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ANALYSIS OF THE RELATIONSHIP BETWEEN WATER QUALITY AWARENESS AND DRINKING WATER CONSUMPTION BEHAVIOR (CASE STUDY: MAJENE CITY AND CAMPALAGIAN VILLAGE, WEST SULAWESI)

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ABSTRACT

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The declining quality of drinking water sources due to contamination poses significant health risks, particularly in rural areas where public awareness about water quality and its impact on health is often limited. In Majene City and Campalagian Village, West Sulawesi, drinking water is predominantly sourced from wells and springs, but these sources have shown elevated levels of pollutants, such as manganese and coliforms, exceeding government standards. This study explores the relationship between water quality awareness and drinking water consumption behavior in these regions using Structural Equation Modeling-Partial Least Squares (SEM-PLS). Data were collected through household surveys and laboratory testing of water samples, focusing on physical, chemical, and biological parameters. SEM-PLS was employed for its ability to analyze latent variables and handle small sample sizes effectively. Results reveal that water quality awareness explains 78.6% of the variance in drinking water consumption behavior ($R^2 = 0.786$), with key indicators such as knowledge of water quality standards and contamination risks strongly predicting positive behavioral changes. Hypothesis testing confirmed a significant positive relationship (path coefficient = 0.887, $p < 0.001$), underscoring the importance of awareness in promoting healthy consumption behaviors. These findings highlight the need for targeted public education campaigns and policy interventions to improve water quality awareness and consumption practices. The study also contributes to the growing application of SEM-PLS in environmental and public health research, offering insights into the complex interplay between awareness and behavior. Future research should consider integrating socio-economic and cultural factors to develop a more holistic understanding of drinking water consumption patterns.

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1. INTRODUCTION

Water has enormous benefits for human life. Water is one of the elements that make up the human body with a percentage of about 70%. Lack of water can make the body experience disorders. Drinking water is an easy and cheap thing to keep the body healthy and fit. The benefits of drinking water for the body include maintaining body fluid levels, helping to provide energy to muscles, helping to control the body's calorie intake, maintaining skin freshness, and protecting the spinal cord and other sensitive tissues in the body [1]. Research published in the American Journal of Clinical Nutrition highlights that even mild dehydration (1-2% loss of body weight in fluids) can impair cognitive function, mood, and energy levels [2].

In general, the most frequently consumed water sources by the community, especially people in villages, are spring water, drinking water company, groundwater (wells), and surface water (rivers). From a water quality point of view, water from springs tends to be clearer than water from surface water sources in general, so the use of water from springs is preferable compared to surface water. However, currently, the existence of springs continues to decline. Groundwater, which often contains higher levels of iron and manganese than other water sources, also needs to be reduced or even stopped because the use of groundwater containing high levels of heavy metals can be harmful to health, besides the continuous use of groundwater can lower the land level [3].

Like the people in other villages, the people in Majene district and the people in Polewali Mandar district generally use groundwater and river water as the main source of water. Unfortunately, according to [4] and the results of research [5] and [6] it is known that river water and groundwater in the two areas have decreased in quality and have even been polluted. Despite this, there is limited understanding of whether local residents are aware of these quality issues and how it influences their behavior. In addition, until now it is not known for sure whether the people who consume polluted well water and river water know the quality status of the water they consume, and to what extent they understand the dangers of consuming water whose water quality has been polluted.

Many studies have highlighted the impact of water quality on public health, emphasizing the need for awareness in influencing behavior [4][5]. For example, [5] showed that contaminated groundwater is a major concern in Majene, while [3] discussed the broader implications of groundwater contamination for community health. These studies suggest a link between water quality awareness and behavior, yet few have explored this relationship quantitatively. Structural Equation Modelling-Partial Least Squares (SEM-PLS) has emerged as a robust tool for analyzing such relationships, as it allows for the simultaneous evaluation of latent variables and their indicators without strict assumptions about data distribution [7]. SEM-PLS has been successfully applied in environmental studies, such as assessing maternal health determinants and poverty modeling in Papua [8], but its use in examining water-related behaviors remains limited. This study fills this gap by applying SEM-PLS to investigate how water quality awareness affects drinking water consumption behavior in rural communities.

