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# Acceptance of SPARING Technology: Extending TAM with Perceptions of New Technology Applied in PT.XYZ

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**A B S T R A C T**

The application of technology has proven able to streamline operational activities in the manufacturing industry, from the receipt of raw materials to the delivery of products, as well as the control of waste generated, particularly in wastewater treatment. The continuous online wastewater monitoring system (SPARING) has become an innovation in the manufacturing industry. An analysis is needed on the level of acceptance of SPARING technology in the wastewater treatment plant division. The research aims to analyse the influencing factors of behavioral intention to use SPARING technology and to provide recommendations for addressing the most influential factors. The study employs a questionnaire method using research variables identified from a combination of the Technology Acceptance Model (TAM). The data collection process involved 36 respondents.

**Contribution to Sustainable Development Goals (SDGs):**
**SDG 6:** Clean Water and Sanitation
**SDG 9:** Industry, Innovation, and Infrastructure
**SDG 12:** Responsible Consumption and Production
**SDG 13:** Climate Action,

## 1. INTRODUCTION

### *1.1. Research Background*

Every business actor is obliged to provide information on environmental protection that is correct, accurate, open, timely, and in compliance with the provisions on environmental quality standards or environmental damage standards. The person responsible for the business and/or activity in monitoring wastewater quality and reporting the implementation of wastewater quality monitoring is required to install and operate Sparing Technology (Continuous Wastewater Quality Monitoring System in the Network) which is written in the Regulation of the Minister of Environment and Forestry of the Republic of Indonesia, namely number P.80/MENLHK/SETJEN/KUM.1/10/2019.

Businesses and/or activities that are required to install and operate Sparing are the rayon industry, pulp and paper industry, paper industry, upstream petrochemical industry, basic oleochemical industry, palm oil industry, oil refinery industry, oil and gas exploration and production, mining and copper, coal mining, textile industry, nickel mining, fertilizer industry, and industrial areas. Each of these industries will be monitored for several important parameters, including pH (potential Hydrogen), COD (Chemical Oxygen Demand), TSS (Total Suspended Solid), and the discharge of liquid waste produced by the industry [1].

Wastewater generated by industrial operations is often discharged directly into the environment, even though it does not meet environmental safety standards. This is extremely harmful to aquatic ecosystems and even to residential areas surrounding industrial areas. Consequently, the government is focused on tightening industrial oversight and preventing environmental damage [1].

In Indonesia, many businesses and/or industrial activities still conduct manual wastewater testing. The process of testing industrial wastewater levels in Indonesia involves collecting samples on-site and transporting them to a laboratory for analysis. This results in a decrease in the accuracy of monitoring wastewater quality results due to factors ranging from the timeliness of wastewater quality analysis to human error, both among workers delivering the wastewater samples for analysis and those conducting the analysis, which directly impact the final results of the wastewater analysis [2]

With Sparing Technology, wastewater quality can be monitored using sensors as supporting components during the monitoring process. To facilitate water quality monitoring, a system that reads sensor values in real time and is connected to the internet is required [1].

## *1.2. Literature Review*

### *1.2.1. Continuous Wastewater Monitoring System in the Network (SPARING).*

The government has implemented various policies, including issuing legal regulations, issuing wastewater discharge permits, and implementing environmental performance assessment (PROPER) programs, as measures to monitor and control water pollution. However, the reality on the ground shows that a number of industrial entities still fail to meet established wastewater quality standards [1].

One approach to improving oversight of industrial wastewater discharge is to implement real-time online monitoring technology at the outlet of industrial wastewater treatment plants (WWTPs). This technology is known as the Continuous and Networked Wastewater Quality Monitoring System (SPARING). The SPARING system automatically monitors, records, and transmits measurement data on specific parameter concentrations and/or wastewater discharge continuously through a network connection.


**Fig 1.** View of SCIFI SPARING Application at PT.XYZ

Fig 1 shows the SCIFI SPARING application, which allows access to the trend of the data obtained. In addition, the SCIFI application not only displays sensor readings for wastewater produced by PT, but also displays data from the sensor readings.XYZ, but also provides solutions for any parameters that are outside the quality range or outspect quality. This is important because updates can be made immediately to correct reading errors that can lead to inaccurate historical data at the application service centre (reviewed directly by the Ministry of Environment/KLH) [2].

