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Economic Valuation of Smart Water Infrastructure: A Contingent Valuation Method Approach

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Abstract This study estimates the economic value of smart water infrastructure using the contingent valuation method (CVM). A double-bounded dichotomous choice format was employed to assess household willingness to pay (WTP) for four digital water technologies, including pipeline digital twin, AI-based purification, treatment plant digital twin, and asset management systems. Based on a nationwide online survey of 1,400 respondents, a bivariate probit model was applied to jointly analyze sequential responses and to derive statistically valid WTP estimates. The analysis confirms that users assign substantial economic value to digital water technologies, suggesting strong consumer support for digital transformation in water services. These findings provide empirical justification for long-term infrastructure investment and offer practical implications for rate-setting and policy design that reflect public preferences and perceived benefits.

Keywords Smart Water Infrastructure, Digital Transformation, Multi-regional Water Supply System, Willingness to Pay, Contingent Valuation Method

I. Introduction

The advancement of the Fourth Industrial Revolution has driven rapid progress in digital technologies across all sectors of society. At the core of this

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transformation are digital technologies such as artificial intelligence, big data, digital twin (DT), internet of things, and cloud computing. These technologies have significantly enhanced efficiency and precision throughout the entire process of data collection, analysis, and utilization, thereby enabling predictive approaches to problem solving. In particular, artificial intelligence ensures a high level of predictive reliability by processing large volumes of data through machine learning and deep learning techniques, while the DT replicates physical systems within virtual environments to allow for the preemptive evaluation of various scenarios and responsive strategies.

These technologies are increasingly integrated into everyday life. Autonomous vehicles operate regardless of the presence of a human driver, and large-scale natural language processing models such as Open AI's Chat GPT and Google's Gemini provide diverse information through interactive communication with users. On video platforms such as YouTube, personalized content recommendation algorithms are implemented with high sophistication. The development of digital technologies thus extends beyond mere convenience, bringing about fundamental changes in both individual lifestyles and broader societal structures.

Although digital technologies were initially adopted in the private sector, their applicability is increasingly recognized in the realm of public infrastructure, including water supply systems. Conventional water supply networks face persistent challenges such as limitations in water quality management, leakage from aging pipelines, and accidents related to supply failures. In particular, data from the Korea Water Resources Corporation in 2023 indicate that approximately 36 percent of national pipelines, totaling around 85 thousand kilometers, have been in use for more than 20 years. This aging infrastructure causes an annual leakage of approximately 670 million cubic meters of treated water, equivalent to the national water supply for 36 days, and results in economic losses of around 691.7 billion Korean won. Persisting with traditional approaches to address these issues often results in inefficient fiscal spending and operational shortcomings. In this context, digital technologies are emerging as a viable alternative. For example, artificial intelligence can be applied to develop predictive leakage detection systems that analyze real-time data to anticipate and mitigate potential failures. Similarly, DT technology enables the simulation of physical changes in a virtual environment, allowing for more systematic facility management and enhanced disaster preparedness.

The implementation of digital technologies in water supply systems also holds significant long-term implications for addressing environmental changes. Anticipated challenges, such as water scarcity driven by climate change and shifting demand patterns due to demographic transitions, pose serious threats to the stability of water supply infrastructure. To effectively respond to these challenges, a smart and flexible water resource management system is essential.

In this regard, the digital transformation of the water sector should not be viewed merely as a localized effort to enhance operational efficiency through technological adoption, but rather as a strategic response to structural changes in future society aimed at improving the quality of public services.

This study aims to objectively assess the economic value of digital transformation in the water supply sector. Specifically, it seeks to quantify the economic benefits generated throughout the transformation process, including technologies such as pipeline digital twin (Pipeline DT), artificial intelligence-based water purification (AI Purification), treatment plant digital twin (Treatment Plant DT), and asset management systems. The analysis is based on survey data, with the pipeline DT and AI purification grouped as one unit and the treatment plant DT and asset management system as another. The methodological framework adopted in this study is the contingent valuation method (CVM), which is used to estimate the monetary value of utility perceived by individuals as a result of the digital transformation in water services.