Therefore, it is necessary to identify the relationship between awareness of drinking water quality and drinking water consumption behavior in the Majene City and Campalagian Village areas. This aims to generate a deeper understanding of how public awareness of drinking water quality can affect their drinking water consumption habits and to evaluate information regarding public awareness and attitudes towards drinking water and water pollution. This paper applies the Structural Equation Modelling-Partial Least Squares (SEM-PLS) method to analyze the complex interrelationship between these variables, as this method is well-suited for handling latent variables in public health studies, SEM-PLS is used because it provides a reliable and robust method for analyzing the relationships between water quality awareness (latent variable) and water consumption behavior (latent variable) in the presence of multiple indicators. Given the sample size of 65 respondents, SEM-PLS is a suitable method as it can handle smaller datasets while providing insights into complex causal relationships. Additionally, the method's flexibility in handling different data types and model complexity makes it ideal for exploring these relationships effectively. The knowledge provided by this study will contribute to the prevention of drinking water contamination and the improvement of water management, especially from the perspective of community participation. These findings are expected to be the foundation for the development of more effective policies and programs in raising awareness of the importance of drinking water quality and promoting healthy and sustainable drinking water consumption behaviors in the region.

2. RESEARCH METHODS

2.1 Data Collection

In this research, the data collection techniques used are divided into two stages as follows:

1. Drinking water quality data

   Drinking water sources are taken in two locations, namely in the city of Majene and in the village of Campalagian. The source of drinking water in the city of Majene is taken from a spring that comes from the village of Paboborang. The selection of the location of this water sample is due to the results of previous researchers who stated that the quality of the water at the location was above the quality standards set by the government. Meanwhile, the water source in Campalagian village is taken from well water based on residents' information that the water source is widely used by residents.

   Samples were analyzed for physical, chemical, and biological parameters to provide a comprehensive assessment of water quality, including Total Dissolved Solids (TDS), potential of hydrogen (pH), dissolved manganese, iron, and bacterial contamination (e.g., coliform, E. coli). Water samples of 500 mL were collected in polyethylene bottles, acidified with HNO3 to a pH of 2, stored in cool conditions, and analyzed at the BTKL laboratory in South Sulawesi province.

2. Survey of public awareness and behavior of drinking water consumption

   Data collection at this stage was carried out by household survey method in Paboborang Majene village and West Katumbangan Campalagian village. The survey instrument included structured questions covering demographic data, water quality awareness indicators, and water consumption behavior indicators. The survey was designed based on a Likert scale (1-5) and pilot-tested to ensure validity and reliability, with a total of 65 samples collected for analysis. Indicators for awareness included knowledge of water quality standards and contamination risks, while behavioral indicators focused on practices such as boiling water, cleaning storage containers, and source preferences.

   Sample selection was carried out by the multi-stage sampling method which is a combination of simple random sampling and systematic sampling techniques. The first stage was carried out using simple random sampling in all hamlets in Paboborang village and all hamlets in West Katumbangan village. The second stage is systematic sampling from selected hamlet areas in the first stage.

2.2 Method

2.2.1 Structural Equation Modeling-Partial Least Square (SEM-PLS)

SEM is one of the statistical techniques used to test and estimate causal relationships based on statistical data and qualitative causal assumptions. SEM techniques can be considered as the second generation of multivariate analysis. In contrast to first-generation techniques, such as factor analysis, discrimination analysis, or multiple regression, SEM allows researchers to simultaneously consider the relationship between multiple independent and dependent constructs. In the SEM technique, it is known that there is a latent variable, this variable cannot be measured directly so it requires an indicator to measure the latent variable [7]. In the development of SEM, there are still limitations related to the classical assumptions that must be met in regression analysis. One of the classic assumptions that must be met is that data must be distributed normally. In addition, the number of samples used in SEM should not be too small because this method is sensitive to sample size. Therefore, for models with as many indicators as 10-15, the recommended sample size is between 200-400 [9].