### *1.2.2. Technology Acceptance Model (TAM)*

As technology advances, researchers continue to strive to understand and adapt to consumer responses in adopting new technology [3]. TAM consists of several main constructs: external variables, Perceived Usefulness (PU), Perceived Ease of Use (PEU), Behavioural Intention to Use (BI), and Actual Use (AU) [4]. Based on the TAM framework, external variables influence PU and PEU as two main cognitive constructs [5]. Furthermore, PEU directly influences PU and attitude toward use, while PU influences attitude and behavioural intention (BI), which ultimately affects actual use (AU) [6].

In TAM, there is a main construct that is used before modifications are made:

a. Perceived Usefulness
   Perceived usefulness indicates how confident a person is that using technology will improve work performance. From this definition, it can be concluded that perceived usefulness is a person's confidence in making decisions [6].
b. Perceived Ease of Use
   Perceived ease of use indicates how confident a person is that using a technology will be free from difficulties. A person believes that a technology is easy to use [7].
c. Behavioral Intention to Use

Modifications to the TAM can include several external factors to provide a more detailed analysis of the technology applied specifically in a given setting. The external factors used are Comfortability, Quality Output, and Personal Knowledge Development.

## *1.3. Research Objective*

This study aims to Analyse the factors that influence behavioural intention to use and to provide recommendations for addressing the most influential factors on SPARING in the wastewater treatment plant unit of PT. XYZ in Padang City, Teluk Bayur, so that the behavioral intention to use increases.

# 2. MATERIALS AND METHODS

### *2.1. Designing the Framework*

The framework will be designed. The Framework Model is shown in Fig 2.

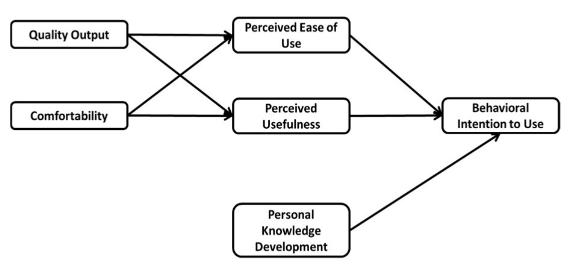


**Fig 2.** Framework Model


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Based on Fig 2, the framework will be analysed using the PLS-SEM approach. In the PLS-SEM approach, the modelling process is divided into two main components: the measurement model (outer model), which represents the relationships between observed indicators and the latent constructs being measured, and the structural model (inner model), which describes the interrelationships among the latent constructs within the model. Each of these two parts of the model has its own testing criteria that must be met in the evaluation process.

### 2.2 Building Hypothesis

Hypotheses are proposed to build a framework.
Hypotheses 1: Quality Output Influences Perceived Ease of Use
Hypotheses 2: Quality Output Influences Perceived Usefulness
Hypotheses 3: Comfortability Influences Perceived Ease of Use
Hypotheses 4: Comfortability Influences Perceived Usefulness
Hypothesis 5: Personal Knowledge Development Influences Behavioral Intention to Use
Hypotheses 6:Perceived Usefulness Influences Behavioral Intension to Use
Hypotheses 7: Perceived Ease of Use Influences Behavioral Intension to Use

### 2.3 Data Collection

This research is quantitative and uses primary data for data analysis. Data were obtained through literature review and questionnaires. The questionnaires were collected directly from 36 employees working at PT. XYZ in Teluk Bayur, Padang City. The respondents were all employees at PT. PRC, including 20 employees from the wastewater treatment plant division of PT. XYZ, 10 employees from the quality control division of PT. XYZ, and 6 employees from the health, safety, and environment division. All respondents were directly involved in technology operations.

The questionnaire used a 5-point Likert scale. A Likert scale is a measurement scale developed by Likert. A Likert scale consists of four or more items that are combined to form a score representing an individual's characteristics, such as knowledge, attitudes, and behaviour. In data analysis, a composite score, usually the sum or average, of all items can be used. The sum of all items is valid because each item is an indicator of the variable it represents [8].