II. Backgrounds

1. Digital Transformation Initiatives by the Korea Water Resources Corporation

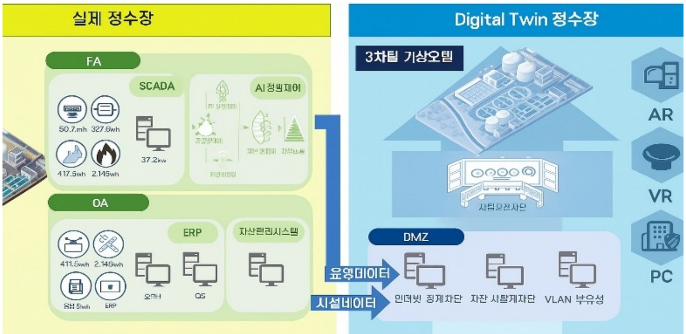
Korea Water Resources Corporation has adopted smart water management[1] as a core future strategy to fulfill its institutional mandate of delivering clean and safe water. This approach integrates digital technologies across the water service process and

ment and supply to include waterfront urban development, water industry promotion, andcontributes to improved water quality control, leakage prevention, risk prediction, and energy efficiency. Collectively, such efforts facilitate a more reliable and stable water supply compared to conventional systems.

Korea Water Resources Corporation is expanding its scope beyond traditional water resource manage international development cooperation. At the center of this transformation lies the digitalization of the water supply system. The smart water treatment plant currently operating in Hwaseong has demonstrated

1 Smart water management refers to the integration of artificial intelligence and information and communication technologies to optimize and advance the entire water supply system. Specifically, it seeks to enhance operational performance across the water management process by combining big data with artificial intelligence and DT technologies.

technological excellence, as evidenced by several prestigious recognitions, including the top award in digital innovation by the United Nations, the Global Lighthouse Network Award from the World Economic Forum, and selection among the top ten technologies of the year at the 2024 Korea Machinery Day. These achievements highlight Korea's potential to lead international standardization in digital water systems and reflect the growing global demand for advanced technologies in the water industry.

Smart Water Purification Plant	
Regional Waterworks Digital Twin	

Source: Korea Water Resources Corporation

Figure 1. Examples of Digital Transformation in Water Supply

While the necessity of digital transformation in the water supply system, as envisioned by Korea Water Resources Corporation, is well recognized, its full-scale implementation requires substantial time and financial investment. To justify such a large-scale initiative, objective and scientifically grounded evidence is essential for gaining support from both the government and the public. This study employs the CVM to systematically evaluate the economic value of digital transformation in water infrastructure, aiming to provide an empirical basis for policy development and implementation by the Korea Water Resources Corporation.

II. Literature Review

Previous studies on multiregional water supply systems (hereafter, water supply systems) have primarily focused on economic valuation and impact analysis, excluding those that address technological effectiveness. Given the large-scale investment in social overhead capital involved in such projects, economic feasibility studies are considered a core step in justifying project implementation. For instance, Lee et al. (2022) analyzed the duplication project of the water transmission pipeline in the Seoul Metropolitan Area, while Choi et al. (2017) focused on the water supply project in the western region of Chungcheongnam-do. In addition, several studies have adopted a macroeconomic approach using input–output models to estimate the economic ripple effects of water supply systems and verify their policy justification (Choi and Lee, 2013; Lee et al., 2013).

On the other hand, studies from a microeconomic perspective have evaluated the economic value of water quality improvement, service disruption, and social benefits associated with water supply systems. Yoo et al. (2007) estimated consumers' willingness to pay for water quality enhancement, while Chae and Kang (2011) emphasized the importance of including not only use values but also non-use values in the valuation of water outage scenarios. Kim and Ryu (2017) assessed the social benefits of water supply policies to demonstrate their legitimacy.

Recently, with the development of digital water technologies, discussions on water supply systems have expanded to practical applications. In particular, smart water management initiatives such as Smart Water City pilot projects have been implemented. These projects aim to improve the efficiency of water services by integrating ICT into water infrastructure, enhancing both quantity and quality management and public trust in tap water (Kim, 2015; Lee and Lee, 2020). Smart water technologies have also been used to upgrade aging pipelines in public facilities such as military bases and have shown measurable improvements in water flow efficiency (Park and Kim, 2020).

