Understanding Community Engagement in Infectious Disease Surveillance: A Multi-Theoretical Predictive Model

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ABSTRACT

INTRODUCTION: Community-based surveillance (CBS) plays a crucial role in early detection and response to communicable disease outbreaks. Understanding the determinants of community participation in CBS is essential for developing effective public health strategies. This study aimed to identify and quantify the key determinants of community participation in communicable disease surveillance, utilising factors from the Theory of Planned Behaviour and Health Belief Model to form a comprehensive predictive model. **MATERIALS AND METHODS:** A cross-sectional study design was used, with a sample of 470 participants interviewed to assess their likelihood of CBS participation using the KAP-CBS-ID questionnaire. Multiple linear regression analysis was utilised to test the relationships between the predictor variables and the likelihood of engaging in CBS. **RESULTS:** The final model demonstrated good predictive capacity, accounting for 51.7% of the variance in behavioural likelihood ($F= 99.49$, $p<0.001$). Five predictors showed significant relationships with CBS participation behaviour. Perceived susceptibility showed the highest predictive power ($\beta=0.255$, $p<0.001$), followed by perceived benefits ($\beta=0.231$, $p<0.001$), intention to accept involvement ($\beta=0.209$, $p<0.001$), and subjective norms ($\beta=0.202$, $p<0.001$). There was a significant negative association between attitudes toward participation ($\beta=-0.104$, $p=0.002$). Knowledge of infectious diseases, self-efficacy, and perceived barriers were not significant predictors and were excluded from the final model. **CONCLUSION**: A multi-theoretical approach to understand CBS participation is supported empirically by these findings. Initiatives to increase CBS participation should emphasize community susceptibility to disease outbreaks, explain the advantages, foster positive social norms, and address unfavourable perceptions of surveillance practices.

KEYWORDS: Public Health Surveillance, Social Determinants of Health, Theory of Planned Behaviour, Health Belief Model, Community Participation.

INTRODUCTION

Communicable diseases are still a major public health challenge worldwide, contributing to substantial morbidity and mortality, particularly in low- and middle-income countries.[1] The emergence and re-emergence of infectious diseases such as COVID-19, Ebola, and the Zika virus have highlighted the critical importance of robust surveillance systems for early detection and rapid response to disease outbreaks.[2,3] Traditional surveillance systems, which primarily rely on healthcare facilities and laboratory-based reporting, often face limitations in terms of timeliness, coverage, and sensitivity, particularly in resource-limited settings and remote areas.[4]

Community-based surveillance has emerged as a complementary approach to strengthen disease surveillance systems by engaging community members in the early detection and reporting of unusual health events.[4,5] CBS helps the community members who are often the first to observe changes in health patterns within their localities to report health events to the authorities.[6] This participatory approach not only enhances the sensitivity and timeliness of disease detection but also promotes community ownership and sustainability of surveillance activities. Despite the recognised benefits of CBS, the level of community participation varies considerably across different settings, influenced by multiple factors that are not fully understood.[7]

Understanding the determinants of community participation in surveillance activities is important for designing effective interventions to improve CBS uptake and sustainability.[8] Previous studies have examined various factors influencing health-related behaviours using different theoretical frameworks. The Theory of Planned Behaviour (TPB) suggests that behavioural intention, which is influenced by attitudes, subjective norms, and perceived behavioural control, is the primary determinant of actual behavior.[9] Similarly, the Health Belief Model (HBM) posits that health-related behaviours are influenced by perceived susceptibility, perceived severity, perceived benefits, perceived barriers, and self-efficacy.[10] While these theories have been applied individually to various health behaviours, studying their factors together and checking which of these factors is more influential in CBS participation remains limited.

This study aimed to identify the key factors of community participation in communicable disease surveillance by integrating the factors from the TPB and HBM into a single predictive model. This study specifically sought to examine the relationships between knowledge of communicable diseases, subjective norms, intention, attitudes, perceived benefits, perceived susceptibility, perceived barriers, self-efficacy, and behavioural likelihood of CBS participation. The findings are expected to inform the design of targeted interventions to enhance community engagement in communicable disease surveillance systems.

