	-0.433	<0.001*	-0.314	0.014*	-0.371	<0.001*
Level of Income	0.164	0.132	0.091	0.405	0.091	0.322
Religion	-0.141	0.301	-0.116	0.206	-0.160	0.180

Note. Corr = correlation coefficient, * indicates statistical significance at $p < 0.05$

Table 7: Estimated regression coefficients, adjusted odds ratios, and p-values from binary logistic regression (BLR) models for knowledge, attitude, and practice (KAP)

Variable	Level	Knowledge			Attitude			Practice		
		Estimate	Adjusted OR	p-value	Estimate	Adjusted OR	p-value	Estimate	Adjusted OR	p-value
		(95% CI)			(95% CI)			(95% CI)		
Gender	Male (Female = Ref.)	0.612	1.84	0.561	1.008	2.74	0.485	-0.041	0.96	0.963
			(0.24, 14.48)			(0.16, 46.46)			(0.17, 5.45)	
Age	31–60 (18–30 = Ref.)	-16.007	0.00	0.995	-15.947	0.00	0.995	1.004	2.73	0.641
			(0.00, Inf)			(0.00, Inf)			(0.04, 184.94)	
	Over 60 (18–30 = Ref.)	-14.594	0.00	0.995	-14.150	0.00	0.995	1.894	6.65	0.505
			(0.00, Inf)			(0.00, Inf)			(0.03, 1.75×10 ³)	
Level of Education	Primary or less (O/L = Ref.)	1.121	3.07	0.447	-1.866	0.16	0.480	-16.301	0.00	0.994
			(0.17, 55.04)			(0.00, 27.29)			(0.00, Inf)	
	A/L (O/L = Ref.)	2.596	13.42	0.044*	5.757	316.52	0.029*	3.210	24.78	0.130
			(1.07, 167.97)			(1.79, 5.59×10⁴)			(0.39, 1.58×10 ³)	
	Degree or Higher (O/L = Ref.)	2.387	10.88	0.107	1.844	6.32	0.243	0.015	1.02	0.992
			(0.60, 198.17)			(0.29, 139.82)			(0.05, 19.98)	
Occupation	Business (Student = Ref.)	14.674	2.36×10 ⁶	0.995	14.872	2.88×10 ⁶	0.995	-1.036	0.36	0.709
			(0, Inf)			(0.00, Inf)			(0.00, 82.01)	
	Government or Private Sector (Student = Ref.)	14.036	1.25×10 ⁶	0.995	15.601	5.96×10 ⁶	0.995	-2.118	0.12	0.316
			(0, Inf)			(0.00, Inf)			(0.00, 7.55)	
	Other (Student = Ref.)	14.888	2.92×10 ⁶	0.995	11.072	6.44×10 ⁴	0.996	-3.782	0.02	0.244
			(0.00, Inf)			(0.00, Inf)			(0.00, 13.27)	

Level of Income	LKR 10,000–50,000 (Below LKR 10,000 = Ref.)	-0.115	0.89	0.947	-4.906	0.01	0.036*	-18.994	0.00	0.994
			(0.03, 27.09)			(0.00, 0.73)			(0.00, Inf)	
	Over LKR 50,000 (Below LKR 10, 000 = Ref.)	-0.139	0.87	0.945	-2.073	0.13	0.391	-17.086	0.00	0.995
			(0.02, 43.94)			(0.00, 14.28)			(0.00, Inf)	
Religion	Other (Buddhist = Ref.)	0.112	1.119	0.913	-2.080	0.13	0.170	-1.682	0.19	0.150
			(0.15, 8.47)			(0.01, 2.45)			(0.02, 1.84)	

Note. BLR = binary logistic regression, OR = odds ratio, CI = confidence interval, Ref. = reference category, Inf. = infinity, O/L = Ordinary Level Examination, A/L = Advanced Level Examination, LKR = Sri Lankan rupees, * indicates statistical significance at $p < 0.05$. Intercepts are omitted for conciseness

Table 8: Goodness-of-fit and discrimination statistics for the binary logistic regression (BLR) models