Moreover, digital transformation technologies such as smart pipelines, AI-based water treatment plants, and digital twins have been increasingly introduced into water supply systems. These technologies contribute to improved operational efficiency, environmental protection, cost savings, and service quality enhancement. In particular, machine learning-based leak detection is actively applied in smart pipeline projects (Park et al., 2023). AI-based water treatment plants offer energy-efficient and eco-friendly solutions, addressing operational challenges and reducing costs. Studies by Lee et al. (2024) and Aparna et al. (2025) applied various AI algorithms, such as artificial neural networks and random forests, to predict water quality, while Forhad et al. (2024) demonstrated that IoT-based water quality monitoring systems enhance plant performance and provide solutions to address future water scarcity (Velayudhan et al., 2022). In Korea, a pilot project in Hwaseong utilizing an AI-based treatment system confirmed its economic effectiveness through empirical validation (Shin et al., 2023). Additionally, digital twin technology, which replicates physical systems in a virtual environment, allows for simulation-based forecasting and adaptive management of future changes (Movva, 2024). Digital twin technology in water supply systems enables real-time diagnostics and autonomous operation of water treatment processes. Therefore, the integration and interoperability among technologies are crucial, and a well-structured implementation strategy is essential (Cho and Jung, 2023).

While previous research on the digital transformation of water supply systems has focused largely on technological development and operational performance, studies on the economic value perceived by consumers remain limited. This study aims to fill this gap by evaluating the economic value of digital transformation from the consumer's perspective. Specifically, it applies the contingent valuation method to estimate consumer willingness to pay for key digital functions such as smart purification and predictive monitoring. In doing so, it seeks to justify such initiatives not only on the basis of technological efficacy but also in terms of consumer-level support. The results indicate substantial public support for these innovations, reinforcing their policy relevance. The findings are expected to provide a valuable foundation for future policymaking and budget allocation, thereby contributing to practical implementation in the public sector.

III. Methodologies

1. Rationale for the Selection of the Valuation Methodology

Consumer preferences for nonmarket goods are typically assessed using either the revealed preference approach or the stated preference approach. The revealed preference approach is applicable when consumer preferences can be inferred from observed choices and actual behavior in the marketplace. In contrast, when actual transactions or observable choices are absent, or when preferences are not clearly revealed, the stated preference approach is more appropriate. This method involves presenting hypothetical scenarios and directly eliciting consumer preferences through survey instruments. Given that the current study deals with a hypothetical context, namely the digital transformation of the water supply system, which remains unfamiliar to most consumers, the stated preference approach is considered suitable. This approach allows for the estimation of consumer perceptions and the utility associated with the proposed technological intervention.

The stated preference approach includes two principal techniques. First, the CVM involves constructing a hypothetical market scenario and directly asking individuals how much they are willing to pay for a given good or service, thereby yielding a monetary measure of value. Second, conjoint analysis estimates preferences indirectly by presenting respondents with various combinations of attributes and prompting them to make choices among these alternatives. Between these two methods, this study adopts the CVM to derive monetary values based on a straightforward and intuitive survey design. Applying this method makes it possible to estimate consumers' willingness to pay (WTP) for digital transformation technologies in water supply systems (Mitchell and Carson, 2013), which serves as a proxy for their perceived utility. Furthermore, CVM is widely employed by reputable institutions, including international organizations and research agencies, to assess the economic value of nonmarket goods such as public services, supporting the methodological validity of its use in this study (Han, 2006).

2. Analytical Framework

This study measures consumer utility regarding digital transformation technologies in water supply systems using WTP as the primary indicator. Since the digital transformation of water infrastructure does not refer to a single unified technology but rather to the application of various innovations across multiple components of the water network, benefits are evaluated across four distinct categories: pipeline DT (hereafter referred to as pipeline DT), artificial intelligence based water treatment facilities, treatment plant DT (hereafter treatment plant DT), and asset management systems.

Although certain digital technologies, such as the pipeline DT and the AI-based treatment plant in Hwaseong, have already been partially implemented, they have not yet been widely adopted to the extent that consumer evaluation and choice are possible. Accordingly, this study constructed a hypothetical market within the survey, presenting respondents with real-world accident cases and the expected benefits of digital transformation, including physical safety, reduction of economic losses, improved water quality, and enhanced waterfront environments. This design enables respondents to realistically perceive the potential benefits, thereby allowing for a more comprehensive measurement of utility. The results are expected to serve as a foundation for future policy decisions and the formulation of funding strategies.