MATERIALS AND METHODS

Study Design and Setting

A cross-sectional study was employed to investigate the determinants of community participation in CBS. Data collection spanned two months (May to June 2024) in Kelantan, Malaysia, followed by data analysis in July 2024. The study protocol was approved by the Human Research Ethics Committee of Universiti Sains Malaysia (Reference No.: USM/JEPeM/22050317).

Study Population and Sampling

The target population comprised community representatives including village leaders, religious leaders, and schoolteachers. Due to logistical constraints, schoolteachers in four districts in Kelantan were selected. Sample size was calculated using the formula for multiple linear regression, considering eight predictor variables, a small effect size (f^2=0.05), alpha=0.05, and power=0.95, yielding a minimum of 480 participants (accounting for 10% non-response). The achieved sample was 470 participants, which was deemed sufficient.

Data Collection Instrument

Data were collected using the KAP-CBS-ID (Knowledge, Attitude, and Perceptions towards Community-Based Surveillance of Infectious Diseases) questionnaire, developed based on extensive literature review incorporating constructs from the TPB and HBM.[11,12] The instrument underwent rigorous validation including content validation by five public health specialists (excellent content validity index), face validity via cognitive interviews with 10 community leaders and pilot testing with 30 community leaders, and construct validity through exploratory and confirmatory factor analysis. Internal consistency reliability was excellent, with Cronbach's alpha ranging from 0.78 to 0.91.[11]

The questionnaire measured: knowledge of infectious diseases (18 general knowledge items, 3 on CBS, 10 on case definition); subjective norms (4 items on social pressure); intention to accept involvement (6 items); attitudes toward participation (6 items); perceived benefits (5 items); perceived susceptibility (5 items); perceived barriers (7 items); and self-efficacy (4 items). The outcome variable, behavioural likelihood of CBS participation, was measured using 7 items. All items used a five-point Likert scale. The questionnaire was translated into Malay using the forward-backward translation technique. [11]

Data Analysis

Data were analysed using JASP software version 0.95.0.0. Descriptive statistics were calculated for all variables. Bivariate relationships between each predictor and the outcome were examined using simple linear regression prior to the multivariate model. Multiple linear regression was conducted using the backward elimination method, beginning with all eight predictors and sequentially removing non-significant variables ($p>0.05$) until only significant predictors remained. Assumptions of linearity, independence, homoscedasticity, and multicollinearity (VIF<10)[13] were verified. Statistical significance was set at $p<0.05$.

RESULTS

Demographic Characteristics of Participants

A total of 470 participants completed the questionnaire. As presented in Table I, the mean age was 43.3 ± 9.5 years. The majority were female (75.3%) and of Malay ethnicity (99.4%). Most were married (79.4%) and government employees (85.5%). Educational level was high, with 87.2% having university education or higher, and 87.7% were public school teachers. Urban residency was reported by 64.0%, and 93.8% had received information about infectious diseases.

Preliminary Analysis

Prior to multiple regression analysis, simple linear regression was performed to examine bivariate relationships (Table II). All predictor variables except perceived barriers (BARR) showed statistically significant relationships with behavioural likelihood. Both BARR and ATT showed negative relationships; however, only ATT was significant.

Regression Model Assumptions

All assumptions were examined and confirmed satisfied. The Q-Q plot of standardised residuals demonstrated approximately normal distribution (Figure 1). Variance inflation factors in the final model ranged from 1.15 to 2.18, well below the threshold of 10, confirming the absence of multicollinearity.[14] Tolerance values ranged from 0.46 to 0.87, all above 0.10.

Table I: Demographic Profile of Study Participants (n=470)

Variable	Frequency
Age (years), mean ± SD	43.3 ± 9.5
Sex	
Female	354 (75.3)
Male	116 (24.7)
Ethnicity	
Malay	467 (99.4)
Others	3 (0.6)
Marital status	
Single	73 (15.5)
Married	373 (79.4)
Divorced	6 (1.3)
Widowed	18 (3.8)
Occupation	
Government employee	402 (85.5)
Private sector	60 (12.8)
Pensioner	3 (0.6)
Others	5 (1.1)
Education level	
Primary school	3 (0.6)
Secondary school (PMR/SRP)	2 (0.4)
Secondary school (SPM)	16 (3.4)
Religious school (Pondok)	2 (0.4)
Diploma	37 (7.9)
University and higher	410 (87.2)
Role	
Public school teacher	412 (87.7)
Religious school teacher	58 (12.3)
Residency	
Urban	301 (64.0)
Rural	169 (36.0)
Received information about infectious diseases	
Yes	441 (93.8)
No	29 (6.2)

