Journal of Universal Community Empowerment Provision
Vol. 6, Issue 2, 2026
Page 93-105
DOI: https://doi.org/10.55885/jucep.v6i2.949

Impact of Community Empowerment on Diarrhea Prevention Through Food Safety (A Case Study)

Nurita Lastri Tampubolon[1,2], Muhammad Hanri[2]
[1]Department of Economics, Faculty of Economics and Business, Universitas Indonesia, Indonesia
[2]Republic of Indonesia Food and Drug Supervisory Agency, Indonesia
*Corresponding Author: Nurita Lastri Tampubolon
Email: nuritalastri.tampubolon@gmail.com

Abstract. *Community empowerment plays an important role in preventive public health interventions, particularly in reducing foodborne diseases such as diarrhea, which remains a major health burden in Indonesia. The Safe Food Village Program (Program Desa Pangan Aman), initiated by the Indonesian Food and Drug Authority (Badan Pengawas Obat dan Makanan), aims to improve food safety awareness and community capacity through empowerment-based interventions. This study examines the impact of the program on diarrhea incidence and evaluates its economic benefits. A quasi-experimental impact evaluation design using observational secondary data was employed, integrating administrative data from BPOM, Village Potential Statistics (Podes) 2018–2019, and the National Socioeconomic Survey (Susenas) 2019. To address non-random program participation, Mahalanobis Distance Matching (MDM) with Kernel weighting was used as the primary estimation model, complemented by regression adjustment and robustness testing using Propensity Score Matching (PSM) Kernel and Ordinary Least Squares (OLS). The findings indicate that participation in the Safe Food Village Program significantly reduced the diarrhea incidence ratio by 0.0085 percentage points (ATT = −0.000085) at the 1% significance level. Although modest in magnitude, the effect is epidemiologically meaningful at the national scale due to the large population coverage. The cost-benefit simulation further shows a positive net benefit of IDR 72.94 billion, with a Benefit-Cost Ratio of 7.63, indicating strong economic feasibility. These findings suggest that community-based food safety interventions can improve public health outcomes while generating substantial economic returns*

Keywords: *: Community Empowerment, Food Safety, Diarrhea, Safe Food Village*

Received: April 4, 2026 Received in Revised: May 30, 2026 Accepted: June 29, 2026

INTRODUCTION

Health is one of the investments in advancing the quality of human resources (Todaro & Smith, 2012; Fort et al., 2017). In 2000, health development reforms in Indonesia began to focus on the importance of community empowerment as a promotive and preventive approach to strengthening public health without neglecting curative and rehabilitative efforts (Rachmat, 2021; Sebong et al., 2025; Paccyne et al., 2026; McCollum et al., 2018; Langlois et al., 2020). However, the effectiveness of community empowerment in improving health outcomes is still debated. Based on a literature review conducted by Laverack (2006) identifying the relationship between community empowerment and health outcomes, it was found that studies related to community empowerment had a significant impact on public health outcomes.

ISSN: 2776-1142 (online) ISSN: 2776-1134 (print)

On the other hand, research by Carr et al. (2008), Weber et al. (2024), Skivington et al. (2021), Greenhalgh et al. (2016), Langford et al. (2015), highlights that there are still limitations in evaluation in the context of health promotion and the need to shift the focus of evaluation from output to outcome, emphasizing the importance of measuring the real impact of public health intervention programs, especially in determining relevant health outcomes and measuring their impact, not just the implementation of the program itself.

Due to the gap in assessing the effectiveness of community empowerment, it is relevant to conduct further research on the impact of empowerment programmes on community health levels (Cyril et al., 2015; O'Mara-Eves et al., 2015; Singh et al., 2015; Lindacher et al., 2018; Kruahong et al., 2023). This research is important considering that strengthening preventive efforts can lead to a reduction in the curative health service budget. Currently, budget allocation for health services remains imbalanced, with a larger focus on curative services compared to preventive ones. The imbalance in spending between curative and preventive indicates that there are still health problems that should be prevented but become serious diseases and even cause death (Ruthsatz & Candeias, 2020; Norheim et al., 2015; Leggio et al., 2017; Volkow & Blanco, 2023).

One of these diseases is diarrhea, which is classified as a group of infectious diseases with the second largest total expenditure after respiratory infections, which amounted to IDR 2.4 trillion in 2018 (Rampedi et al., 2024; Kitole et al., 2024; Sulistyaningrum et al., 2022). The Indonesian Nutritional Status Survey 2020 shows the prevalence rate of diarrhea in Indonesia is 9.8%, contributing to mortality in children aged 29 days to 11 months and also being associated with stunting (Derso et al., 2017). Food contaminated by pathogens or chemicals is responsible for more than 200 diseases including diarrhea (World Health Organization, 2005), highlighting the need for food safety education and prevention efforts. In line with the government's focus on health development, food safety efforts will be achieved through community empowerment.

The Safe Food Village is one of the community empowerment programs. The program was initiated by Indonesian Food and Drug Authority (Badan POM) that aims to empower communities and increase awareness of food safety (Najemi et al., 2019; Wulandari et al., 2019; Bariyah, 2024). The program focuses on interventions in both the supply and demand sides of the food chain. On the demand side, communities are empowered to be more independent and informed about food safety. On the supply side, supervision is provided throughout the production and distribution process (Pop et al., 2018; Koumboulis et al., 2023; Chen et al., 2021).

