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Analyzing User Acceptance of AI Based Water Quality Monitoring through the UTAUT2 Framework

Qurotul Aini[1], Marviola Hardini[2], Adam Faturahman[3], Dwi Apriliasari[4*], Alexander Chou Kiboy[5]
[1]Faculty of Information Technology, Kristen Satya Wacana University, Indonesia
[2]Business Digital, Sundara Group, Indonesia
[3]Computer Science, Bosindo, Indonesia
[4]Faculty of Science and Technology, University of Raharja, Indonesia
[5]Computer System, Ijiis Incorporation, Singapore
[1]aini@raharja.info, [2]marviola@raharja.info, [3]adam.faturahman@raharja.info, [4]dwi.apriliasari@raharja.info [5]houki@ijiis.asia
***Corresponding Author**

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ABSTRACT

This research explores the factors influencing user acceptance and utilization of AI-enhanced water quality systems by applying the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework. **AI technology has become increasingly** important in improving water quality management by analyzing real-time data from multiple sources, helping to enhance environmental sustainability and public health. **This study aims** to identify and analyze the factors that affect user behavioral intention toward adopting AI-based water quality systems, particularly focusing on perceived usefulness, ease of use, social norms, and motivation. **Data were collected from** 357 respondents who had used AI-based water quality systems for at least three months and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software. **The findings indicate** that perceived ease of use, social norms, and motivation have a significant influence on behavioral intention to adopt the systems, while perceived usefulness shows no significant effect. **These results validate the UTAUT2 model** applicability to AI-driven environmental technologies and provide practical guidance for developers and policymakers to enhance user engagement, affordability, and usability of AI-based water quality systems to promote sustainable environmental management and public well-being.

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1. INTRODUCTION

The implementation of AI-based water quality monitoring systems is closely aligned with Sustainable Development Goal (SDG) 3, which seeks to ensure healthy lives and promote well being for all [1]. Access to clean and safe water is a fundamental determinant of human health, and AI technologies can play a transformative role in minimizing exposure to harmful pollutants. By continuously analyzing real time water data from multiple sources, AI-enabled systems can identify contamination patterns early, provide timely alerts, and support proactive public health interventions [2]. This contributes directly to preventing waterborne diseases and improving community well being, highlighting how technological innovation supports sustainable health management [3].

AI-enhanced water monitoring directly supports SDG 6, which emphasizes ensuring the availability and sustainable management of clean water and sanitation for all [4, 5]. Through automated data collection, predictive analytics, and intelligent recommendations, AI systems enhance the ability to monitor water quality efficiently and accurately. These systems empower governments, industries, and communities to take informed action toward pollution control and resource conservation [6]. Moreover, by providing accessible digital tools for environmental monitoring, AI promotes greater transparency and accountability in water governance, ensuring that sustainable water management practices are both data driven and equitable [7].

Beyond health and sanitation, the integration of AI into environmental monitoring contributes to SDG 9 and SDG 13 by fostering innovation and enhancing resilience to climate related risks [8]. AI-based infrastructure enables the development of smart environmental management systems that can adapt to changing ecological conditions and support sustainable industrial operations [9]. By reducing human error and improving predictive accuracy, these intelligent technologies help mitigate the effects of pollution and climate variability on water ecosystems. Therefore, the adoption of AI-based water quality monitoring not only drives technological advancement but also strengthens global efforts toward sustainable infrastructure and climate resilience [10].

2. LITERATURE REVIEW

The Literature Review emphasizes the critical relationship between water quality and human health, noting that poor water conditions can cause serious respiratory and cardiovascular diseases [11]. It explains that advancements in technology, particularly AI augmented water quality systems, are instrumental in monitoring and enhancing water conditions by collecting and analyzing real time data from multiple sources. The section further highlights that the successful adoption of such AI based technologies is influenced by several determinants identified in the Comprehensive Model of Technology Acceptance and Use (UTAUT2), which encompasses performance expectations, effort requirements, social impact, and enabling conditions, behavioral intention, and usage behavior [12]. Which validated UTAUT2 across various fields like education, healthcare, and environmental systems, this study applies the model to explore how perceived usefulness, ease of use, social norms, and motivation influence user adoption of AI enhanced water quality systems, thus providing a strong theoretical basis for the research framework [13].