Data are presented as mean ± standard deviation or n (%). PMR, Penilaian Menengah Rendah (lower secondary assessment); SRP, Sijil Rendah Pelajaran (lower education certificate); SPM, Sijil Pelajaran Malaysia (Malaysian certificate of education).

Table II: Bivariate Relationships Between Predictor Variables and Behavioural Likelihood (n=470)

Variable	Unstandardised Coefficient	SE	β	t	p
Knowledge (KID)	0.178	0.046	0.176	3.860	<0.001
Subjective norms (SN)	0.598	0.053	0.462	11.28	<0.001
Intention (INT)	0.595	0.043	0.536	13.74	<0.001
Attitudes (ATT)	-0.274	0.043	-0.284	-6.407	<0.001
Perceived benefits (BEN)	0.699	0.045	0.583	15.53	<0.001
Perceived susceptibility (SUS)	0.612	0.040	0.581	15.46	<0.001
Perceived barriers (BARR)	-0.002	0.034	-0.003	-0.059	0.953
Self-efficacy (SE)	0.769	0.052	0.568	14.92	<0.001

SE, standard error; β, standardized coefficient.

Regression Model Assumptions

All assumptions were examined and confirmed satisfied. The Q-Q plot of standardised residuals demonstrated approximately normal distribution (Figure 1). Variance inflation factors in the final model ranged from 1.15 to 2.18, well below the threshold of 10, confirming the absence of multicollinearity.[14] Tolerance values ranged from 0.46 to 0.87, all above 0.10.

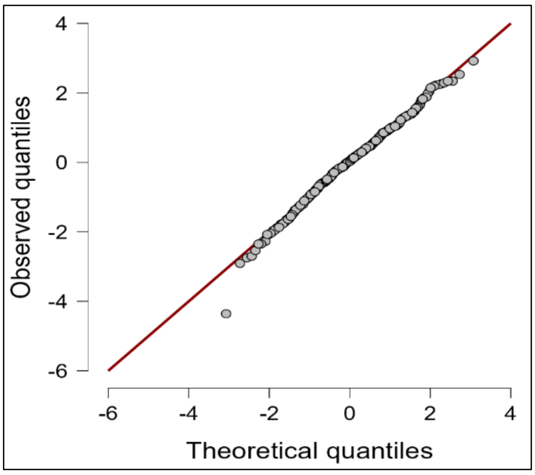

Figure 1: Q-Q Plot of Standardized Residuals

Multiple Linear Regression Analysis

The backward elimination method was employed for variable selection in the multiple regression analysis. The process began with all eight predictor variables entered Model 0 (M_0). Through three sequential elimination steps, variables with non-significant relationships were removed one at a time based on their p-values. Model 1 (M_1) removed self-efficacy ($p=0.256$ in M_0), Model 2 (M_2) removed perceived barriers ($p=0.183$ in M_1), and Model 3 (M_3) removed knowledge of infectious diseases ($p=0.114$ in M_2). The backward elimination process terminated at Model 3, which retained only statistically significant predictors ($p<0.05$).

Table III presents the model comparison across all four models (M_0 to M_3). While the initial model (M_0) with all eight predictors explained 52.3% of variance (Adjusted $R^2=0.515$), the final parsimonious model (M_3) with five significant predictors explained 51.7% of variance (Adjusted $R^2=0.512$), representing only a minimal reduction of 0.6% in explained variance. The final model demonstrated improved parsimony with lower Akaike Information Criterion (AIC=2,194.290) and Bayesian Information Criterion (BIC=2,223.359) values compared to the initial model, indicating better model fit with fewer predictors. The final model remained highly significant ($F(5,464)=99.49$, $p<0.001$), confirming its strong predictive capacity.