3. Survey Design

The CVM can be implemented using various survey formats, including open-ended questions, dichotomous choice, double-bounded dichotomous choice (DBDC), payment card, ranking, rating, and spike models. Among these, the present study adopts the dichotomous choice format. Originally developed by Bishop and Heberlein (1979), this format asks respondents to answer either "yes" or "no" to a predetermined bid amount. The dichotomous choice approach retains the advantages of binary questioning while addressing the limitations associated with limited information and reducing the potential for strategic bias, thereby enabling more accurate estimation of WTP (KDI, KEEA, 2012). In the current study, respondents were randomly assigned an initial bid. If the response was "yes," a follow-up bid twice the initial amount was presented. If the response was "no," a lower bid at half the initial amount was offered. In cases where respondents rejected the half bid, additional questions were asked to determine whether they were willing to pay even a minimal amount or not willing to pay at all. This sequential procedure allows for a more precise estimation of consumer WTP (Chae and Cho, 2019).

4. Estimation Method: Bivariate Probit Model

The bivariate probit model is used in the CVM to jointly analyze responses to two sequential questions, namely the initial WTP and the follow-up response. This model is widely applied in the analysis of contingent valuation data based on double-bounded formats, as it enables the estimation of responses to both bid levels within a unified specification. The method assumes that the error terms of the two binary dependent variables are correlated and does not impose conditional independence between them. Based on this specification, the model estimates the probability of accepting the initial bid and uses this information to derive the mean WTP. The estimation is based on the following equations:

$$Y_{1i} = X_{1i}\beta_{1i} + \epsilon_{1i}$$
$$Y_{2i} = X_{2i}\beta_{2i} + \epsilon_{2i}$$

The observed variables in this model are defined as follows:

$$Y_{1i} = \{\begin{matrix} 1\ if\ Y_{1i} > 0 \\ 0\ otherwise \end{matrix}, Y_{2i} = \{\begin{matrix} 1\ if\ Y_{2i} > 0 \\ 0\ otherwise \end{matrix}$$

$$\begin{matrix}\epsilon_{1i} \\ \epsilon_{2i}\end{matrix} \sim N\left(\begin{pmatrix}0 \\ 0\end{pmatrix}, \begin{pmatrix}1 & \rho \\ \rho & 1\end{pmatrix}\right)$$

The respondent's WTP is inferred from their response to the first bid, and the mean WTP is computed using the standard formula based on the estimated intercept and the coefficient of the bid variable:

$$\text{Mean WTP} = -\frac{\beta_0}{\beta_1}$$

If the correlation coefficient ρ is statistically significant, it suggests that the responses to the first and second bids are not independent. In such cases, the bivariate probit model is preferred over separate univariate models, as it appropriately captures the joint structure of the response process.

IV. Data and Variables

1. Survey Data

CVM estimates the economic value of non-market goods by constructing a hypothetical market through a structured survey. It is particularly effective in measuring consumer utility related to environmental resources, public goods, and infrastructure improvements, allowing monetary valuation based on respondents' stated WTP. However, CVM is also subject to limitations stemming from respondents' subjective preferences and financial capacity (KDI, 2008). Accordingly, rigorous survey design is essential to ensure reliable WTP estimation.

In this study, the CVM survey was conducted across regions of South Korea, excluding Busan, Daejeon, and Jeju, where the use of the national water supply system is relatively limited. A stratified sampling method was applied to allocate respondents proportionally by household size and gender within each selected city. The survey was administered online.

Given the potential for response fatigue when evaluating all four smart water infrastructure components simultaneously, the survey was divided into two modules: (1) pipeline DT and AI purification, and (2) treatment plant DT and asset management system. Each module was completed by a separate sample of 700 households.

2. Variable Description

The independent variables used in this study are summarized in Table 1. The main objective of the CVM is to estimate WTP, which can be interpreted as the threshold amount at which a respondent's WTP changes. The core components for deriving the basic WTP are the intercept and the coefficient on the bid variable. Although the other covariates are not directly involved in the calculation of WTP, their inclusion in the model allows for the estimation of unbiased coefficients by controlling for potential confounding effects, thereby improving the reliability of the WTP estimates.