SEM-PLS is an alternative method in the structural equation model that allows testing the relationship between latent variables and various indicators simultaneously. PLS is often referred to as soft modeling because it does not require certain assumptions, such as a multivariate normal distribution, a specific measurement scale, or a large sample size. This method is designed for the purpose of causal-predictive analysis, especially in situations with high levels of complexity and limited theoretical support [10]. SEM-PLS is a robust analytical approach known for its versatility across all data scales, minimal dependence on assumptions, and suitability for small sample sizes. It can be applied to confirm existing theories, establish relationships without a theoretical foundation, or conduct hypothesis testing [11]. In the SEM-PLS method, there are two models that need to be known, namely the outer model and the inner model.

The outer model (measurement model) is a measure that shows the relationship between latent variables and their indicators. The design of this outer model includes two types, namely reflective and formative models [8]. In a reflective construct, causality describes the relationship between the construct and its indicators, whereas in a formative construct, the construct represents the causal outcome of its indicators [12]. The Inner model (structural model) is a measure of the relationship between endogenous (dependent) latent variables and exogenous (independent) latent variables [13].

Illustrations of the outer model and inner model can be seen in Figure 1 below [7]:

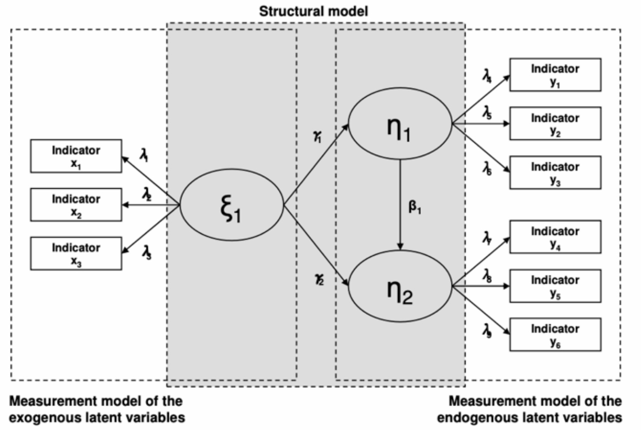

Figure 1. Example of Path Diagram SEM-PLS

Where η is the endogenous latent variable, ξ is the exogenous latent variable, γ is the path coefficient connecting the endogenous latent variable with the exogenous latent variable, λ is the loading factor, β is the path coefficient connecting the endogenous latent variable with another endogenous latent variable, x is the indicator of the exogenous latent variable, and y is the indicator of the endogenous latent variable.

2.2.2. Outer Model Evaluation

We evaluate the outer model by applying four techniques

1. Loading factor. An indicator is considered valid if it has a loading factor of more than 0.708, since they demonstrate that the construct clarifies over 50 percent of the indicator's variance, thus ensuring acceptable indicator reliability [14].
2. Composite Reliability (CR) and Cronbach's alpha. Internal consistency reliability is evaluated using Cronbach's alpha (α) and Composite Reliability (CR). A threshold value of 0.70 for both metrics is generally deemed acceptable and is commonly used in PLS-SEM research [15].
3. Average Variance Extraction (AVE). This test measures the extent to which the variance of indicators can be explained by the latent variable. The AVE value is considered good or valid if each variable has an AVE value ≥ 0.50, indicating that 50% or more of the variance of the indicators can be explained [16].
4. Discriminant validity. This is typically determined by analyzing the cross-loadings, where an indicator's outer loading on its associated construct should exceed its loadings on any other constructs [17].

2.2.3. Inner Model Evaluation

R-squared, as in linear regression, represents the extent to which the exogenous variable can account for the variance in the endogenous variable [18].

2.2.4. Hypothesis Test

The hypothesis is tested using the bootstrap resampling method, with a minimum number of bootstraps of 5000, and the number of cases must correspond to the number of observations in the original sample [19].