3. RESEARCH METHODOLOGY

The Research Methodology section explains that this study uses the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach integrated with the Unified Theory of Acceptance and Use of Technology version 2 (UTAUT2) framework to examine the determinants affecting the adoption of AI enhanced water quality systems [14]. The PLS-SEM method was chosen for its ability to handle complex relationships between latent variables, even with non normal data or relatively small sample sizes. Data were collected through an online survey of 357 respondents who had used AI based water quality systems for at least three months [15]. The research model includes four independent variables PU, PEOU, SN, and MOT and one dependent variable, BI. Each construct was measured using multiple indicators and analyzed using SmartPLS software to test reliability and validity through AVE, Composite Reliability, and Cronbach Alpha [16]. The hypotheses were examined using bootstrapping to determine the significance of path coefficients, allowing the study to identify which variables most strongly influence user behavioral intentions toward adopting AI enhanced water quality systems [17].

3.1. Independent Variable

Perception of Usefulness is an independent variable used to understand the extent to which users perceived usefulness of AI enhanced Water Quality Systems influences other factors [18]. Similarly, PEOU is also an independent variable aimed at determining how users perceived ease of use affects the adoption and utilization of the system [19]. SN serves as another independent variable, measuring the extent to which social norms within the user community affect the acceptance of AI driven water quality monitoring systems. Lastly, MOT is considered an independent variable as well, used to examine how individual motivations such as concern for the environment or health affect users intention to use the system [20].

3.2. Dependent Variable

The key outcome variable in this study is BI, represents users willingness and commitment to accept and utilize AI driven water quality monitoring systems [16]. Within the UTAUT2 framework, BI captures how perceptions, motivations, and social influences shape users decisions to engage with the technology. It is measured through four indicators (BI1–BI4) related to users intentions, effort, and consistency in system usage [21]. The results show that PEOU, SN, and MOT significantly affect Behavioral Intention, while PU has a weaker effect. This suggests that ease of use, social support, and personal motivation play a more dominant role in shaping users intention to adopt AI based water quality systems [22].

Table 1. Smart PLS Indicator

Code	Definition
PU 1	The extent to which the system is useful in achieving the goal.
PU 2	The use of technology increases effectiveness in achieving goals.
PU 3	Ease of daily use without distractions.
PU 4	Positive impact in the long run.
PEOU 1	The extent to which the interface or system is easy for users to understand and use.
PEOU 2	Ease of understanding and mastering the system without requiring a long time.
PEOU 3	Low level of complexity so that users don't find it difficult or intimidating.
PEOU 4	The extent to which the system can be seamlessly integrated into the user daily routine without disrupting their activities.
PEOU 4	The extent to which the system can be seamlessly integrated into the user daily routine without disrupting their activities.
SN 1	The extent to which individuals feel positive pressure from their social environment to adopt or use AI enhanced water Quality Systems.
SN 2	The degree to which individuals adhere to social norms that support the use of these systems, including if their social group encourages use.
SN 3	The extent to which individuals receive recommendations or positive feedback from friends, family or the community regarding the use of this system.
SN 4	The general public understanding of and support for AI enhanced water quality systems as a desirable standard.
MOT 1	The level of individual motivation to use AI-enhanced Water Quality Systems due to concern for the environment and efforts to protect nature.
MOT 2	Individuals motivation for using the system is due to personal health concerns, such as avoiding the negative effects of water pollution.
BI 1	The degree of positive intention people have to embrace and utilize AI enhanced water quality systems.