The dependent variables are constructed in three distinct forms, as detailed below. Dependent variable 1 is coded as 1 if the respondent answered "yes" to the initial bid amount, and 0 otherwise. Dependent variable 2 is coded as 1 if the respondent, who initially answered "yes," also accepted a follow-up bid amount equal to twice the initial bid, and 0 otherwise. Dependent variable 3 is coded as 1 if the respondent, who initially answered "no," accepted a lower bid amount equal to half the initial bid, and 0 otherwise. The bid amounts presented in the survey ranged from KRW 1,000 to KRW 10,000.

Table 1. Description of Variables

Variable		Description
Dependent Variable	Dep 1	Response "Yes" to the initial bid amount (Dep 1 = 1)
	Dep 2-1	Response "Yes" to a follow-up bid equal to twice the initial bid (Dep 1 = 1, Dep 2 = 1)
	Dep 2-2	Initial response "No" and response "Yes" to a follow-up bid equal to half the initial bid (Dep 1 = 0, Dep 2 = 1)
Independent Variable	Age	Age
	Gender	Male = 1, Female = 0 (reference group)
	Education	Edu1: High school or less (reference group)
		Edu2: University graduate
		Edu3: Graduate school graduate
	Job	Job1: Public servants and professionals (reference group)
		Job2: Salaried worker
		Job3: Self-employed
		Job4: Others (e.g., agriculture, homemaker)
	Children	Presence of children
	Household Size	Number of household members
	Region	Metropolitan areas = 1, other regions = 0

To estimate WTP, the model controls for a set of independent variables encompassing demographic, socioeconomic, and regional characteristics. While these variables are not the core components of the model, their inclusion ensures unbiased and reliable estimation of WTP by accounting for potential confounding factors. The demographic and socioeconomic variables include age, gender, education level, employment status, presence of children, and household size. Age is treated as a linear variable, and gender is coded as male = 1 and female = 0. Education is classified into three levels: high school or less (reference group), university graduate, and graduate school graduate. Employment status includes salaried workers, self-employed individuals, and others (e.g., farmers, homemakers), with public servants and professionals serving as the reference category. Since the benefits of digital water infrastructure may derive not only from individual gains but also from altruistic motives, the presence of children and household size are also included as explanatory variables. The regional variable distinguishes between metropolitan areas (special and metropolitan cities) and other provinces, with the latter used as the reference category.

V. Results

1. Descriptive Statistics

Table 2 presents the response frequencies by technology type for the dichotomous choice questions related to digital transformation in water services. Among the 700 respondents for each module, the number of individuals who answered “yes” to both the initial bid and the follow-up bid set at twice the initial amount was 171 for pipeline DT, 165 for AI purification, 179 for treatment plant DT, and 156 for asset management system. These results suggest that approximately 22 to 25 percent of respondents expressed highly favorable views toward digital transformation technologies in water services.

For respondents who answered “yes” to the initial bid but “no” to the follow-up double-bid, the counts were 178 for pipeline DT, 159 for AI purification, 188 for treatment plant DT, and 183 for asset management system. This group appears to find the initially proposed payment acceptable but expresses reluctance toward paying higher amounts, indicating conditional support for digital transformation under moderate cost burdens.

Table 1. Response Types by Smart Water Technology

Response Type	Pipeline DT		AI Purification		Treatment Plant DT		Asset Management System	
	Frequency	%	Frequency	%	Frequency	%	Frequency	%
Yes-Yes	171	24.43	165	23.57	179	25.57	156	22.29
Yes-No	178	25.43	159	22.71	188	26.86	183	26.14
No-Yes	91	13	88	12.57	94	13.43	102	14.57
No-No	260	37.14	288	41.14	239	34.14	259	37

The number of respondents who initially answered "no" but subsequently accepted a reduced bid (half the initial amount) was 91 for pipeline DT, 88 for AI purification, 94 for treatment plant DT, and 102 for asset management system. These respondents demonstrate some level of WTP, albeit only under a lower financial commitment.

Finally, the proportion of respondents who rejected both the initial and follow-up bids ranged from approximately 34 to 41 percent across technologies. This indicates that a considerable segment of the population remains skeptical or unwilling to support the digital transformation of the water supply system, even under reduced cost scenarios.