These interventions aim to increase the demand for safe and healthy food, encouraging food producers to meet this demand. By ensuring safe and accurate labeling of food, people are protected from foodborne illnesses and the associated medical costs. This is in line with the findings of Rasu et al. (2015), Haun et al. (2015), Magnani et al. (2018) who found that health literacy is associated with the amount of health care costs incurred, especially in the use of emergency services.

Several studies have shown that community empowerment programs in the field of health can increase health knowledge, change behavior, and ultimately reduce morbidity rates (Haldane et al., 2019; Lin et al., 2019; Suryani et al., 2025). Research describing how empowerment programs are carried out and examining the relationship between daily behavior that impact the risk of diarrhea can be seen in a study Jahan (2000) which found that the SAFE (Sanitation and Family Education) program was successful in improving health understanding and behavior in Bangladesh communities.

Furthermore, the study Ali & Shahreen (2024) concluded that teaching germ theory to illiterate villagers in Bangladesh contributed to encouraging behavioral change, better hygiene, and a reduction in the incidence of diarrhea. However, these studies have not further analyzed whether the reduction in incidence is proportional to the cost of implementing the program. Therefore, this study will examine the impact of the Safe Food Village program nationally and analyze the program's impact on community health levels as measured by the number of

ISSN: 2776-1142 (online) ISSN: 2776-1134 (print)

preventable cases of diarrhea, as well as analyze the economic benefits gained by reducing the number of diarrhea cases.

METHODS

Research Design

This study employed a quasi-experimental impact evaluation design using observational secondary data to estimate the causal effect of the Safe Food Village Program (*Program Desa Pangan Aman*) on diarrhea prevention in Indonesia. A quasi-experimental approach was considered appropriate because participation in the program was not randomly assigned but administratively determined based on eligibility criteria established by the Indonesian Food and Drug Authority (*Badan Pengawas Obat dan Makanan* or BPOM). Such non-random assignment may introduce selection bias because villages participating in the program could systematically differ from non-participating villages in institutional readiness, economic potential, and public health infrastructure. Therefore, a matching-based counterfactual framework was applied to reduce selection bias and improve comparability between treated and untreated villages.

Research Context and Data Collection

The study was conducted at the national level in Indonesia, focusing on villages participating in the Safe Food Village Program during 2018. This study integrated three secondary datasets. First, administrative data from BPOM were used to identify villages receiving the intervention. Second, Village Potential Statistics (*Podes*) 2018 and 2019 from Statistics Indonesia provided village-level socioeconomic, infrastructural, and health-related variables. Third, the National Socioeconomic Survey (*Susenas*) 2019 supplied district-level average household size used to estimate village population. Podes 2018 was used to construct baseline covariates and matching variables, while Podes 2019 was used to obtain diarrhea incidence data. Since Podes 2019 records diarrhea cases occurring during the previous 12 months, the dataset reflects health outcomes after or during program implementation in 2018, thereby supporting temporal validity, although variation in intervention timing across villages remains a limitation.

Sample and Variable Measurement

The treatment group consisted of 105 villages that participated in the Safe Food Village Program in 2018. The comparison group consisted of villages that did not participate in the program. However, not all non-participating villages were directly used as controls. Villages with incomplete covariate information and observations outside the common support region were excluded during the matching stage to ensure comparability. The final dataset consisted of 83,868 village observations. The dependent variable was the diarrhea incidence ratio, measured as the proportion of diarrhea cases relative to the total village population. The ratio was calculated using the following formula:

Diarrhea Incidence Ratio = Number of Diarrhea Cases / Estimated Village Population ...(1)

The number of diarrhea cases was obtained from Podes 2019. Since Podes does not provide direct village population data in the relevant module, village population was estimated using:

Estimated Village Population = Number of Households × Average Household Size ...(2)

The number of households was obtained from Podes, while average household size was derived from district-level Susenas 2019 data. Although this estimation may introduce measurement error due to within-district heterogeneity, it provides a practical approximation in the absence of direct village-level population statistics. Matching variables were selected based on official program eligibility criteria, including village leadership commitment, economic potential through food industries, the presence of Village-Owned Enterprises (*BUMDes*), tourism potential, local food development potential, foodborne disease history, and community empowerment activities. Additional control variables included access to sanitation, drinking

ISSN: 2776-1142 (online) ISSN: 2776-1134 (print)

water source, government health facilities, and fecal disposal infrastructure, which are theoretically associated with diarrhea incidence.

Data Analysis and Validity

The primary analytical technique used in this study was Mahalanobis Distance Matching (MDM) with Kernel weighting, chosen for its ability to reduce multidimensional covariate imbalance and efficiently utilize multiple control observations (Bittmann, 2019). To estimate program impact after matching, regression adjustment was applied using the following model:

$$Yi = \beta 0 + \beta 1Ti + \gamma Zi + \varepsilon i \ ...(3)$$

where *Yi* represents diarrhea incidence ratio, *Ti* denotes treatment status, and *Zi* represents control variables. The coefficient β1 estimates the Average Treatment Effect on the Treated (ATT). Bootstrap standard errors were estimated using 500 replications.