The hypothesis testing process involves the preparation of two competing hypotheses, namely the null hypothesis and the alternative hypothesis. If the P value ≤ 0.05, the null hypothesis is rejected, if it is greater than the null hypothesis fails to be rejected [20]. In this study, the t-test was used to determine whether there is a significant difference between the observed sample mean and the expected value, providing insights into the relationship between the variables. The following are the hypotheses in this study are: H0: There is no effect of drinking water quality awareness (WQA) on drinking water consumption behavior (WCB) and H1: There is an effect of drinking water quality awareness (WQA) on drinking water consumption behavior (WCB)

3. RESULTS AND DISCUSSION

3.1 Results of Drinking Water Quality Analysis

Water samples sourced from community drinking water sources in Paboborang Majene Village, and communities in Katumbangan Campalagian village were analyzed at the BTKL laboratory in South Sulawesi province. From the sample analysis, the following data was obtained:

Table 1. Water Quality Data of Paboborang and Katumbangan Campalagian Village

Parameter	Type	Unit	Test Result of Water Source		Maximum Allowable Limit
			Paboborang Majene village	Katumbangan Campalagian village	
TDS	Physical	mg/L	750	254	< 300
pH	Chemical	-	7,18	6,97	$6,5 - 8,5$
Hardness	Chemical	mg/L	296	85,20	500
Dissolved manganese	Chemical	mg/L	122,80	0,1898	0,1
Dissolved iron	Chemical	mg/L	$< 0,0076$	0,0283	0,2
Amount of Coliform	Biological	CFU/100 mL sample	1830	123	0
Escherichia coli	Biological	CFU/100 mL sample	460	20	0

Source: *BTKL Laboratory Test Analysis*

Based on Table 1, the laboratory analysis of water quality revealed significant differences between the two study locations. In Paboborang, TDS levels exceeded the maximum allowable limits, indicating potential risks to long-term water consumption. Additionally, manganese and biological contaminants (e.g., coliform and E. coli) exceeded safety standards in both Paboborang and Campalagian, underscoring the need for water treatment interventions. The pH levels in both locations were within acceptable ranges, which may reduce immediate corrosive effects but do not mitigate the contamination risks.

Analysis of the water data indicates that physical and biological parameters, particularly coliform presence, are critical indicators of unsafe drinking water practices in these areas. Previous studies [21] have shown that high coliform levels are often linked to inadequate sanitation infrastructure and poor water storage practices. This highlights the importance of community education on water handling.

The characteristics of the respondents are shown in Table 2 with a total of 65 respondents, 54% are from Majene Village, while 46% are from Campalagian Village. Most of the respondents were women (77%). In terms of age, among the 51 respondents with available age group information, the majority of respondents (45%) are between 45-70 years old, indicating that this age group is likely to have more experience understanding the importance of water quality and its impact on health.

Table 2. Respondents Characteristics

Category	Respondent Characteristics	Frequency	Percentage
Village	Campalagian	30	46%
	Majene	35	54%
Gender	Man	15	23%
	Woman	50	77%

Category	Respondent Characteristics	Frequency	Percentage
Age	16-25 year	7	11%
	26-45 year	15	23%
	45-70 year	29	45%
Last Education	None	4	6%
	Primary School	27	42%
	Junior High School	16	25%
	Senior High School	13	20%
	Bachelor Degree	5	8%
Job Type	Civil Servant/Police	3	5%
	Housewife	41	63%
	Other	15	23%
	Farmer	3	5%
	Entrepreneur	3	5%

However, majority of the respondents had a last education at the elementary level (42%), with only 8% finishing undergraduate education. It is also interesting considering that lower levels of education may be related to limited awareness about water quality and its impact on health. 63% of respondents are housewives, who play an important role in daily decisions related to water consumption.