The strongly disagree indicator is given a point of 1 until the strongly agree indicator is given a point of 5. The variables used are one dependent variable, namely behavioral intention to use, and five independent variables, namely comfortability, quality output, perceived ease of use, perceived usefulness, and personal knowledge development [8].

### 2.4. Data Analysis

Data obtained through questionnaires will be analysed using Partial Least Squares – Structural Equation Modelling (PLS-SEM) with SmartPLS version 4. Partial Least Squares (PLS) and variance-based Structural Equation Modeling (SEM) methods are used for the analysis. PLS analyses the relationships among variables in a complex model, whereas SEM analyses cause-and-effect relationships. The results of the analysis using these methods are dominant hypotheses based on a predetermined scale. The steps in using PLS-SEM include determining the specifications of the inner and outer models from the proposed initial model. Subsequently, inner and outer models are tested to determine whether the proposed hypotheses have a significant effect [9].

Based on the conclusions regarding the hypotheses' significance, further studies will be conducted on the hypotheses that have proven significant, using a fishbone diagram to identify solutions applicable to PT.XYZ

## 3. RESULT AND DISCUSSION

The primary data obtained from the questionnaire were then processed using SmartPLS Ver. 4 software. Based on the 36 respondents who completed the questionnaire, the scores are obtained in Table 1.

**Table 1.** Respondents' Answer Results from the Questionnaire.

| ***Construct/Variable*** | | **Total Respondents Answer** | | | | |
|---|---|---|---|---|---|---|
| | | **SS (5)** | **S (4)** | **N (3)** | **TS (2)** | **STS (1)** |
| ***Comfortability* (C)** | **C1** | 11 | 21 | 4 | 0 | 0 |
| | **C2** | 9 | 25 | 2 | 0 | 0 |
| | **C3** | 9 | 24 | 3 | 0 | 0 |
| | **C4** | 8 | 26 | 2 | 0 | 0 |
| | **C5** | 6 | 23 | 7 | 0 | 0 |
| ***Quality Output* (Q)** | **Q1** | 9 | 23 | 4 | 0 | 0 |
| | **Q2** | 7 | 22 | 7 | 0 | 0 |
| | **Q3** | 10 | 23 | 3 | 0 | 0 |
| | **Q4** | 11 | 25 | 0 | 0 | 0 |
| | **Q5** | 9 | 23 | 4 | 0 | 0 |
| ***Perceive Usefullness* (PU)** | **PU1** | 8 | 25 | 3 | 0 | 0 |
| | **PU2** | 11 | 19 | 6 | 0 | 0 |
| | **PU3** | 10 | 22 | 4 | 0 | 0 |
| | **PU4** | 9 | 24 | 3 | 0 | 0 |
| | **PU5** | 8 | 25 | 3 | 0 | 0 |
| ***Perceived Ease of Use* (PEU)** | **PEU1** | 10 | 21 | 5 | 0 | 0 |
| | **PEU2** | 9 | 25 | 2 | 0 | 0 |
| | **PEU3** | 8 | 27 | 1 | 0 | 0 |
| | **PEU4** | 10 | 22 | 4 | 0 | 0 |
| | **PEU5** | 10 | 21 | 5 | 0 | 0 |
| **Behavioural Intention to Use (BI)** | **BI1** | 11 | 20 | 5 | 0 | 0 |
| | **BI2** | 7 | 23 | 6 | 0 | 0 |
| | **BI3** | 9 | 23 | 4 | 0 | 0 |
| | **BI4** | 9 | 26 | 1 | 0 | 0 |
| | **BI5** | 9 | 26 | 1 | 0 | 0 |
| **Personal Knowledge** | **PKD1** | 11 | 23 | 2 | 0 | 0 |
| | **PKD2** | 7 | 26 | 3 | 0 | 0 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Development (PKD)** | **PKD3** | 10 | 21 | 5 | 0 | 0 |
| | **PKD4** | 8 | 26 | 2 | 0 | 0 |
| | **PKD5** | 10 | 22 | 4 | 0 | 0 |

The data processing in this study using SmartPLS version 4 began with an outer model test. The outer model test aims to ensure that the indicators used to measure the variables are valid and reliable. The outer model tests include convergent validity, discriminant validity, and construct validity.