Table 1 presents the indicators used in the SmartPLS analysis to measure each construct within the research model, aligning with the UTAUT2 framework [23]. The table defines the operational meaning of all indicators associated with the five main constructs, namely PU, PEOU, SN, MOT, and BI. Each construct consists of four indicators designed to capture different dimensions of user perception and behavior toward AI enhanced water quality systems [24]. For instance, the PU indicators assess how effectively the system helps users achieve their goals and improve performance, while PEOU indicators evaluate the simplicity, clarity, and ease of integrating the system into daily routines [25]. SN indicators emphasize the influence of social environment, recommendations, and public awareness on user adoption, and MOT indicators highlight both intrinsic and extrinsic motivations, such as environmental concern, health awareness, and external incentives . Lastly, the BI indicators measure user intentions, willingness, and commitment to continue using the AI based system [26].

3.3. Hypothesis

The study proposes five hypotheses related to the influence of various factors on the intention to use AI driven water quality monitoring systems BI [27]. Hypothesis 1 (H1) states that there is no significant influence between PU and users intention to adopt AI-driven water quality monitoring systems [28]. Hypothesis 2 (H2) suggests that PEOU has a significant influence on the intention to use AI-enhanced Water Quality Systems. Hypothesis 3 (H3) posits that SN significantly influence the intention to use the system [29]. Hypothesis 4 (H4) indicates that MOT has a significant influence on the intention to use AI enhanced Waters Quality Systems. Lastly, Hypothesis 5 (H5) proposes that water quality awareness significantly affects the behavioral intention to adopt AI driven water quality monitoring systems. By testing these hypotheses through statistical analysis, the study aims to identify the significant relationships between the independent and dependent variables [30].

4. RESULTS AND DISCUSSION

In this study will examine the relationship between latent variables and their indicators or the outer model explains how each indicator relates to its latent variable [31]. There are several stages in testing the outer model, namely average AVE. composite reliability and Cronbach alpha. convergent validity value is the loading factor value on the latent variable with its indicators [32]. The expected loading factor value is 0.7, but if the outer loading value is 0.5 it can still be tolerated to be included in the model. and the following is a research model after the value of each indicator is entered and processed using PLS Algorithm in figure 1 [33].

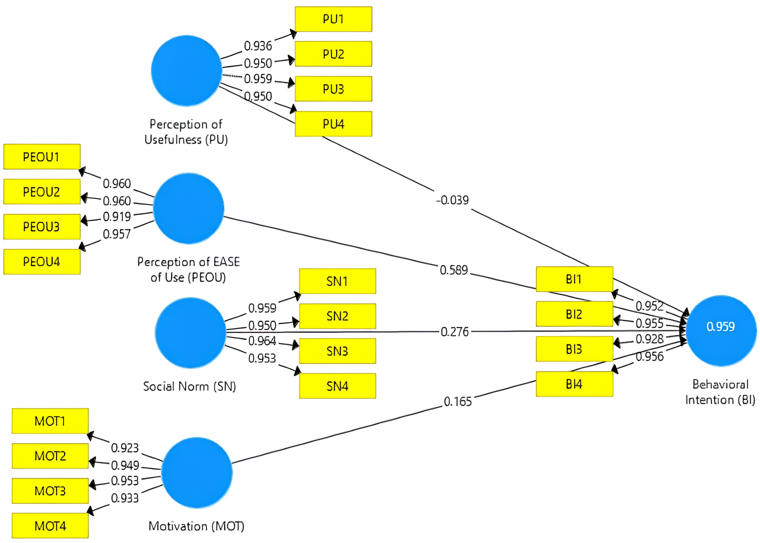

Figure 1. Path diagram between variables

The figure 1 above illustrates the structural model output generated through SmartPLS, depicting the relationships between the latent constructs and their corresponding indicators based on the UTAUT2 framework [13]. Each blue circle represents a latent construct PU, PEOU, SN, MOT, and BI while the yellow boxes represent their observed indicators [34]. The outer loading values for all indicators are above 0.90, indicating a strong correlation between each indicator and its corresponding construct, thereby confirming excellent convergent validity [35]. The inner model paths show that PEOU (0.589), SN (0.276), and MOT (0.165) have positive and significant effects on Behavioral Intention, whereas PU (-0.039) shows a weak and non significant influence [36]. The value of 0.959 inside the BI construct reflects its high reliability and internal consistency. Overall, the model demonstrates that ease of use, social norms, and user motivation play crucial roles in shaping behavioral intention toward adopting AI driven water quality technologies, while perceived usefulness contributes minimally to user intention in this context [37].