The latent variables used in this study are water quality awareness (WQA) with 10 indicators and drinking water consumption behavior (WCB) with 10 indicators which can be seen in **Table 3** bellow:

Table 3. Description Analysis

Latent Variable	Indicator	Description
Water Quality Awareness (WQA)	WQA1	Knowledge of the water sources used
	WQA2	Understanding the importance of the quality of the water consumed
	WQA3	Awareness of contaminants that affect water quality
	WQA4	Regular water quality checks at home
	WQA5	The belief that water quality affects family health
	WQA6	Knowledge of good water quality standards
	WQA7	Understanding the negative impacts of contaminated water
	WQA8	Habit of looking for information about water quality
	WQA9	Knowledge of simple ways to test water quality at home
	WQA10	Discussion about water quality with family or neighbors
Water Consumption Behavior (WCB)	WCB1	Drinking water consumption according to daily needs
	WCB2	Ensuring clean and safe drinking water
	WCB3	Preference for consuming bottled water over tap/well water
	WCB4	Pay attention to water quality when eating/drinking outside
	WCB5	Clean the water storage container regularly
	WCB6	Habit of boiling water before drinking
	WCB7	Bring your own drinking water when traveling
	WCB8	Do not drink water if in doubt about its hygiene
	WCB9	Avoid drinking water from untrusted sources
	WCB10	Teaching children to check the quality of water before drinking

The percentage of respondents' answers in each indicator is shown in **Table 4** as follows:

Table 4. The Percentage of Respondents' Answers

Indicator	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
WQA1	52%	46%	0%	0%	2%
WQA2	23%	37%	5%	9%	26%
WQA3	23%	29%	14%	17%	17%

Indicator	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
WQA4	18%	34%	17%	14%	17%
WQA5	22%	37%	2%	11%	29%
WQA6	14%	25%	18%	17%	26%
WQA7	15%	35%	12%	9%	28%
WQA8	5%	12%	6%	23%	54%
WQA9	5%	17%	6%	25%	48%
WQA10	5%	31%	14%	17%	34%
WCB1	28%	55%	15%	2%	0%
WCB2	31%	68%	2%	0%	0%
WCB3	3%	12%	28%	43%	14%
WCB4	14%	43%	8%	8%	28%
WCB5	46%	31%	22%	2%	0%
WCB6	15%	5%	9%	5%	66%
WCB7	9%	12%	34%	15%	29%
WCB8	6%	31%	18%	22%	23%
WCB9	9%	26%	17%	22%	26%
WCB10	14%	25%	8%	11%	43%

Table 4 is the frequency of respondents answering question items in the form of a likert scale on 10 indicators of Water Quality Awareness (WQA) and 10 indicators of Drinking Water Consumption Behavior (WCB). The WQA1 indicator showed the most positive results, with 52% of respondents strongly agreeing and 46% agreeing, indicating that most respondents have a high awareness of water quality. However, in WQA8, there were 54% of respondents who strongly disagreed, indicating significant dissatisfaction with one aspect of water quality. In general, the WQA indicator has a varied distribution of responses, with some indicators such as WQA2, WQA5, and WQA6 showing dissatisfaction, where the proportion of respondents who strongly disagree reaches 26%, 29%, and 26% respectively. 31% of respondents strongly agree and 68% agree with the WCB2 indicator which shows good behavior related to drinking water consumption. In contrast, WCB6 showed that 66% of respondents strongly disagreed, indicating unhealthy water consumption behaviors or lack of awareness regarding the importance of water quality. Other indicators, such as WCB3 and WCB4, show a larger proportion in the disagreement category, reflecting the presence of doubts or lack of attention to correct water consumption behavior.

While there are some indicators that indicate a high level of awareness, there are also indicators that indicate dissatisfaction or negative attitudes that can indicate a lack of knowledge or attention to water quality issues. This may be influenced by the respondents' educational background and their understanding of the impact of water quality on health. Likewise, in the WCB variable, there are several indicators that show that the community still does not implement good water consumption behavior.