To ensure validity, balance diagnostics were conducted using standardized mean differences and variance ratios. Good balance was indicated when standardized mean differences approached zero and variance ratios approached one (Huang et al., 2021). Reliability of the estimation was further assessed through robustness testing using Propensity Score Matching (PSM) Kernel and Ordinary Least Squares (OLS). Consistent results across models strengthened confidence in the estimated causal effect of the Safe Food Village Program.

RESULTS AND DISCUSSION

The research data, which include information about the number of observations, mean values, standard deviations, and the minimum and maximum values for each variable used in the study, are presented in Table 1.

Descriptive Statistics of Research Variables

Table 1. Summary Statistics of Research Variables

Variable	Villages that participate in Safe Food Village Program				Villages that do not participate Safe Food Village Program			
	Mean	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
Independent Variable								
Participation in Safe Food Village Program	1	0	1	1	0	0	0	0
Dependent Variable								
Diarrhea incidence ratio	0	0	0	0	.0001	.0046	0	1.033
Matching Variable								
has committed to developing health facilities	.48	.50	0	1	.36	.48	0	1
has committed to empowerment in health sector	.55	.49	0	1	.42	.49	0	1
has economic potential through the development of micro and small food industries	.67	.47	0	1	.38	.48	0	1
has economic potential with the presence of ready-to-eat food businesses	.019	.137	0	1	.18	.38	0	1

ISSN: 2776-1142 (online) ISSN: 2776-1134 (print)

Variable	Villages that participate in Safe Food Village Program				Villages that do not participate Safe Food Village Program			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
has a Village-Owned Enterprise development program	.32	.47	0	1	.19	.39	0	1
has tourism development potential	.07	.26	0	1	.04	.20	0	1
has potential for local food development	.49	.50	0	1	.31	.46	0	1
ever had a foodborne disease	.05	.23	0	1	.03	.18	0	1
has activities in agricultural and non-agricultural empowerment	.21	.41	0	1	.14	.35	0	1
has activities in community capacity enhancement	.43	.49	0	1	.28	.44	0	1
Control Variable								
existence of government health facilities	.80	.40	0	1	.70	.45	0	1
sanitation and clean water infrastructure	.42	.49	0	1	.36	.48	0	1
source of drinking water	.89	.30	0	1	.70	.45	0	1
fecal landfill	.62	.48	0	1	.48	.49	0	1
Observation	105 villages				83.763 villages			
Total	**83.868 villages**							

Source: Podes 2018 and 2019, Badan POM 2018, Susenas 2018, processed

Table 1 presents the descriptive statistics of all research variables before the matching process. The baseline comparison reveals substantial differences between villages participating in the Safe Food Village Program and those not participating. Program villages generally exhibited higher mean values across several institutional readiness and infrastructure indicators, including commitment to health facility development, health-sector empowerment activities, economic potential through food industries, Village-Owned Enterprise (BUMDes) development, and access to sanitation and clean water infrastructure. These differences suggest that villages selected for the program were not randomly chosen but tended to have stronger institutional capacity and better supporting infrastructure prior to intervention.

This pattern provides empirical evidence of potential selection bias, as villages with better governance capacity and public health readiness were more likely to be included in the program. Such pre-existing differences imply that a direct comparison between participating and non-participating villages could produce biased estimates of program impact. Therefore, the descriptive results in Table 1 strongly justify the use of a matching approach to construct a more appropriate counterfactual group and reduce observable bias in the impact estimation.

Matching Results and Balance Diagnostics

Table 2 demonstrates that all treatment groups are well-matched with the control groups to be used in the estimation.

ISSN: 2776-1142 (online) ISSN: 2776-1134 (print)

Table 2. Matching Statistics Using MDM Kernel

Matching Statistics	Value
Treated villages	105
Matched treated villages	105
Unmatched treated villages	0
Control villages used	47,485
Unused control villages	36,278
Total control villages	83,763
Common support achieved	Yes
Bandwidth	2.2e−308

Source: Processed by authors using Podes 2018 data.

Table 2 presents the matching statistics using the Mahalanobis Distance Matching (MDM) Kernel method. All 105 treated villages were successfully matched, indicating that no treated observations were excluded during the matching process. From the pool of 83,763 non-participating villages, 47,485 control villages were used to construct weighted counterfactual observations, while 36,278 controls remained unused due to lower similarity in covariate characteristics. This indicates adequate overlap between treatment and control groups. The matching process also satisfied the common support assumption, confirming that each treated village had comparable control observations within the covariate space. The bandwidth value of 2.2e−308 reflects the kernel weighting parameter used to assign weights to control observations according to multidimensional similarity.