Table III: Model Comparison for Backward Elimination Process (n=470)

Model	R	R^2	Adjusted R^2	RMSE	AIC	BIC	F	df	p
M_0	0.723	0.523	0.515	2.470	2,194.630	2,236.158	63.23	8,461	<0.001
M_1	0.722	0.522	0.515	2.471	2,193.949	2,231.324	72.03	7,462	<0.001
M_2	0.721	0.520	0.514	2.473	2,193.756	2,226.977	83.60	6,463	<0.001
M_3	0.719	0.517	0.512	2.477	2,194.290	2,223.359	99.49	5,464	<0.001

R, multiple correlation coefficient; R^2, coefficient of determination; RMSE, root mean square error; AIC, Akaike information criterion; BIC, Bayesian information criterion; F, F-statistic; df, degrees of freedom.

The results of the final multiple linear regression model (M_3) are presented in Table IV. Five predictor variables demonstrated statistically significant relationships with behavioural likelihood of CBS participation. Perceived susceptibility to infectious diseases emerged as the strongest predictor ($\beta=0.255$, $p<0.001$), indicating that individuals who perceive their community to be more vulnerable to infectious disease outbreaks are significantly more likely to engage in CBS activities. For every one-unit increase in perceived susceptibility, behavioural likelihood increased by 0.268 units (unstandardised coefficient =0.268, SE =0.044), holding all other variables constant.

Perceived benefits of CBS participation were the second strongest predictor (β=0.231, p<0.001), demonstrating that individuals who recognize the advantages of participating in surveillance activities for themselves and their community show higher behavioural likelihood. The unstandardized coefficient of 0.277 (SE=0.051) indicates a substantial positive relationship between perceived benefits and CBS participation likelihood.

Intention to accept involvement in CBS activities showed a significant positive relationship with behavioural likelihood (β=0.209, p<0.001). This finding supports the central tenet of the Theory of Planned Behaviour that behavioural intention is a key determinant of actual behaviour.[9] The unstandardised coefficient of 0.232 (SE=0.044) suggests that participants who expressed stronger intentions to participate in CBS were significantly more likely to engage in such activities.

Subjective norms demonstrated a significant positive relationship with behavioural likelihood (β=0.202, p<0.001), indicating that perceived social pressure and normative expectations from family, friends, and community leaders significantly influence CBS participation. The unstandardised coefficient of 0.261 (SE=0.046) suggests that social influence plays an important role in shaping community engagement in surveillance activities.

Attitudes toward participation showed a significant negative relationship with behavioural likelihood (β=-0.104, p=0.002). The unstandardised coefficient of -0.100 (SE=0.032) indicates that higher scores on the attitudes scale, which measured unfavourable evaluations of CBS, were associated with lower behavioural likelihood. This finding confirms that negative attitudes toward CBS participation act as barriers to engagement.

Three predictor variables (knowledge of infectious diseases, perceived barriers, and self-efficacy) were excluded from the final model through the backward elimination process as they did not demonstrate statistically significant relationships with behavioural likelihood when accounting for other predictors in the model.

Table IV: Final Multiple Linear Regression Model Coefficients for Predictors of Behavioural Likelihood (n=470)

Variable	Unstandardised Coefficient	Standard Error	Standardised Coefficient (β)	t	p	Tolerance	VIF
(Intercept)	9.402	1.202	-	7.826	<0.001	-	-
Subjective norms (SN)	0.261	0.046	0.202	5.621	<0.001	0.785	1.274
Intention (INT)	0.232	0.044	0.209	5.321	<0.001	0.618	1.618
Attitudes (ATT)	-0.100	0.032	-0.104	-3.098	0.002	0.821	1.218
Perceived benefits (BEN)	0.277	0.051	0.231	5.414	<0.001	0.489	2.044
Perceived susceptibility (SUS)	0.268	0.044	0.255	6.053	<0.001	0.459	2.178

Model Summary: R^2=0.517, Adjusted R^2=0.512, $F(5,464)$=99.49, p<0.001 VIF, variance inflation factor.