After defining the variables, the next step is to develop a research model with the design shown in Fig 3.

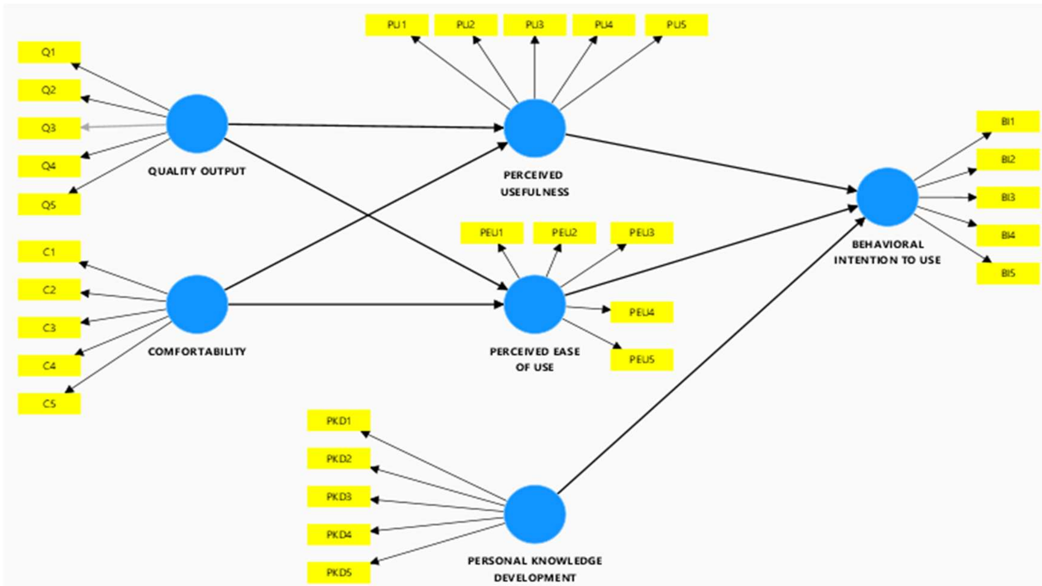


**Fig 3.** Initial Model Design

### *3.1. Outer Model Test*

The measurement model test was conducted in stages, including testing for convergent validity, discriminant validity, and composite reliability.

### *3.1.1. Convergent Validity Test*

The validity test was conducted using correlations between indicator scores and their constructs. If there is a change in a particular indicator within a construct, then other indicators of the construct will also change. The following are the SmartPLS calculation results from Table 2.

**Table 2.** Result Convergent Validity Test *(Loading Factor)*.

| Var. | BI | C | PEU | PKD | PU | Q | Ket |
|---|---|---|---|---|---|---|---|
| **BI1** | 0.76 | | | | | | **V.** |
| **BI2** | 0.81 | | | | | | **V.** |
| **BI3** | 0.79 | | | | | | **V.** |
| **BI4** | 0.83 | | | | | | **V.** |
| **BI5** | 0.82 | | | | | | **V.** |
| **C1** | | 0.77 | | | | | **V.** |
| **C2** | | 0.82 | | | | | **V.** |
| **C3** | | 0.77 | | | | | **V.** |
| **C4** | | 0.84 | | | | | **V.** |
| **C5** | | 0.86 | | | | | **V.** |
| **PEU1** | | | 0.78 | | | | **V.** |
| **PEU2** | | | 0.78 | | | | **V.** |
| **PEU3** | | | 0.84 | | | | **V.** |
| **PEU4** | | | 0.74 | | | | **V.** |
| **PEU5** | | | 0.80 | | | | **V.** |
| **PKD1** | | | | 0.72 | | | **V.** |
| **PKD2** | | | | 0.86 | | | **V.** |
| **PKD3** | | | | 0.79 | | | **V.** |
| **PKD4** | | | | 0.79 | | | **V.** |
| **PKD5** | | | | 0.75 | | | **V.** |
| **PU1** | | | | | 0.81 | | **V.** |
| **PU2** | | | | | 0.72 | | **V.** |
| **PU3** | | | | | 0.78 | | **V.** |
| **PU4** | | | | | 0.81 | | **V.** |
| **PU5** | | | | | 0.78 | | **V.** |
| **Q1** | | | | | | 0.75 | **V.** |
| **Q2** | | | | | | 0.84 | **V.** |
| **Q3** | | | | | | 0.77 | **V.** |
| **Q4** | | | | | | 0.82 | **V.** |
| **Q5** | | | | | | 0.77 | **V.** |