Statistic	Knowledge	Practice	Attitude
Deviance	42.929	50.271	43.757
Hosmer-Lemeshow χ^2	12.219	2.322	9.228
Hosmer-Lemeshow p-value	0.142	0.940	0.323
Likelihood-ratio χ^2	29.633	24.754	25.711
Likelihood-ratio p-value	0.009	0.037	0.028
AUC	0.891	0.837	0.876

Note. BLR = binary logistic regression, AUC = area under the receiver operating characteristic curve

other demographic characteristics did not fully reflect the national population profile of Sri Lanka, which includes a higher proportion of rural residents and individuals with lower educational attainment (Amaratunga et al., 2020; Government of Sri Lanka, 2022). Consequently, the observed levels of knowledge, attitudes, and practices (KAP) may overestimate population-level awareness and compliance, particularly among underserved or hard-to-reach communities. Therefore, the findings of this study should be interpreted in light of the sociodemographic characteristics and sampling approach used. In addition, the use of non-probability convenience sampling limits the representativeness of the sample and restricts the generalisability of the findings to the wider Sri Lankan population. Individuals with limited internet access, lower digital literacy, or limited exposure to the networks through which the survey was disseminated may have been underrepresented. Therefore, the reported KAP levels and associations should be interpreted as findings from the study sample rather than as nationally representative estimates. Future studies using probability-based sampling and larger, geographically representative samples are warranted to obtain more generalisable estimates of KAP in the Sri Lankan population.

The relatively small sample size also warrants caution in interpreting the CFA results. Although the use of the DWLS estimator was appropriate for the ordinal and non-normal item responses, the estimates of factor loadings, standard errors, and model-fit indices may still be sensitive to sampling variability with a sample of 80 participants. Therefore, the final CFA structure should be regarded as preliminary rather than definitive, and its stability and reproducibility should be evaluated using a substantially larger independent sample in future research.

Although the KAP dimensions were positively correlated, each binary outcome was modelled separately to obtain outcome-specific estimates and to facilitate comparison of BLR and RF performance for each KAP dimension. This approach does not explicitly account for the covariance among the three KAP outcomes. Future studies with larger samples could investigate the three KAP dimensions jointly using multivariate modelling approaches that explicitly account for their dependence. Furthermore, the analysis was limited to the selected sociodemographic

characteristics available from the survey, and potentially relevant behavioural, socioeconomic, health-related, and contextual factors were not examined. Therefore, the identified associations should not be interpreted as representing all possible determinants of KAP towards COVID-19.

Gender was a consistently non-significant variable in the present study, in contrast to findings reported in several regional studies conducted in other countries (Ngwewondo et al., 2020; Hathurusinghe et al., 2021). This divergence may partly reflect the relatively homogeneous educational profile of the present sample, as well as Sri Lanka's high female literacy and equitable access to public health information and health services (World Bank, 2024; Amaratunga et al., 2020). Similar patterns have been reported in settings with strong public health communication systems, whereas studies from lower-income or resource-constrained contexts often document pronounced gender-based disparities linked to unequal access to education and healthcare (Akalu et al., 2020; Azlan et al., 2020).

In comparison with international evidence, the overall KAP levels observed in this study are broadly consistent with findings from middle-income and developed countries, where structured public health messaging and higher educational attainment have been associated with better awareness and preventive behaviours (Azlan et al., 2020; Al Demour et al., 2021). Conversely, studies conducted in less-developed settings have reported greater heterogeneity in knowledge and practices, often influenced by socioeconomic constraints, limited trust in institutions, and restricted access to accurate information (Akalu, et. al., 2020; Blendon, et. al., 2004). These contrasts highlight the importance of contextual and structural factors in shaping public responses during infectious disease outbreaks.

An important limitation of the CFA is that the final measurement model was developed and refined using the same dataset. Consequently, the favourable model-fit indices observed for the final model may partly reflect sample-specific characteristics and should not be interpreted as evidence that the measurement structure is universally stable. The present study therefore provides evidence of model fit within the study sample, but independent-sample validation is required to establish the stability and

generalisability of the factor structure, item loadings, and overall model fit. Future studies using sufficiently large and independent samples should cross-validate the final measurement model before it is generalised to broader populations.