3.2 Structural Equation Modeling Partial Least Square (SEM-PLS) Analysis

After collecting survey data regarding water quality awareness and drinking water consumption behavior, the survey data was analyzed using the Structural Equation Modeling-Partial Least Square (SEM-PLS) technique. To ensure accurate and efficient analysis, SmartPLS 4 software was utilized as it provides a user-friendly interface and advanced statistical capabilities for handling complex models. SmartPLS 4 enables researchers to assess relationships between latent variables, perform bootstrapping for hypothesis testing, and evaluate model fit with various reliability and validity measures. The use of SmartPLS 4 in this study enhances the robustness of the findings by allowing a comprehensive examination of the structural relationships within the dataset.

3.2.1 Constructing a path diagram

The initial step in SEM-PLS involves constructing a path diagram that represents the relationships between latent variables (WQA and WCB) and their observed indicators. The path diagram also includes hypothesized causal relationships between the latent variables. In this study, the model was constructed with ten indicators for WQA and ten indicators for WCB.

3.2.2 Outer Model Testing

The outer model test is measured based on the value of the loading factor to measure the extent to which the indicator represents the latent variable.

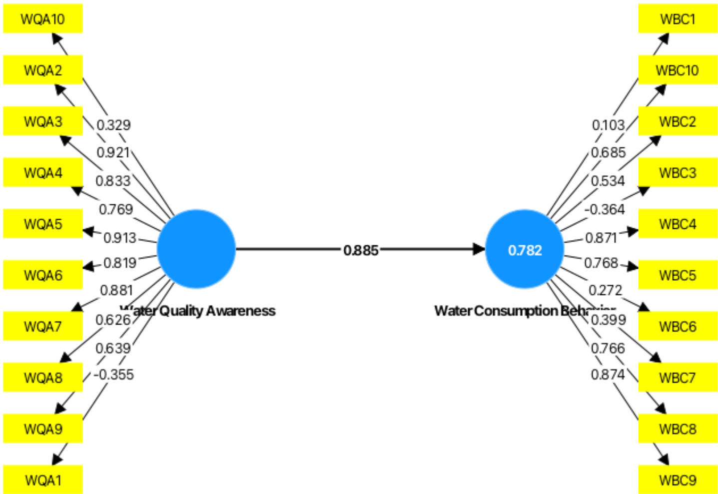

Figure 2. Path Diagram with Loading Factor

Figure 2 shows that of the ten indicators representing water quality awareness variables, there are six indicators that have a loading factor above 0.7, namely WQA2, WQA3, WQA4, WQA5, WQA6, and WQA7. While the other four indicators, namely WQA1, WQA8, WQA9 and WQA10 have a loading factor smaller than 0.7, this shows that these indicators do not have enough contribution in measuring water quality awareness. Therefore, the four indicators will be removed from the model. Four indicators that can be maintained in the variables of drinking water consumption behavior are (WCB4, WCB5, WCB8, WCB9). While the other six indicators can be removed from the model because of the lack of ability of the indicators to represent the variables of drinking water consumption behavior. The retained indicators demonstrate strong factor loadings, ensuring that they effectively represent their respective constructs. This step reduces model complexity and enhances interpretability.

3.2.3 Outer Model Evaluation

The outer model evaluation is as follows:

1. After the non-compliant indicators are removed, a new path chart is obtained in **Figure 3** below:

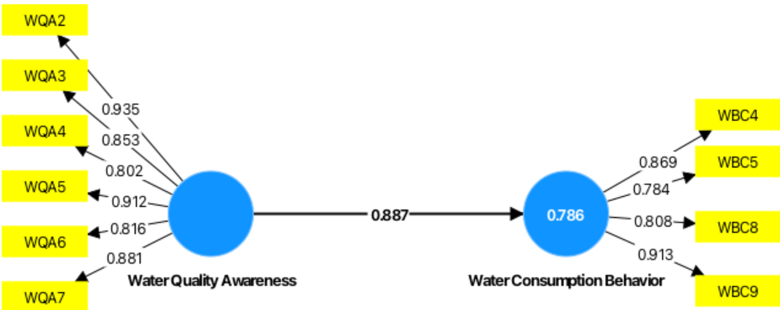

Figure 3. Number of Indicators after Selection on the Path Diagram

All indicators that have been selected from the outer model test have met the value of the loading factor greater than 0.708, so this model is considered to be able to measure the two latent variables.