The output of the loading factor using the variables Comfortability (C), Quality Output (Q), Personal Knowledge Development (PKD), Perceived Ease of Use (PEU), Perceived Usefulness (PU), and Behavioral Intention to Use (BI) shows loading factor values greater than 0.5; therefore, all statements are considered valid. This result indicates that the indicators or statements used are correlated with their respective variables.

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Since the loading factor values for all statement items are greater than 0.5, all proposed statements are considered to have convergent validity.

#### 3.1.2. Discriminant Validity Test

If the average variance extracted (AVE) value is greater than 0.5, the variable is considered valid. The AVE estimation results are shown in Table 4.3.

**Table 3.** AVE Result on *Convergent Validity Test*

| Construct | Average Variance Extracted (AVE) | Remark |
|---|---|---|
| BI | 0.641 | Valid |
| C | 0.659 | Valid |
| PEU | 0.620 | Valid |
| PKD | 0.611 | Valid |
| PU | 0.608 | Valid |
| Q | 0.623 | Valid |

#### 3.1.3. Reliability Test

Reliability constructs can be evaluated using either the composite reliability or Cronbach's alpha. Both of these methods are used to assess the reliability of indicators for a variable.

**Table 4.** Value of *Cronbach's Alpha* & *Composite Reliability*

| ***Construct*** | **Cronbach's Alpha** | ***Composite Reliability*** | **Remark** |
|---|---|---|---|
| *BI* | 0.860 | 0.899 | **Valid** |
| *C* | 0.870 | 0.906 | **Valid** |
| *PEU* | 0.846 | 0.891 | **Valid** |
| *PKD* | 0.840 | 0.887 | **Valid** |
| *PU* | 0.838 | 0.886 | **Valid** |
| *Q* | 0.848 | 0.892 | **Valid** |

All variables have good reliability, as the composite reliability values for all constructs and variables are above 0.7.

#### 3.1.4. Fit Model Test

**Table 5.** Result of *Standardized Root Mean Square Residual* (SRMR)

| **Parameter** | **Rule of Thumb** | **Saturated model** | **Estimated model** | **Remark** |
|---|---|---|---|---|
| **SRMR** | Lower than 0.1 | 0.096 | 0.096 | Model Fit |

The SRMR result obtained was 0.096. Based on the model fit test table created in this study, the collected data indicate that the model can be used to analyze the relationships among the latent variables. Therefore, this model has strong predictive capability and accurately represents the data. Since the SRMR value (0.096) is below 0.1, the data fit the hypotheses, and the model is deemed fit.

### 3.2. Inner Model Test

Three main components are evaluated in the PLS-SEM inner model to assess the significance of relationships between variables. These are the significance of relationships (hypothesis testing), the coefficient of determination (R-square), and the effect size.

#### 3.2.1. R Square Value

The $R^2$ generated by PLS-SEM explains the dependent variable in terms of the independent variables; in other words, the R2 indicates the variance in the construct accounted for by several independent variables [9]. The $R^2$ value ranges from 0 to 1 (the larger the $R^2$ value, the better the model). The R2 value in this study is shown in Table 6.

**Table 6.** Result of R-Square Test

| ***Variable*** | **R-*Square*** | **Remark** |
|---|---|---|
| *BI* | 0.986 | Strong |
| *PEU* | 0.989 | Strong |
| *PU* | 0.987 | Strong |

The analysis result shows an R-squared value of 0.986 for the variable intention to use (BI), which indicates that 98.6% of the independent variables can explain the BI variable, while other factors explain the remaining 1.4%, thus the relationship between the independent variables and BI falls into the strong category (above 70%). The same applies to the other two variables.

#### 3.2.2. Effect Size

The specific impact of an independent variable on predicting a dependent variable is measured by the effect size. When a particular independent variable is removed from the model, the change in $R^2$ is observed. By calculating $f^2$, researchers can determine which independent variable has the greatest effect on the dependent variable in the model. The $f^2$ value is considered small if < 0.02, medium if between 0.02 and 0.15, and large if > 0.35, thereby providing further insight into how latent variables interact.