DISCUSSION

This study examined the determinants of community participation in infectious disease surveillance using a multi-theoretical approach integrating constructs from the Theory of Planned Behaviour and Health Belief Model. The use of backward elimination regression allowed for the identification of the most parsimonious and statistically robust model, retaining only those predictors with significant independent contributions to explaining CBS participation likelihood. The findings provide important insights into the factors that influence community engagement in CBS activities and have significant implications for public health practice and policy.

The final regression model explained 51.7% of the variance in behavioural likelihood of CBS participation, indicating substantial predictive capacity. This level of explained variance is comparable to or exceeds that reported in similar studies examining health-related behaviours using integrated theoretical frameworks, where explained variance typically ranges from 30% to 55%.[15,16] For instance, a meta-analysis of the Health Belief Model's effectiveness in predicting health behaviours reported a mean variance explained of 36%,[15] while studies combining TPB and HBM constructs have reported R^2 values ranging from 0.42 to 0.58.[16,17] The strong model fit suggests that combining constructs from both theoretical frameworks provides a comprehensive understanding of factors influencing CBS participation, supporting the utility of multi-theoretical approaches in behavioural research.[17]

Perceived susceptibility to infectious diseases emerged as the strongest predictor of CBS participation likelihood, consistent with the HBM and previous research demonstrating that risk perception drives health-protective behaviors.[18,19] Similar patterns have been observed in studies of community participation in COVID-19 prevention measures, where heightened perceived susceptibility was associated with increased protective behaviors.[19,20] A cross-sectional study in Thailand found that community leaders with higher perceived susceptibility to infectious diseases were 2.3 times more likely to engage in prevention activities.[19] This finding suggests that interventions aimed at enhancing community awareness of disease risks and vulnerabilities may effectively promote CBS uptake, though messaging must be balanced to avoid inducing excessive fear.[21]

Perceived benefits were the second strongest predictor, demonstrating that individuals who recognise the advantages of surveillance activities for personal and community health are more likely to participate. This also aligns with the HBM's emphasis on perceived benefits as a key motivator and is consistent with previous research in community health program participation.[22] A systematic review of community-based health interventions found that clear articulation of program benefits was associated with 40-60% higher participation rates across diverse settings.[22] The practical implication is that communication strategies should clearly articulate CBS participation benefits, emphasizing both individual advantages (early detection, prompt treatment) and community benefits (outbreak prevention, community protection) using concrete examples and testimonials from community members.[20,22]

The significant positive relationship between intention and behavioural likelihood supports the TPB's central proposition that behavioural intention is the most proximal determinant of actual behaviour.[23] Meta-analytic evidence indicates that intention typically accounts for 25-40% of variance in health behaviours, with stronger relationships observed when intentions are specific and recent.[23] This suggests that interventions designed to strengthen community members' intentions to participate in CBS activities may effectively translate motivation into engagement. Strategies to enhance behavioural intention might include implementation intentions (specific if-then plans), goal-setting exercises, and commitment mechanisms that create psychological accountability and bridge the intention-behaviour gap.[24,25]

Subjective norms demonstrated a significant positive relationship with CBS participation, highlighting the importance of social influences in shaping health-related behaviours, particularly in collectivist cultural contexts.[26,27] Research in similar contexts has shown that social normative influences can account for substantial variance in health behaviours in communities with strong social cohesion.[26] A study examining health volunteer participation in China found that subjective norms were the strongest predictor among participants from rural, collectivist communities.[26] The practical implication is that interventions should leverage social networks and community structures to create supportive social norms about CBS participation, such as engaging respected community leaders as CBS champions and creating visible recognition programs for active participants.[27]

The significant negative association between unfavourable attitudes and behavioural likelihood confirms that negative perceptions and concerns about CBS act as barriers to participation. This aligns with previous studies demonstrating that concerns about time burden, privacy, confidentiality, or lack of trust can significantly impede participation in community surveillance programs.[28] Research following disaster situations has shown that negative attitudes often emerge when communities prioritise immediate assistance over long-term prevention activities.[28] Studies applying the TRA and TPB have consistently shown that negative attitudes must be addressed alongside building positive attitudes to maximise behavioural intention.[29,30] Public health programs must proactively address community concerns through transparent communication about data use and confidentiality protections, and by demonstrating tangible community benefits from CBS activities.[28]