The comparative evaluation of the classification models showed that BLR generally outperformed RF across the three KAP dimensions in the present sample. BLR achieved higher AUC, accuracy, recall, and F1-scores, although RF showed higher precision for knowledge and practice. The lower recall of RF resulted in lower F1-scores, indicating a less favourable balance between precision and recall. This finding suggests that BLR may be more appropriate for the present data when the objective is to identify and interpret associations between sociodemographic characteristics and KAP outcomes. Although RF can capture complex and non-linear relationships, its potential advantages were not evident in the present sample.

Finally, the analysis suggests that not all KAP questionnaire items contributed equally to predictive performance, indicating variation in the informativeness of individual questions. Items assessing fundamental knowledge and core preventive behaviours appeared more informative than those capturing less frequent or context-specific actions. Similar observations have been reported in prior KAP validation studies, which emphasise the importance of scale optimisation to balance statistical robustness and practical feasibility (Goni et al., 2020; Flora & Curran, 2004). This highlights the potential value of developing shorter, standardised KAP instruments that retain a minimum set of highly informative items while reducing respondent burden and enhancing applicability for rapid public health surveillance and decision-making.

CONCLUSION

This study provides evidence that knowledge, attitudes, and practices towards COVID-19 are interrelated and that education and other selected sociodemographic characteristics are associated with KAP in the study sample. BLR demonstrated higher AUC, accuracy, recall, and F1-scores than RF across all three KAP dimensions, whereas RF achieved higher precision for knowledge and practice. These findings suggest that sociodemographic characteristics, particularly educational attainment, may be relevant when designing health education and public health interventions.

Although the study provides useful evidence for understanding KAP and identifying potentially important sociodemographic factors, the relatively small sample and non-probability convenience sampling limit the representativeness and generalisability of the findings to the wider Sri Lankan population. Future studies using larger samples and probability-based sampling across a broader range of geographic and sociodemographic groups are recommended to provide nationally generalisable evidence and to inform public health strategies for future

pandemics. The present study therefore provides evidence of model fit within the study sample, but independent-sample validation is required to establish the stability and generalisability of the factor structure, item loadings, and overall model fit.

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DECLARATION OF CONFLICT OF INTEREST

The authors declare no conflicts of interest.

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AUTHOR CONTRIBUTION

All authors contributed to the study conception and design. Material preparation and data collection: **R.S.R. & M.E.E.**; Design of analysis procedure and data analysis: **H.S.J. & L.S.N.**; Writing the first draft: **H.S.J.** All authors commented on and altered previous versions of the manuscript. All authors have accepted responsibility for the content of the manuscript, reviewed all results, and approved the final version.

DATA AVAILABILITY STATEMENT

Data and materials are available from the corresponding author on reasonable request.

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Appendix 1 - Sample Questionnaire**Assessment of Knowledge, Attitudes, and Practices (KAP) towards COVID-19 among the local community****A) BACKGROUND INFORMATION OF THE RESPONDENT**

- 1) District: 2) Village
- 3) Gender: 4) Age 5) Education.....
- 6) Occupation

B) KNOWLEDGE ABOUT COVID-19

- 7) What causes Covid-19? ☐ Bacterium ☐ Virus ☐ Worm ☐ Fungus

☐ Don't know ☐ Other (specify)

- 8) How does it enter the human body? *Please check all that apply.*

Through ☐ Mouth ☐ Eyes ☐ Nose ☐ Don't know

☐ Other (specify)

- 9) Who are considered to be more vulnerable for COVID-19? *Please check all that apply.*

☐ Old age ☐ Underlying medical condition ☐ Children ☐ Pregnancy

☐ Other (specify) ☐ Don't know

- 10) Is there a cure for COVID-19 ☐ yes ☐ No ☐ Don't know

10.1) If Yes, What is it?

.....

Please check.

	Yes	No	Not Sure
11. COVID-19 is a highly contagious infection	☐	☐	☐
12. It spreads via respiratory droplets of infected individuals	☐	☐	☐
13. Virus containing droplets can move about 1m through air	☐	☐	☐
14. Eating or close contact with wild animals can result in the infection	☐	☐	☐
15. All infected people will develop severe disease or have symptoms	☐	☐	☐
16. Fever, fatigue, dry cough and body aches are main symptoms	☐	☐	☐
17. People without symptoms can spread the disease	☐	☐	☐
18. Stuffy nose, runny nose and sneezing are less common symptoms	☐	☐	☐
19. This virus mainly affects the functions of lungs	☐	☐	☐
20. Some of the patients lose the ability to taste or smell	☐	☐	☐
21. PCR test is the best method to diagnose COVID-19 patients	☐	☐	☐
22. Drinking alcohol can protect you against Covid-19	☐	☐	☐
23. High temperatures or sunlight may protect you from COVID-19	☐	☐	☐
24. BCG vaccination may reduce COVID-19 deaths	☐	☐	☐
25. Washing hands with soap kills the virus	☐	☐	☐