**Table 7.** Result of Effect Size Test ($f^2$)

| **Hyphotesis** | $f^2$ | **Remark** |
|---|---|---|
| **PEU -> BI** | 0.153 | Moderate |
| **PKD -> BI** | 0.015 | Weak |
| **PU -> BI** | 0.157 | Moderate |
| **Q -> PEU** | 0.665 | Strong |
| **Q -> PU** | 0.752 | Strong |
| **C -> PEU** | 0.862 | Strong |
| **C -> PU** | 0.596 | Strong |

The $f^2$ value considered weak is the influence of personal knowledge development on behavioural intention to use, with a value of 0.015. This result is categorized as small, indicating that personal knowledge development has a weak effect on behavioral intention to use. The $f^2$ values considered moderate are the influence of perceived ease of use on behavioural intention to use (0.153) and perceived usefulness on behavioural intention to use (0.157). The $f^2$ value considered strong is comfortability's influence on perceived ease of use (0.862), comfortability's influence on perceived usefulness (0.596), quality output's influence on perceived ease of use (0.665), and quality output's influence on perceived usefulness (0.752).

### *3.2.3 Significance Test*

The final stage is the significance test to determine the effect of exogenous variables on endogenous variables. The significance test for latent variables in SmartPLS can be performed using the bootstrap method. The following are the results of the data bootstrapping process using SmartPLS 4.

**Table 8.** Result of Bootstrapping Data

| Hypotesis | *Original Sample* (O) | *Standard Deviation* (STDEV) | T *Statistics* | P *Values* |
|---|---|---|---|---|
| **C -> PEU** | 0.532 | 0.152 | 3.508 | 0.000 |
| **C -> PU** | 0.470 | 0.193 | 2.435 | 0.007 |
| **PEU -> BI** | 0.374 | 0.265 | 1.412 | 0.079 |
| **PKD -> BI** | 0.110 | 0.169 | 0.649 | 0.258 |
| **PU -> BI** | 0.512 | 0.269 | 1.902 | 0.029 |
| **Q -> PEU** | 0.467 | 0.152 | 3.078 | 0.001 |
| **Q -> PU** | 0.528 | 0.193 | 2.736 | 0.003 |

Based on the criteria, a hypothesis is said to have a significant positive effect if the path coefficient is positive and the P-value is less than α (5%). It was found that 5 out of 7 proposed hypotheses, namely comfortability toward perceived ease of use, comfortability toward perceived usefulness, perceived usefulness toward behavioral intention to use, quality output toward perceived ease of use, and quality output toward perceived usefulness, have P-values less than 5%, so these 5 hypotheses are considered to have a significant positive effect. Meanwhile, the other 2 hypotheses, namely perceived ease of use toward behavioural intention to use and personal knowledge development toward behavioural intention to use, have P-values greater than 5% (0.05), so these 2 hypotheses are considered not significant.

## *3.3 Problem-Solving Recommendations*

Based on the results of hypothesis testing using Smart PLS Ver. 4, a discussion will be conducted on recommendations for problem-solving for hypotheses identified as having a significant impact. In this study, 5 hypotheses are significant.

Next, a fishbone diagram will be created based on the problems that occur. The process of creating a fishbone diagram involves discussion and brainstorming, as well as further analysis to identify root causes and control the outputs of the statements.

Discussions are conducted by the researchers, utility managers, and wastewater treatment plant operators, and the fishbone diagram will be shown in Fig 4.

In Fig. 4, the fishbone diagram shows the root causes of the problem, as shown in Table 9.