Table 2. AVE Value

Variables	AVE
Perception of Usefulness (PU)	0.900
Perception of EASE of USE (PEOU)	0.901
Social Norm (SN)	0.915
Motivation (MOT)	0.883
Behavioral Intention (BI)	0.899

Table 2 presents the Average Variance Extracted (AVE) values for each construct in the research model as indicators of convergent validity [38]. All constructs PU, PEOU, SN, MOT, and BI have AVE values above 0.50, indicating that each construct explains more than 50% of the variance in its indicators [39, 40]. PEOU (0.901) and SN (0.915) show the highest AVE values, demonstrating strong correlations and high reliability among their indicators [41]. Meanwhile, MOT has the lowest AVE value (0.883) but still meets the minimum requirement, confirming adequate validity. Overall, these results indicate that all measurement items possess strong convergent validity and are suitable for further structural model analysis [42].

Table 3. Composite Reliability Value

Variables	Composite Reliability
Perception of Usefulness (PU)	0.973
Perception of EASE of USE (PEOU)	0.973
Social Norm (SN)	0.977
Motivation (MOT)	0.968
Behavioral Intention (BI)	0.973

Table 3 presents the Composite Reliability values for each construct within the structural model, employed to assess construct reliability and internal consistency of measurement indicators [43]. All constructs PU, PEOU, SN, MOT, and BI show very high reliability, with values ranging from 0.968 to 0.977, all exceeding the 0.70 threshold [44]. The highest reliability is observed in Social Norm (0.977), indicating strong consistency in representing users social perceptions. PU, PEOU, and BI each have a reliability of 0.973, while MOT scores slightly lower at 0.968 but still reflects excellent consistency [45].

4.1. Structural Model Testing

When conducting Partial Least Square (PLS) analysis, the inner model testing evaluates the model suitability using the R square value, where 0.75 indicates a strong model, 0.50 moderate, and 0.25 weak [46].