2. Composite Reliability (CR) and Cronbach's Alpha measure the internal consistency of the indicators that make up a construct, showing how well they represent the same latent variable but Cronbach's alpha is more sensitive to the number of indicators present in the latent variable, so it can provide additional information about reliability.

Table 5. Composite Reliability value

Construct	Composite reliability (ρ_α)	Cronbach's alpha
Water Quality Awareness	0.939	0.934
Water Consumption Behaviour	0.870	0.865

Table 5 shows the reliability value measured through Cronbach's alpha and composite reliability for the drinking water quality awareness latent variable shows a Cronbach's alpha value of 0.934 and composite reliability of 0.939, this indicates that the indicators used to measure the latent variable have very high internal consistency, meaning that each indicator measured is well correlated with each other. In the latent variable of drinking water consumption behavior, it showed good results, with Cronbach's alpha value of 0.865 and composite reliability of 0.870. Although these values are still in the good category, both values are lower than in the drinking water quality awareness latent variable. This value also indicates that there are some indicators that may need more attention to improve their consistency.

3. Average Variance Extraction (AVE) provides a more comprehensive picture of how the entire set of indicators together represents that latent variable. In other words, AVE values are used to ensure that the overall measurement model is robust, not just on individual indicators.

Table 6. Average Variance Extraction

Construct	Average Variance Extraction (AVE)
Water Quality Awareness	0.753
Water Consumption Behaviour	0.714

In **Table 6**, about 70% of the variance of the indicators in each latent variable can be explained by the latent variable. In other words, these two variables substantially explain the variance of each indicator, namely six indicators to measure water quality awareness and four indicators to measure water consumption behavior. It also shows that the indicators of the two variables have good convergent validity, meaning that they do reflect or correlate highly with the latent variables that should be measured.

4. Discriminant validity was tested using cross-loading. Cross-loading is used to measure the extent to which indicators of a latent variable have a higher correlation with its own construct compared to other latent variables. **Table 7** shows the results of the discriminant validity using cross loading.

Table 7. Cross-loading Value

Indicator	Water Quality Awareness	Water Consumption Behaviour
WQA2	0.935	0.868
WQA3	0.853	0.734
WQA4	0.802	0.744
WQA5	0.912	0.815
WQA6	0.816	0.654
WQA7	0.881	0.779
WCB4	0.812	0.869
WCB5	0.763	0.784
WCB8	0.652	0.808
WCB9	0.752	0.913

All indicators of the drinking water quality awareness latent variable (WQA) have a higher cross loading value in the latent variable itself compared to the drinking water consumption behavior latent variable (WCB), the highest cross loading value is in the WQA indicator of 0.935. Then the highest value in the drinking water consumption behavior latent variable (WCB) lies in WCB9 with a value of 0.913. This result indicates that the measured latent variable can already be explained by the indicator.

3.2.4 Inner Model Evaluation

This test is carried out by looking at the R-squared (R^2) value. The R-squared (R^2) value is 0.786 and the Adjusted R-squared is 0.783. This means that about 78.6% of the variation in the latent variable of drinking water consumption behavior (WCB) can be explained by the latent variable of drinking water quality awareness (WQA) and the remaining 21.4% is explained by other variables outside this model. The R-squared value obtained shows that there is a strong relationship between water quality awareness and their behavior in consuming water. Although SEM-PLS does not rely on traditional fit indices like covariance-based SEM, it ensures model quality through measures like R^2, AVE, and the path coefficient. The high R^2 value supports the adequacy of the structural model in explaining behavioral variance

3.2.5 Hypothesis Test

The hypothesis test on the structural equation modeling (SEM) model with partial least squares (PLS) was carried out using the bootstrapping method on the Smart-PLS software. The bootstrapping method is a statistical technique to measure the accuracy of model estimation. This method involves repeated sampling of the original data and the calculation of path coefficients and p-values for each relationship between variables in the model, in this case to see the effect of water quality awareness on drinking water consumption behavior.