Table 3 summarizes the descriptive statistics of the independent variables for pipeline DT, AI purification, treatment plant DT, and asset management system. The average age of respondents was approximately 46.2 years, with a gender distribution of 51 percent male and 49 percent female. In terms of education, 19.7 percent of respondents had completed high school or less (Edu1), 68.9 percent held a university degree (Edu2), and 11.4 percent had completed graduate-level education (Edu3). Regarding employment status, 48.6 percent were salaried workers (Job2), followed by 27.0 percent in other occupations (e.g., agriculture, homemaking) (Job4), 14.7 percent public servants or professionals (Job1), and 9.7 percent self-employed (Job3). About 26.4 percent of respondents reported having children, and the average household size was 1.64 persons. Regionally, 39.3 percent of the sample resided in special or metropolitan cities (Region), while 60.7 percent lived in other regions.

Table 2. Descriptive Statistics of Variables

Variables	Pipeline DT & AI Purification				DT & Asset Management System			
	Mean	Std. Dev.	Min.	Max	Mean	Std. Dev.	Min.	Max
Age	46.16	13.18	20	69	46.01	12.91	21	69
Gender	0.5114	0.5002	0	1	0.5114	0.5002	0	1
Edu1	0.1971	0.3981	0	1	0.2143	0.4106	0	1
Edu2	0.6886	0.4634	0	1	0.6800	0.4668	0	1
Edu3	0.1143	0.3184	0	1	0.1057	0.3077	0	1
Job1	0.1471	0.3545	0	1	0.1429	0.3502	0	1
Job2	0.4857	0.5002	0	1	0.4743	0.4997	0	1
Job3	0.0971	0.2964	0	1	0.1071	0.3095	0	1
Job4	0.2700	0.4443	0	1	0.2757	0.4472	0	1
Children	0.2643	0.4413	0	1	0.3014	0.4592	0	1
Household Size	1.6400	0.8536	0	6	1.6043	0.8570	0	5
Region	0.3929	0.4887	0	1	0.3929	0.4887	0	1
#	700							

Note: Independent variables controlled in the bivariate probit model were applied consistently for both the pipeline DT & AI purification module and the treatment plant DT & asset management module.

The descriptive statistics for the independent variables related to treatment plant DT and asset management system, which were analyzed separately from the previous technologies, are as follows. The average age of respondents was approximately 46.0 years. The gender distribution was relatively balanced, with 51 percent male and 49 percent female. In terms of education level, 68.0 percent were university graduates (Edu2), followed by 21.4 percent with a high school diploma or less (Edu1), and 10.6 percent with a graduate-level degree (Edu3). With respect to employment status, salaried workers (Job2) accounted for 47.4 percent, followed by 27.6 percent in other occupations (Job 4), 14.3 percent in public service or professional fields (Job1), and 10.7 percent self-employed (Job3). Approximately 30.1 percent of respondents reported having children, and the average household size was 1.60 persons. Regarding regional distribution, 39.3 percent of respondents resided in special or metropolitan cities, while 60.7 percent lived in other areas.

2. WTP Estimation Results

Tables 4 and 5 present the results of the bivariate probit models for pipeline DT, AI purification, treatment plant DT, and asset management system. As noted earlier, the survey was conducted separately for pipeline DT and AI purification, and for treatment plant DT and asset management system; hence, the results are also reported separately. In this survey, the first question assesses the respondent's willingness to pay (WTP) for the initially presented bid amount. The second question elicits the respondent's WTP for a follow-up bid, which is set at either twice the initial amount (if the response to the first question is "Yes") or half the initial amount (if the response is "No"). For pipeline DT and AI purification, the correlation coefficient (ρ) between the two response equations was statistically significant at the 1 percent level, indicating that the bivariate specification is appropriate. Since WTP estimation is based on the first equation, only the results from that equation are discussed here.

The bid variable (Bid Amount), a key explanatory factor, exhibited a negative and statistically significant relationship with the dependent variable for both technologies, confirming that a higher bid amount is associated with a lower probability of acceptance. Most of the remaining covariates showed consistent directional effects, although their statistical significance varied across models. Age was positively associated with WTP, and male respondents were more likely to accept the bid than female respondents; both effects were statistically significant at the 5 percent level across the two technologies. Compared to those with a high school education or less (Edu1), respondents with a graduate degree (Edu2) showed a lower probability of accepting the bid, with statistical significance. In terms of occupation, only the category "other occupations (Job4)" was negatively associated with WTP at a statistically significant level, relative to the reference group of public servants and professionals (Job1). The presence of children and household size were both positively associated with WTP, although statistical significance varied by technology. Finally, respondents residing in metropolitan areas (Region) exhibited a lower probability of acceptance compared to those in other regions; however, this effect was statistically significant only in the pipeline DT model.