The exclusion of knowledge of infectious diseases from the final model was unexpected, given traditional emphasis on health education in public health programs. This finding contrasts with studies demonstrating that knowledge improves behavioural likelihood and engagement in health behaviours.[31,32] However, recent investigations have also reported similar nonsignificant findings. For instance, a study examining Polish adolescents found that better health-related knowledge was not related to favourable health behaviour.[33] Similarly, research on 1,920 Japanese health management specialists revealed a critical distinction: basic-level (functional) health literacy showed no significant relationship with health-related lifestyle behaviours, with regression analyses indicating no statistical significance ($p=0.80$, 0.10, and 0.15 across different models).[34] This warrants further investigation, potentially reflecting CBS's specific nature, measurement limitations, or ceiling effects due to participants' high educational level (87.2% university-educated) in this study.

The non-significant relationship between self-efficacy and CBS participation was unexpected, given its established role in behavioural theories.[34] Several explanations may account for this finding. For instance, practical barriers such as time constraints or resource limitations may exert greater influence than self-efficacy in determining actual participation.[35] Or measurement limitations in assessing self-efficacy within the specific CBS context may have contributed to the null result. Future research should explore whether self-efficacy becomes more important for complex CBS tasks requiring specialized skills.[35,36]

Similarly, the non-significant relationship between perceived barriers and CBS participation contrasts with HBM predictions. The study population of educated school teachers may have faced minimal objective barriers, or participants may not have yet encountered significant obstacles, since many had not previously engaged in formal CBS activities. Additionally, the strong positive predictors in the model may have overshadowed barrier effects. This finding suggests that in populations with enabling conditions (education, resources, social support), motivational factors may be more critical than barrier reduction. However, perceived barriers may become more salient once individuals actually attempt to engage in CBS activities, suggesting potential value in longitudinal studies examining how barrier perceptions evolve with experience.[20] This study has several strengths including a theory-driven approach integrating multiple established behavioural frameworks, adequate sample size (n=470) calculated based on statistical power considerations, use of a rigorously validated questionnaire with demonstrated reliability during exploratory and confirmatory phases, and rigorous validation, systematic analytical approach beginning with bivariate analyses before multivariate modelling, and verification of regression assumptions with acceptable multicollinearity indices (VIF<2.2).

However, several limitations should be acknowledged. The cross-sectional design precludes causal inferences about relationships between predictor variables and behavioural likelihood, as temporal precedence cannot be established. Self-reported measures may be subject to social desirability bias and recall bias. The study was conducted in a specific geographic context (Kelantan, Malaysia) among a relatively homogeneous population (primarily Malay school teachers with high educational levels), which may limit generalisability to other settings with different cultural, social, economic, and epidemiological contexts. The measure of behavioural likelihood rather than actual CBS participation represents an intermediate outcome, and the relationship between likelihood and actual behaviour may be influenced by additional factors not captured in this study. Future research should employ longitudinal designs to establish temporal relationships, incorporate objective measures of actual CBS participation behaviours, conduct studies in diverse settings to examine the generalisability of findings, and include qualitative components to provide a deeper understanding of the mechanisms underlying the relationships identified.

CONCLUSION

This study provides empirical evidence supporting a multi-theoretical approach to understanding community participation in infectious disease surveillance. The backward elimination regression analysis identified five key determinants that independently predict CBS participation likelihood, accounting for 51.7% of variance. The results show that behavioural likelihood of CBS participation is mainly influenced by perceived susceptibility, perceived benefits, behavioural intention, and social norms, while negative attitudes act as barriers. Knowledge, self-efficacy, and perceived barriers were not significant predictors in the final model, indicating that information- or confidence-based interventions alone may be inadequate. The model's strong predictive power (51.7% variance explained) demonstrates that integrating constructs from the Theory of Planned Behaviour and Health Belief Model offers a comprehensive framework for explaining CBS participation.

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CONFLICT OF INTEREST

There were no conflicts of interest between the contributors of this research.

INSTITUTIONAL REVIEW BOARD (ETHICS COMMITTEE)

The study protocol was approved by the Human Research Ethics Committee of Universiti Sains Malaysia (Reference No.: USM/JEPeM/22050317.

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