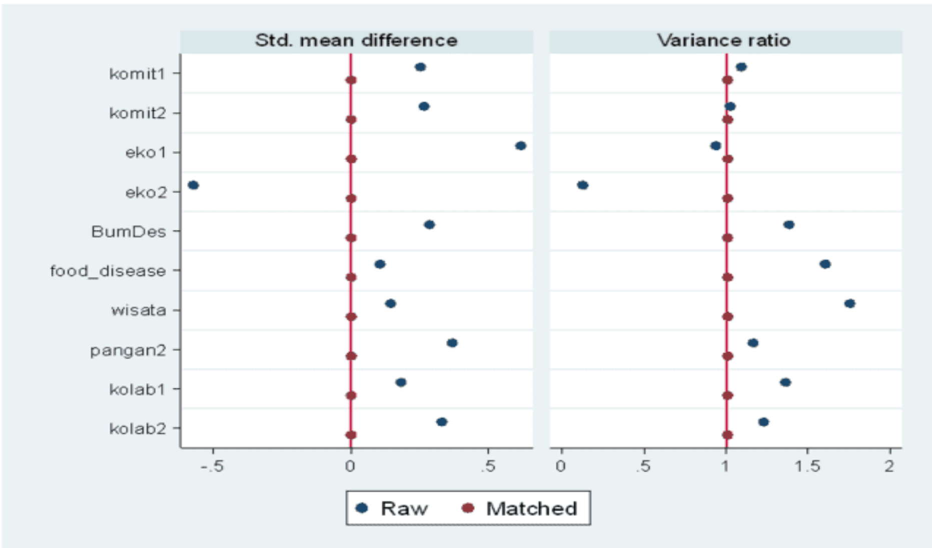

Figure 1. Balancing Diagnostic Results in Matching Stage

Impact Estimation of the Safe Food Village Program

Table 3 below presents the results of the main estimation model, the MDM Kernel, which shows consistent impact estimations, significantly negative at the 1% level in equations (1) to (4).

Table 3. Impact of the Safe Food Village Program - National Analysis

	Dependent Variable: Diarrhea Incidence Ratio			
	(1)	(2)	(3)	(4)
Participation in Safe Food Village Program (ATT)(1 = Yes; 0 = No)	- 0.000090***	- 0.000091***	- 0.000087***	- 0.000085***
	(0.00002)	(0.00002)	(0.00002)	(0.00001)
Observations	83,868	83,868	83,868	83,868
Control Variables				

ISSN: 2776-1142 (online) ISSN: 2776-1134 (print)

Number of health facilities	Yes	Yes	Yes	Yes
Access to sanitation and clean water infrastructure	No	Yes	Yes	Yes
Drinking water source	No	No	Yes	Yes
Final disposal of feces	No	No	No	Yes

Bootstrap standard errors in parentheses with 500 repetitions

*p<0.1, **p<0.05, ***p<0.01

Table 3 presents the impact estimation results using the MDM Kernel model with regression adjustment. Across all four model specifications, participation in the Safe Food Village Program shows a negative and statistically significant effect at the 1% level, indicating a consistent association between program participation and lower diarrhea incidence. The estimated ATT coefficient ranges from −0.000090 to −0.000085, demonstrating strong coefficient stability across specifications. The preferred specification is Model (4), which includes all control variables and reports an ATT coefficient of −0.000085.

For consistent interpretation, the ATT coefficient is expressed as both a proportion and percentage-point reduction. Specifically, the coefficient −0.000085 indicates that participation in the Safe Food Village Program reduced the diarrhea incidence ratio by 0.0085 percentage points among treated villages. Although the numerical magnitude appears small, the effect remains practically meaningful when scaled to the national population. Because diarrhea is a high-frequency preventable disease, even a modest percentage-point reduction can translate into a substantial number of prevented cases, lower healthcare expenditures, and reduced productivity loss.

These findings suggest that community-based food safety interventions generate measurable public health benefits at scale. After obtaining the estimation results, robustness tests are performed to compare the results of the main model with other models, including Propensity Score Matching (PSM) with Kernel algorithm. In addition, results from the Ordinary Least Squares (OLS) model were also included to analyze the effectiveness of the main model in minimizing bias from confounding variables. The results of all these models are shown in Table 4.

Robustness Testing

Table 4. Recapitulation of the Impact of the Safe Food Village Program

Recapitulation of the Impact of the Safe Food Village Program - National			
	OLS	PSM Kernel	MDM Kernel
Participation in the Safe Food Village Program - ATT (1 = yes, 0 = no)	-0.000120***	-0.000085***	-0.000085***
	(0.00001)	(0.00002)	(0.00002)
Observations	83868	83868	83868

Bootstrap standard errors in parentheses with 500 repetitions

*p<0.1, **p<0.05, ***p<0.01

Table 4 compares the main MDM Kernel estimates with alternative estimation methods, namely Propensity Score Matching (PSM) Kernel and Ordinary Least Squares (OLS). The OLS model produced a larger coefficient of −0.000120, suggesting a stronger estimated program effect. However, because OLS does not explicitly account for non-random program selection, this estimate likely overstates the true impact due to residual selection bias.

In contrast, both the PSM Kernel and MDM Kernel models produced an identical ATT coefficient of −0.000085, equivalent to a 0.0085 percentage-point reduction in diarrhea incidence. The consistency between these two matching-based estimators strengthens

ISSN: 2776-1142 (online) ISSN: 2776-1134 (print)

confidence in the robustness of the main findings. The difference between OLS and matching-based estimates further confirms that correcting for observable selection bias is essential in this study. Without matching, the program effect would likely be overestimated due to baseline differences between participating and non-participating villages.