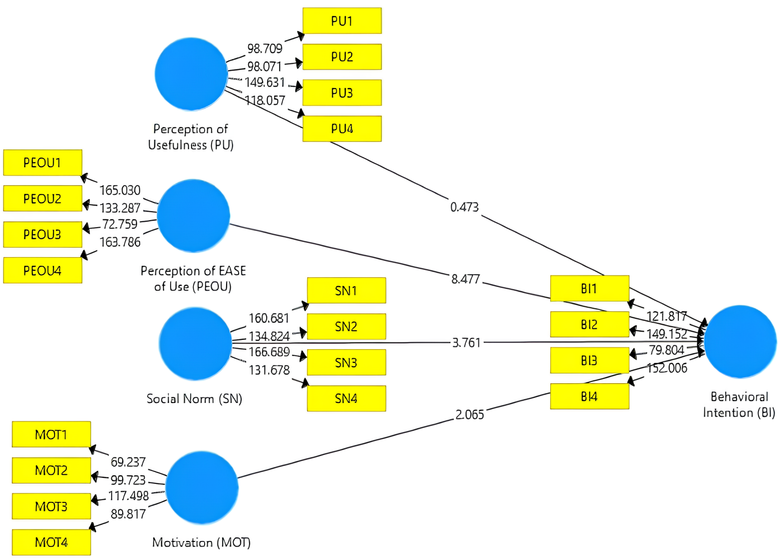

Figure 2. R Square value

Figure 2 illustrates the R Square values that explain the structural relationships among variables, showing that PU, PEOU, SN, and MOT act as exogenous variables influencing BI. The diagram indicates that SN has the strongest effect on BI, suggesting that social influences play a major role in encouraging users to adopt or continue using AI enhanced water Quality Systems [47]. T Statistic analysis reveals that Perceived Ease of Use (T = 8.477) has the most significant effect on Behavioral Intention, followed by Social Norm (T = 3.761) and Motivation (T = 2.065), all significant at the 5% level (T > 1.96). In contrast, Perceived Usefulness (T = 0.473) shows no significant effect, indicating that while ease of use, motivation, and social norms strongly shape behavioral intentions, perceived usefulness has a relatively minor influence.

5. MANAGERIAL IMPLICATIONS

The findings of this study provide several important managerial implications for developers, policymakers, and stakeholders involved in promoting AI enhanced water quality systems. Since Perceived Ease of Use, Social Norms, and Motivation significantly influence users behavioral intentions, managers should focus on designing systems that are user friendly, intuitive, and seamlessly integrated into daily activities. Increasing social awareness through campaigns, community endorsements, and collaborations with influencers can strengthen positive social norms toward system adoption. Moreover, motivation can be enhanced by emphasizing the health and environmental benefits of using AI-based water quality systems. Policy makers should also consider providing incentives or subsidies to make these systems more affordable, thereby encouraging broader adoption. Collectively, these managerial actions can foster greater public trust, engagement, and sustained utilization technologies, ultimately contributing to improved water quality and public well being.

6. CONCLUSION

The findings of this study highlight the key factors influencing the acceptance and utilization of AI enhanced water quality systems using the UTAUT2 framework. The analysis reveals that perceived ease of use, social norms, and motivation significantly affect user behavioral intentions, while perceived usefulness shows a weaker and non significant relationship. This suggests that individuals are more likely to adopt AI based water quality systems when they find them easy to use, socially supported, and aligned with their personal or environmental motivations rather than solely based on their perceived benefits. The results demonstrate that the user experience and social environment play a more crucial role than functional performance in shaping user acceptance.

From a theoretical perspective, the study contributes to validating and extending the application of the UTAUT2 model in the context of environmental and AI based technologies. It provides empirical evidence that UTAUT2 can effectively explain user behavior toward adopting intelligent environmental systems, emphasizing the importance of motivational and social dimensions in addition to technological factors. This strengthens the model relevance beyond traditional information technology settings and supports its adaptability to emerging innovations that integrate AI for sustainability and public health purposes.

Practically, the study offers several implications for developers, policy makers, and technology provide rs. To enhance adoption, system designers should prioritize user friendly interfaces, provide clear information on the benefits of usage, and promote affordability to ensure accessibility for broader user groups. Policymakers and organizations can also leverage social influence strategies such as community campaigns, influencer endorsements, and educational initiatives to encourage greater public engagement with AI-based water quality systems. By focusing on usability, awareness, and motivation, stakeholders can foster wider acceptance, leading to improved water quality monitoring, better environmental management, and ultimately, enhanced public well being.

7. DECLARATIONS

7.1. About Authors

Qurotul Aini (QA) https://orcid.org/0000-0002-7546-5721

Marviola Hardini (MH) https://orcid.org/0000-0003-3336-2131

Adam Faturahman (AF) https://orcid.org/0000-0001-9727-9092

Dwi Apriliasari (DA) https://orcid.org/0000-0001-5597-0475

Alexander Chou Kiboy (AC) https://orcid.org/0009-0009-3858-1852

7.2. Author Contributions

Conceptualization: QA; Methodology: MH; Software: AF; Validation: DA and AC; Formal Analysis: QA and AF; Investigation: AC; Resources: MH; Data Curation: AF; Writing Original Draft Preparation: AF and DA; Writing Review and Editing: QA and AF; Visualization: AC; All authors, QA, MH, AF, DA, and AC, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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7.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

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