Table 3. Bivariate Probit Estimation Results: Pipeline DT & AI Purification

Variable	Pipeline DT				AI Purification			
	First Question		Second Question		First Question		Second Question	
Intercept	-0.1947		-0.5569	**	-0.2701		-0.3973	
Bid Amount	-0.0732	***	-0.0199	*	-0.0817	***	-0.0301	**
Age	0.0106	**	0.0050		0.0115	***	0.0085	
Gender	0.2499	**	0.1372		0.2076	**	-0.0001	
Edu2	-0.0109		0.0907		0.0000		-0.0074	
Edu3	-0.4189	**	-0.1991		-0.3781	*	-0.1990	
Job2	-0.2760	*	-0.1901		-0.1424		-0.2763	*
Job3	- 0.0394		-0.0581		0.0119		-0.1999	
Job4	-0.4905	***	-0.3436	**	-0.4876	***	-0.6133	***
Children	0.2604	**	0.2703	**	0.3319	***	0.3775	***
Household Size	0.1648	***	0.0775		0.0786		0.0354	
Region	-0.1936	*	0.0114		-0.0860		0.0196	
ρ			0.4201	***			0.5240	***
-2LL	1777.314				1742.62			
AIC	1827				1793			
#	700				700			

Notes: (1) Pipeline DT model: First Question: Yes = 349, No = 351; Second Question: Yes = 324, No = 376
(2) AI Purification model: First Question: Yes = 262, No = 438; Second Question: Yes = 253, No = 447
(3) *** 0.01 < p, ** 0.05<p, * 0.1<p

Table 5 reports the results of the bivariate probit estimations for the treatment plant DT and asset management system. In both models, the estimated correlation coefficient (ρ) between the two response equations was positive and statistically significant at the 1 percent level, confirming the appropriateness of the bivariate specification.

Table 4. Bivariate Probit Estimation Results: Treatment Plant DT & Asset Management System

Variable	Treatment Plant DT				Asset Management System			
	First Question		Second Question		First Question		Second Question	
Intercept	-0.1947		-0.3451		-0.1890		-0.6414	**
Bid Amount	-0.0732	***	-0.0011		-0.0909	***	0.0011	
Age	0.0106	**	-0.0004		0.0009		0.0037	
Gender	0.2499	**	0.1235		0.3415	***	0.0580	
Edu2	-0.0109		-0.2844	**	-0.1453		-0.1660	
Edu3	-0.4189	**	-0.4011	**	-0.0400		-0.3426	*
Job2	-0.2760	*	-0.0007		0.2121		-0.0001	
Job3	-0.0394		-0.0021		-0.0107		0.2052	
Job4	-0.4905	***	-0.0085		0.2536		-0.1670	
Children	0.2604	**	0.1656		0.0441		0.2636	**
Household Size	0.1648	***	0.1272	**	0.1670	***	0.1339	**
Region	-0.1936	*	0.0196		0.0698		-0.0755	
ρ			0.3166	***			0.2850	***
-2LL	1,818.41				1,791.8			
AIC	1,868				1,842			
#	700				700			

Notes: (1) Treatment Plant DT: First Question: Yes = 367, No = 333; Second Question: Yes = 273, No = 427
(2) Asset Management System: First Question: Yes = 339, No = 361; Second Question: Yes = 258, No = 442
(3) *** 0.01 < p, ** 0.05<p, * 0.1<p

The bid variable (Bid Amount) showed a negative and statistically significant association with the dependent variable in both technologies, indicating that a higher bid amount is associated with a lower probability of acceptance. Age and gender were both positively associated with the probability of acceptance, but only the gender variable was statistically significant. Compared to respondents with a high school education or less (Edu1), those with more advanced educational attainment showed a lower likelihood of accepting the bid, although the differences were not statistically significant. In terms of employment status, salaried workers (Job2) and those in other occupations (Job4) had a positive association with the outcome, whereas those in self-employed jobs (Job3) showed a negative relationship. Household characteristics such as the presence of children, the number of household members, and whether the respondent resided in a metropolitan area were all positively associated with the dependent variable. Among these, only the number of household members was statistically significant.