Cost-Benefit Simulation

Table 5. Cost Components Related to Diarrhea Disease

Cost Components	Cost Subcomponents
Direct Health Costs (DHC)	Costs of initial doctor visit, treatment costs, laboratory testing costs
Direct Non-Health Costs (DNHC)	Transportation costs to healthcare facilities, non-medical patient expenses, mortality-related non-medical costs
Indirect Costs (IC)	Productivity loss due to illness, productivity loss due to premature death, follow-up productivity loss, economic losses due to reputation damage and loss of consumer trust, losses from product recalls

To determine the value of each identified cost subcomponent, Rahayu *et.al.*, (2016) used various supporting data. Regarding data on the number of patients used per year, their study used baseline data reported in 2013. Because these data do not represent actual case counts, the number of cases were estimated based on the assumption that there are 99 unreported cases annually for every reported case in developing countries (World Health Organization, 2008). The study mentioned that the total cost incurred due to diarrhea in one year in 2013 amounted to US$ 78,001,095, approximately IDR 823.768 billion. To determine the cost incurred for one case of diarrhea, the total cost was divided by the number of cases, resulting in a cost of IDR 4,874,371 per person. When converted to the year of this study (2018), the total cost incurred is equivalent to IDR 6,119,335 per person after incorporating inflation rate. Based on the data above, the author formulated a cost-benefit estimate using converted baseline data for the number of diarrhea cases in the following Table 6.

Table 6. Cost-Benefit Simulation of Safe Food Village Program

Description of Cost-Benefit Simulation		
Number of diarrhea cases	Converted total number of diarrhea cases	1,714,700
ATT of Safe Food Village Program	Estimated ATT based on MDM Kernel model	0.008
Number of cases prevented	ATT × Number of diarrhea cases	13,718
Benefit	Cost saved per individual (IDR 6,119,335.80) × Number of cases prevented	83,942,600,793
Cost	Budget for Safe Food Village Program (2018)	11,000,000,000
Net Benefit	Benefit − Cost	72,942,600,793
Benefit-Cost Ratio (BCR)	Benefit ÷ Cost	7.63

Table 6 presents the economic evaluation of the Safe Food Village Program using cost-benefit simulation. The analysis compares total program costs with estimated economic benefits derived from prevented diarrhea cases. The simulation estimates 1,714,700 diarrhea cases, including both reported and unreported cases. Based on the ATT estimate from the MDM Kernel model, the program contributed to a measurable reduction in diarrhea incidence, generating substantial economic savings through reduced medical expenditures and productivity loss. The estimated economic burden per diarrhea case in 2018 was IDR 6,119,335.80, including direct health costs, direct non-health costs, and indirect costs. Using this valuation, the total economic benefit of the program reached IDR 83.94 billion. The Safe Food Village Program required a total implementation budget of IDR 11 billion in 2018. After subtracting implementation costs from

ISSN: 2776-1142 (online) ISSN: 2776-1134 (print)

total benefits, the estimated net benefit reached IDR 72.94 billion. The Benefit-Cost Ratio (BCR) was calculated at 7.63, indicating that every rupiah invested in the program generated approximately 7.63 rupiah in economic return. Since the BCR is substantially greater than 1, the program can be considered economically feasible and socially beneficial.

These findings demonstrate that the Safe Food Village Program delivers benefits not only in terms of improved health outcomes but also in economic efficiency. Even relatively modest reductions in diarrhea incidence can produce substantial cost savings when applied at the national scale. Based on the table above, the cost-benefit simulation using the estimated number of diarrhea cases, which includes unreported cases, shows that the benefits far outweigh the budget spent on the implementation of the program. In this context, estimates must consider the rate of unreported cases within the public health system, as not all individuals affected by diarrhea will develop a diagnosis and/or be recorded in government health data (On & Rahayu, 2017).

The findings demonstrate that the Safe Food Village Program has a statistically significant impact on reducing diarrhea incidence, indicating that community empowerment can serve as an effective preventive public health strategy. Although the estimated reduction of **0.0085 percentage points** appears numerically small, its significance becomes more meaningful when interpreted at the population level. Given Indonesia's large rural population and the high prevalence of diarrheal disease, even modest reductions in incidence can translate into substantial public health gains. This suggests that empowerment-based interventions targeting food safety can complement conventional curative healthcare by reducing preventable disease burdens before they escalate into more severe health outcomes.

The effectiveness of the program may be explained by its dual intervention mechanism targeting both demand and supply sides of food safety. On the demand side, the program improves community awareness, health literacy, and household food handling behavior. On the supply side, it strengthens monitoring and encourages safer production and distribution practices among food producers, vendors, and small-scale food industries. This finding aligns with previous studies showing that food safety education and community-based health interventions contribute to behavioral changes that reduce diarrhea risk. Younie et al. (2020) found that improving community understanding of germ transmission promoted better hygiene practices, while Sheth & Obrah (2004) reported that food safety education significantly reduced diarrhea incidence among children. The present study extends this literature by providing national-scale empirical evidence from Indonesia using a quasi-experimental evaluation framework.