**Table 9.** *Action Plan* for *Low Level of Comfortability* & *Quality Output*

| No. | *Root Cause* | *Action Plan* |
|---|---|---|
| 1 | *Hardware* Damaged | Propose to provide stock of several hardware components (pH, COD, TSS and flow rate sensors, minimum 1 unit for each sensor) |
| 2 | *Bug software* | Request to create automatic software updates |
| 3 | Fouling or dirt sticks to the sensor | Make a cleaning schedule to sensor once a week |
| 4 | There is sediment in the tank | Make a cleaning schedule to tank once a week |
| 5 | *Tank is Empty* | Create SOPs so that the tank is not empty |
| 6 | There is no calibration schedule | Make a calibration schedule once a year |
| 7 | There is no cleaning schedule | Make a cleaning schedule once a month |
| 8 | There are no standard operating guidelines for the tools | Creating a General SOP for Operating SPARING Tools |
| 9 | No training was conducted on the knowledge of SPARING technology and its SOPs. | Conducting training every year, which is carried out by a speaker who is an expert in the SPARING technology sector. |

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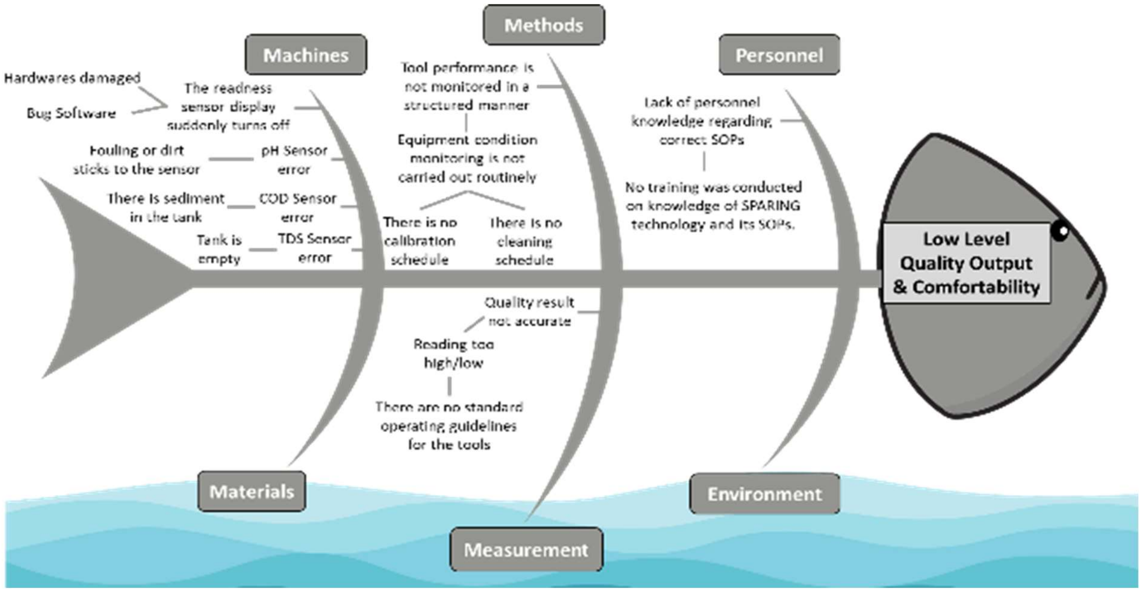


**Fig 4.** Fish Bone Diagram Influence Comfort & Quality Output

## 4. CONCLUSION

Based on the data processing results for analyzing the acceptance of SPARING technology, it can be concluded that five of the seven hypotheses were accepted: comfort significantly influences perceived ease of use, comfort significantly influences perceived usefulness, output quality significantly influences perceived usefulness, output quality significantly influences perceived ease of use, and perceived usefulness significantly influences behavioral intention to use. Therefore, to increase acceptance of SPARING technology, it is necessary to improve the level of comfort and output quality.

Based on this hypothesis, the causes of the low level of unsafety and quality accuracy that can occur during the application of SPARING technology as perceived by users are partly due to technical issues, including sudden shutdown of the sensor reading display, sensor errors, anomalies in sensor readings that cause spikes in trends, and the need for additional monitoring due to real-time readings in the SPARING system. Providing solutions as recommendations for resolving hypotheses that are indicated to have a significant influence on behavioral intention to use, namely comfortability and quality output, has been analyzed using fish bone diagram analysis where the solutions include creating standard operating procedures (SOPs) for proper tool operation, cleaning bucket tanks and SPARING sensors, creating SPARING sensor calibration schedules, submitting stock provision of hardware components at SPARING and others. The solution is expected to increase user acceptance of SPARING technology at PT.XYZ.

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