C. PRACTICES TOWARDS COVID-19

26. How often do you wear a mask ☐ Always ☐ Most of the time

☐ Sometimes ☐ Hardly ☐ Never

27. What kind of mask do you wear? ☐ N95 respirator masks ☐ surgical masks

☐ Cloth masks ☐ Other (specify)

28. Where/how did you get mask? ☐ Make it at home ☐ buy from Pharmacy

☐ buy from other boutiques ☐ order online ☐ Other

29. What do you do with the mask after wearing it? ☐ Reuse it ☐ Dispose

☐ Wash and reuse ☐ Other (Specify)

30. How often do you wash your hands ☐ Always ☐ Most of the time

☐ Sometimes ☐ Hardly ☐ Never

31. How often do you use hand sanitizer ☐ Always ☐ Most of the time

☐ Sometimes ☐ Hardly ☐ Never

32. How often do you go to crowded places ☐ Always ☐ Most of the time

☐ Sometimes ☐ Hardly ☐ Never

33. How often do you travel in public transport ☐ Always ☐ Most of the time

☐ Sometimes ☐ Hardly ☐ Never

34. Do you practice any home remedies to prevent getting COVID-19? Yes No

34.1 If yes, what are they?

.....

34.2 How often do you use them?

35. Do you or your family members use any of the following;

Please check all that apply.

Drink 'paspanguwa' packets

Drink 'perumkaaya'

Burn margosa leaves around the house.

Wash the house floor and surfaces with turmeric water and neem leaves

Drink lime, orange, mandarin juice to get enough vitamin C

Take Vitamin D

Other

36. As a family, what are the practices you followed during the period of lockdown?

Please check all that apply.

Did not leave the house at all

Removed and disinfested all plastic bags in which material was brought in from shops

Did not order any food from outside/ only had home cooked food

Ordered food from outside

After returning home, wash hands and face thoroughly before entering the house

Any clothes worn outside were dried under sunlight and washed before taking inside

Any Other Practices

37. Practices you followed during lockdown and still following after lockdown was lifted *Please check all that apply*

Did not leave the house at all

Removed and disinfested all plastic bags in which material was brought in from shops

Only had home cooked food

Ordered food from outside

After returning home, wash hands and face thoroughly before entering the house

Any clothes worn outside were washed and dried under sunlight before taking inside

Any Other Practices

38. If you have a sick person in your house, what do you do? *Please check all that apply*

A. Avoid unnecessary exposure to the ill person

- B. Avoid sharing items
- C. Use dedicated bathrooms
- D. Identify frequently touched surfaces by the ill person and clean and disinfect those daily.

39. Which method is better to cover your mouth and nose when you are coughing or sneezing? *Please check all that apply*

With flexed elbow

With a disposable tissue which can be discarded after use

With a handkerchief that was used repeatedly

With your palm

D. ATTITUDE TOWARDS COVID-19 CONTROL AND PREVENTION

40. It is important to avoid crowded places.

Strongly Agree Agree Neutral Disagree Strongly Disagree

41. It is important to wash hands.

Strongly Agree Agree Neutral Disagree Strongly Disagree

42. It is important to wear masks in public places.

Strongly Agree Agree Neutral Disagree Strongly Disagree

43. Quarantine of infected people is necessary and important.

Strongly Agree Agree Neutral Disagree Strongly Disagree

44. Community should follow the guidelines of health ministry

Strongly Agree Agree Neutral Disagree Strongly Disagree

45. If there is a vaccine I am willing to take it.

Strongly Agree Agree Neutral Disagree Strongly Disagree

46. The government is controlling the COVID-19 health crisis very well.

Strongly Agree Agree Neutral Disagree Strongly Disagree

Any other comments

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Thank you for your cooperation.