From a policy perspective, the economic findings reinforce the program's strategic value. The positive net benefit of **IDR 72.94 billion** and the **Benefit-Cost Ratio of 7.63** indicate that the Safe Food Village Program generates returns substantially exceeding implementation costs. This suggests that preventive health investments based on community empowerment are not only socially beneficial but also economically efficient. The findings support policy shifts toward stronger preventive spending, particularly in countries where health budgets remain heavily concentrated on curative services (Dieleman et al., 2017; Wang & Wang, 2021). Expanding the Safe Food Village Program and integrating it with sanitation, nutrition, and primary healthcare initiatives could further amplify its impact on public health outcomes.

Despite these contributions, this study has several limitations. First, the quasi-experimental design reduces but does not completely eliminate bias from unobserved confounding factors because program participation was not randomized. Second, the estimation of village population using district-level household averages may introduce measurement error in the diarrhea incidence ratio. Third, variation in program implementation intensity across villages could not be fully captured due to data limitations. Future studies should incorporate longitudinal or panel data, direct village-level population records, and implementation quality

ISSN: 2776-1142 (online) ISSN: 2776-1134 (print)

indicators to produce more precise impact estimates and better understand the mechanisms through which community empowerment improves health outcomes.

CONCLUSION

This study demonstrates that the Safe Food Village Program has a statistically significant impact (0.008 percentage points) on reducing the incidence of diarrhea. Therefore, it is recommended that stakeholders continue to implement this program by expanding the number of villages that can be intervened. Synergies between programs can be an effort to accelerate the intervention in more villages. After obtaining the impact estimation of the Safe Food Village Program on reducing diarrhea incidents, the results were further analyzed using a cost-benefit simulation method to compare the economic benefits of the Safe Food Village Program against the costs incurred to implement the program. The calculations show that using converted diarrhea data yielded a positive net benefit of IDR 72.94 billion and a benefit-cost ratio of 7.63 (>1). This indicates that economically, the Safe Food Village Program offers greater benefits compared to the budget of its implementation, making the program relevant and worthwhile. However, these findings are susceptible to being considered costly if the cost-benefit simulation is performed using a reported number of diarrhea cases.

SUGGESTION

Therefore, the government needs to collaboratively update and improve data to ensure the recorded number of diarrhea cases is accurate for use in analysis purposes, particularly for the prevention and control of diarrhea through community empowerment programs.

ACKNOWLEDGMENT

We thank Indonesian Food and Drug Authority (Badan POM) for providing the data of this research, as well as the mentors in University of Indonesia for academic support.

REFERENCES

Ali, M., & Shahreen, T. (2024). Hygiene promotion interventions and their effectiveness in protecting public health in Rohingya refugee settlements in Bangladesh. *International Journal of Research and Scientific Innovation*, *11*(15), 83-115.

Bariyah, K. (2024). The Jurisdiction of Civil Servants of The POM Agency in Investigating Drug and Food Circulation Crimes in Indonesia. *Jurnal Legisci*, *2*(1), 13-26. https://doi.org/10.62885/legisci.v2i1.393

Bittmann, F. (2019). *Stata: A really short introduction*. Walter de Gruyter GmbH & Co KG.

Carr, S. M., Lhussier, M., Wilkinson, J., & Gleadhill, S. (2008). Empowerment evaluation applied to public health practice. *Critical Public Health, 18*(2), 161–174. https://doi.org/10.1080/09581590701499327

Chen, S., Gong, F., Zhang, M., Yuan, J., Liao, S., Chen, H., ... & Hu, X. (2021). Planning and scheduling for industrial demand-side management: State of the art, opportunities and challenges under integration of energy internet and industrial internet. *Sustainability*, *13*(14), 7753. https://doi.org/10.3390/su13147753

Cyril, S., Smith, B. J., Possamai-Inesedy, A., & Renzaho, A. M. (2015). Exploring the role of community engagement in improving the health of disadvantaged populations: a systematic review. *Global health action*, *8*(1), 29842. https://doi.org/10.3402/gha.v8.29842

Derso, T., Tariku, A., Biks, G. A., & Wassie, M. M. (2017). Stunting, wasting and associated factors among children aged 6–24 months in Ethiopia. *BMC Pediatrics, 17*, 96. https://doi.org/10.1186/s12887-017-0848-2

Dieleman, J., Campbell, M., Chapin, A., Eldrenkamp, E., Fan, V. Y., Haakenstad, A., ... & Murray, C. J. (2017). Evolution and patterns of global health financing 1995–2014: development assistance for health, and government, prepaid private, and out-of-pocket health spending in 184 countries. *The Lancet*, *389*(10083), 1981-2004.