The following are the values of the path coefficient and p-value on both variables:

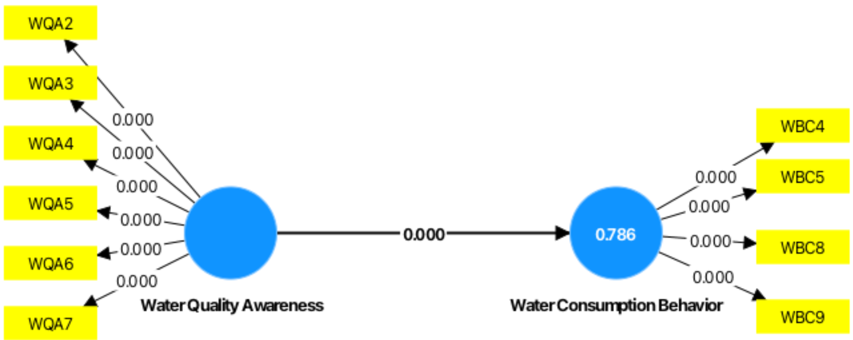

Figure 4. Path Coefficient

The results of **Figure 4** show a p-value smaller than 0.001 so it is concluded that it rejects the null hypothesis which means that there is an influence between drinking water quality awareness (WQA) and drinking water consumption behavior (WCB). In addition, the pathway efficiency of 0.887 also showed that there was a strong positive influence of drinking water quality awareness on drinking water consumption behavior.

Overall, these results show that the higher the public's awareness of water quality, the better their behavior in consuming drinking water. The high R^2 value (0.786) indicates that 78.6% of the variation in drinking water consumption behavior can be explained by water quality awareness, while the strong path coefficient ($0.887, p < 0.001$) confirms a positive relationship between these variables. Key indicators such as knowledge of water quality standards (WQA2) and the habit of maintaining clean water storage (WCB5) were shown to have a substantial impact on drinking water behavior. These findings emphasize the importance of public knowledge about water contamination risks and practical actions in ensuring safe drinking water consumption. Statistically, the model is supported by strong reliability and validity metrics, including Cronbach's alpha (> 0.85) and AVE values (> 0.7), which confirm that the indicators accurately represent their respective latent variables.

In this research, SEM-PLS was chosen for its ability to handle small sample sizes and non-normal data, making it suitable for rural and resource-limited settings. The findings suggest that increasing public awareness through targeted education campaigns and community-based initiatives can significantly improve water consumption practices. Educating communities on the importance of water testing, safe storage methods, and recognizing contamination risks can lead to healthier behaviors and improved public health outcomes. While the study provides valuable insights, it is limited by its focus on two specific areas and does not account for other factors such as socio-economic conditions, cultural practices, or infrastructure challenges. Future research should consider a broader scope by integrating these variables and conducting longitudinal studies to assess how awareness and behavior change over time. In addition, utilizing modern technology such as low-cost water testing kits and mobile applications could complement awareness campaigns by providing practical tools for communities to monitor and improve their water quality. Combining these approaches with the findings of this study could support more effective and sustainable strategies for addressing water quality issues in rural areas.

4. CONCLUSIONS

Water quality awareness plays a crucial role in shaping drinking water consumption behavior, particularly in rural areas like Majene and Campalagian, West Sulawesi. Laboratory analysis revealed significant contamination in drinking water sources, posing serious health risks. SEM-PLS analysis showed that 78.6% of variations in consumption behavior are influenced by water quality awareness, highlighting the importance of public knowledge on water standards, contamination risks, and safe water practices.

The study emphasizes the need for public education programs and policy interventions to improve water safety. Additionally, technology, such as smart sensors, mobile apps, and low-cost water testing kits, can empower communities to monitor and improve water quality. Future research should explore socio-economic and cultural factors while integrating technological solutions to develop sustainable and scalable strategies for addressing water quality challenges in rural areas.

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