Based on the estimation results presented in Tables 4 and 5, the WTP for each technology was derived as shown in Table 6. The estimated WTP values were 2,404.7 KRW for pipeline DT, 3,306.0 KRW for AI purification, 2,473.2 KRW for treatment plant DT, and 2,079.3 KRW for asset management system. Although direct comparisons are limited due to the survey being conducted separately for pipeline DT and AI purification versus treatment plant DT and asset management system, the overall results suggest that respondents perceive AI purification as having the highest economic value. This is followed by pipeline DT and treatment plant DT, while asset management system is associated with the lowest perceived value.

Table 5. WTP Estimated from Bivariate Probit Models (KRW)

Variable	Pipeline DT	AI Purification	Treatment Plant DT	Asset Management System
WTP (KRW)	2,404.7	3,306.0	2,473.2	2,079.3

Note: The WTP estimates are based solely on the first response in the bivariate probit model. This approach is adopted due to two concerns that arise when using the second response: (1) potential response bias, and (2) inflation of the second bid, which may reduce the reliability of the estimated coefficient on the bid variable (β).

VI. Conclusion

The adoption of digital transformation technologies in the water supply system is a long-term national project that requires considerable time and substantial fiscal investment. Although the current water supply infrastructure in Korea has been operating in a relatively stable manner, the integration of digital technologies has the potential to significantly enhance the existing system of water provision and management. These technologies provide not only direct benefits, such as improving water safety and reducing economic losses through accident prevention, but also indirect benefits including environmental protection, improved energy efficiency, and reductions in operational costs. When users perceive that the utility they gain from such technologies is sufficiently high, their attitudes toward digital transformation in the water sector are likely to become more favorable. In turn, a broader recognition of these positive perceptions can serve as a foundation for securing public support and procedural legitimacy for future investments in digital water infrastructure.

To quantify the utility perceived by users, this study applied the CVM. The technologies were grouped into two categories: pipeline DT and AI purification, and treatment plant DT and asset management system. A structured survey was conducted, and WTP was estimated as a measure of perceived utility. For the analysis, a bivariate probit model was used based on the format of a double-bounded dichotomous choice question, expressed without hyphenation to comply with formal restrictions.

The key findings of the analysis are summarized as follows. The WTP estimated using the bivariate probit model was 2,405 KRW for pipeline DT, 3,306 KRW for AI purification, 2,473 KRW for treatment plant DT, and 2,079 KRW for asset management system. Given that the average monthly water bill per household in 2023 was 16,724 KRW (based on an average household size of 2.2 persons), these WTP values represent a relatively high level of perceived value. This suggests that users recognize and are prepared to financially support the added value provided by smart infrastructure, despite already receiving stable and affordable water services. Therefore, this willingness provides a practical basis for legitimizing future investment and tariff reform associated with digital transformation in the public water sector.

This study demonstrates that consumers assign meaningful economic value to digital transformation in water supply systems, as indicated by their WTP for various smart infrastructure technologies. Although current water services in Korea are stable, the integration of technologies such as digital twins and AI-based purification presents an opportunity to improve operational efficiency, reduce risks, and enhance public service quality. Based on the analysis, two policy directions are recommended. First, a phased tariff adjustment scheme should be introduced, aligning gradual increases in water bills with the pace of digital technology deployment. This would enhance financial feasibility while minimizing public resistance. Second, pilot projects should be launched in selected municipalities to implement and evaluate digital water technologies under real-world conditions. Such trials would help build public trust, provide technical validation, and inform scalable investment strategies. Continued monitoring of user preferences is also advised to ensure that long-term planning remains aligned with evolving public expectations.

Despite the contributions of this study, the digital transformation of the water supply system remains in its early stages, and consumers' understanding of the associated public services may still be limited. As a result, judgments about economic value may lack clarity. Accordingly, it is recommended that further valuation studies be conducted during later stages of project implementation in order to capture more informed preferences and reassess the economic justification for continued investment.

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