Fort, A. L., Deussom, R., Burlew, R., Gilroy, K., & Nelson, D. (2017). The human resources for health effort index: a tool to assess and inform strategic health workforce investments. *Human resources for health*, *15*(1), 47. https://doi.org/10.1186/s12960-017-0223-2

Greenhalgh, T., Jackson, C., Shaw, S., & Janamian, T. (2016). Achieving research impact through co-creation in community-based health services: literature review and case study. *The Milbank Quarterly*, *94*(2), 392-429. https://doi.org/10.1111/1468-0009.12197

Haldane, V., Chuah, F. L., Srivastava, A., Singh, S. R., Koh, G. C., Seng, C. K., & Legido-Quigley, H. (2019). Community participation in health services development, implementation, and evaluation: A systematic review of empowerment, health, community, and process outcomes. *PloS one*, *14*(5), e0216112. https://doi.org/10.1371/journal.pone.0216112

Haun, J. N., Patel, N. R., French, D. D., Campbell, R. R., Bradham, D. D., & Lapcevic, W. A. (2015). Association between health literacy and medical care costs in an integrated healthcare system: a regional population based study. *BMC health services research*, *15*(1), 249. https://doi.org/10.1186/s12913-015-0887-z

Huang, W., Ye, J., Qiu, Y., Peng, W., Lan, N., Cui, W., ... & Li, Y. (2021). Propensity-score-matching analysis to compare efficacy and safety between 16-gauge and 18-gauge needle in ultrasound-guided biopsy for peripheral pulmonary lesions. *BMC cancer*, *21*(1), 390. https://doi.org/10.1186/s12885-021-08126-7

Jahan, A. R. (2000). Promoting health literacy: Prevention of diarrhoeal disease. *Health Promotion International, 15*(4), 285–291. https://doi.org/10.1093/heapro/15.4.285

Kitole, F. A., Lihawa, R. M., & Mkuna, E. (2024). Comparative analysis on communicable and non-communicable diseases on catastrophic spending and impoverishment in Tanzania. *Global Social Welfare*, *11*(2), 123-134. https://doi.org/10.1007/s40609-022-00241-y

Koumboulis, F. N., Fragkoulis, D. G., & Georgakopoulos, P. (2023). A distributed supervisor architecture for a general wafer production system. *Sensors*, *23*(9), 4545. https://doi.org/10.3390/s23094545

Kruahong, S., Tankumpuan, T., Kelly, K., Davidson, P. M., & Kuntajak, P. (2023). Community empowerment: A concept analysis. *Journal of advanced nursing*, *79*(8), 2845-2859. https://doi.org/10.1111/jan.15613

Langford, R., Bonell, C., Jones, H., Pouliou, T., Murphy, S., Waters, E., ... & Campbell, R. (2015). The World Health Organization's Health Promoting Schools framework: a Cochrane systematic review and meta-analysis. *BMC public health*, *15*(1), 130. https://doi.org/10.1186/s12889-015-1360-y

Langlois, E. V., McKenzie, A., Schneider, H., & Mecaskey, J. W. (2020). Measures to strengthen primary health-care systems in low-and middle-income countries. *Bulletin of the World Health Organization*, *98*(11), 781. https://doi.org/10.2471/BLT.20.252742

Laverack, G. (2006). Improving health outcomes through community empowerment: a review of the literature. *Journal of Health, Population and Nutrition*, 113-120.

Leggio, M., Lombardi, M., Caldarone, E., Severi, P., D'emidio, S., Armeni, M., ... & Mazza, A. (2017). The relationship between obesity and hypertension: an updated comprehensive overview on vicious twins. *Hypertension research*, *40*(12), 947-963. https://doi.org/10.1038/hr.2017.75

Lin, S. C., Chen, I. J., Yu, W. R., Lee, S. Y. D., & Tsai, T. I. (2019). Effect of a community-based participatory health literacy program on health behaviors and health empowerment

ISSN: 2776-1142 (online) ISSN: 2776-1134 (print)

among community-dwelling older adults: a quasi-experimental study. *Geriatric Nursing*, *40*(5), 494-501.

Lindacher, V., Curbach, J., Warrelmann, B., Brandstetter, S., & Loss, J. (2018). Evaluation of empowerment in health promotion interventions: a systematic review. *Evaluation & the health professions*, *41*(3), 351-392.

Magnani, J. W., Mujahid, M. S., Aronow, H. D., Cené, C. W., Dickson, V. V., Havranek, E., ... & Willey, J. Z. (2018). Health literacy and cardiovascular disease: fundamental relevance to primary and secondary prevention: a scientific statement from the American Heart Association. *Circulation*, *138*(2), e48-e74. https://doi.org/10.1161/CIR.0000000000000579

McCollum, R., Limato, R., Otiso, L., Theobald, S., & Taegtmeyer, M. (2018). Health system governance following devolution: comparing experiences of decentralisation in Kenya and Indonesia. *BMJ global health*, *3*(5).

Najemi, A., Purwastuti, L., & Nawawi, K. (2019). The role of the food and drug supervisory agency (BPOM) in managing circulation of cosmetics and hazardous foods. *Berumpun: International Journal of Social, Politics, and Humanities*, *2*(2), 76-92. https://doi.org/10.33019/4ntr7f35

Norheim, O. F., Jha, P., Admasu, K., Godal, T., Hum, R. J., Kruk, M. E., ... & Peto, R. (2015). Avoiding 40% of the premature deaths in each country, 2010–30: review of national mortality trends to help quantify the UN Sustainable Development Goal for health. *The Lancet*, *385*(9964), 239-252.

O'Mara-Eves, A., Brunton, G., Oliver, S., Kavanagh, J., Jamal, F., & Thomas, J. (2015). The effectiveness of community engagement in public health interventions for disadvantaged groups: a meta-analysis. *BMC public health*, *15*(1), 129. https://doi.org/10.1186/s12889-015-1352-y

Paccyne, S., Ross, J., Kartika, M. P., Rosas, A. D., Dewi, S., Hirschhorn, L. R., & Bitton, A. (2026). PCIPHC: Indonesia Case Study: Pursuing Person-Centered Primary Care in a Decentralized Health System: Indonesia's Efforts to Strengthen Primary Healthcare Services Through Integrated Networks at the Community Level. In *People-Centered Integrated Primary Healthcare System Development in Asia and Beyond* (pp. 187-230). https://doi.org/10.1142/9789819807468_0007

Pop, C., Cioara, T., Antal, M., Anghel, I., Salomie, I., & Bertoncini, M. (2018). Blockchain based decentralized management of demand response programs in smart energy grids. *Sensors*, *18*(1), 162. https://doi.org/10.3390/s18010162

Rachmat, R. H. H. (2021). *Pemikiran Dasar, Pola Pikir Dasar untuk Penguatan Pembangunan Kesehatan Tahun 2000 sampai Tahun 2045*. UGM PRESS.

Rampedi, P. N., Ogunrombi, M. O., & Adeleke, O. A. (2024). Leading paediatric infectious diseases—current trends, gaps, and future prospects in oral pharmacotherapeutic interventions. *Pharmaceutics*, *16*(6), 712. https://doi.org/10.3390/pharmaceutics16060712

Rasu, R. S., Bawa, W. A., Suminski, R., Snella, K., & Warady, B. (2015). Health literacy impact on national healthcare utilization and expenditure. *International journal of health policy and management*, *4*(11), 747. https://doi.org/10.15171/ijhpm.2015.151

Ruthsatz, M., & Candeias, V. (2020). Non-communicable disease prevention, nutrition and aging. *Acta Bio Medica: Atenei Parmensis*, *91*(2), 379. https://doi.org/10.23750/abm.v91i2.9721

Sebong, P. H., Ferdiana, A., Tegu, F. A. R., Harbianto, D., Soviandhi, R., Sinaga, A., ... & Utarini, A. (2025). Participatory development of Indonesia's national action plan for zero leprosy:

strategies and interventions. *Frontiers in Public Health*, *13*, 1453470. https://doi.org/10.3389/fpubh.2025.1453470

Sheth, M., & Obrah, M. (2004). Diarrhea prevention through food safety education. *Indian Journal of Pediatrics, 71*(10), 879–882. https://doi.org/10.1007/BF02830824

Singh, D., Negin, J., Otim, M., Orach, C. G., & Cumming, R. (2015). The effect of payment and incentives on motivation and focus of community health workers: five case studies from low-and middle-income countries. *Human resources for health*, *13*(1), 58. https://doi.org/10.1186/s12960-015-0051-1

Skivington, K., Matthews, L., Simpson, S. A., Craig, P., Baird, J., Blazeby, J. M., ... & Moore, L. (2021). Framework for the development and evaluation of complex interventions: gap analysis, workshop and consultation-informed update. *Health technology assessment (Winchester, England)*, *25*(57), 1. https://doi.org/10.3310/hta25570

Sulistyaningrum, I. H., Kristina, S. A., & Mukti, A. G. (2022). The Normative Cost of Twenty Most Prominent Diseases in Yogyakarta, Indonesia: A Delphi Consensus Study. *Bangladesh Journal of Medical Science*, *21*(2), 291-301.

Suryani, P., Yudiernawati, A., & Wahyuni, T. D. (2025). Innovative strategies in community empowerment to promote sustainable healthy living behavior. *The Journal of Academic Science*, *2*(2), 665-674. https://doi.org/10.59613/2phqek64

Todaro, M. P., & Smith, S. C. (2009). *Economic development*. London: Pearson education.

Volkow, N. D., & Blanco, C. (2023). Substance use disorders: a comprehensive update of classification, epidemiology, neurobiology, clinical aspects, treatment and prevention. *World Psychiatry*, *22*(2), 203-229.

Wang, F., & Wang, J. D. (2021). Investing preventive care and economic development in ageing societies: empirical evidences from OECD countries. *Health economics review*, *11*(1), 18. https://doi.org/10.1186/s13561-021-00321-3

Weber, P., Birkholz, L., Straub, R., Kohler, S., Helsper, N., Dippon, L., ... & Semrau, J. (2024). The limitations and potentials of evaluating economic aspects of community-based health promotion: A critical review. *Applied Health Economics and Health Policy*, *22*(2), 165. https://doi.org/10.1007/s40258-023-00864-y

Wulandari, W., Suparno, B. A., & Prayudi, P. (2024). Audit Komunikasi Program Intervensi Keamanan Pangan Jajanan Anak Sekolah Balai Besar Pengawas Obat dan Makanan di Yogyakarta. *Eruditio: Indonesia Journal of Food and Drug Safety*, *5*(1), 44-56. https://doi.org/10.54384/eruditio.v5i1.206

Younie, S., Mitchell, C., Bisson, M. J., Crosby, S., Kukona, A., & Laird, K. (2020). Improving young children's handwashing behaviour and understanding of germs: The impact of A Germ's Journey educational resources in schools and public spaces. *PloS one*, *15*(11), e0242134. https://doi.org/10.1371/journal.pone.0242134

ISSN: 2776-1142 (online) ISSN: 2776-1134 (print)