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Evaluating the Dynamic Psychological and Behavioral Changes of Water-Saving in Public Buildings Under Effective Interventions

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Key Points:

- The expanded theory of planned behavior demonstrates the intricate relationship between water-saving psychology and behavior
- The optimized dynamic behavior intervention model effectively evaluates psychological shifts in individuals leading to behavior changes
- Field experiments in three representative public buildings precisely compare various interventions, revealing nuanced phenomena of the time lag effect

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract This paper addresses the critical aspect of water conservation in public buildings within the context of sustainable urban water resources management. While conventional approaches rely on pricing controls and water-saving appliances, this research emphasizes the key consideration of psychological factors influencing users' willingness to conserve water. Through a survey involving 1,206 volunteers, an expanded theory of planned behavior model is constructed and analyzed to evaluate the impact of water-saving attitudes, subjective norms, self-efficacy, and perceived behavioral control on individuals' water-saving behavior. Intervention experiments conducted in three types of public buildings equipped with smart water meters unveil the nuanced dynamics of real-time water-saving behavior and its responsiveness to external interventions. Findings underscore the collective influence of subjective norms, water-saving attitudes, self-efficacy, and perceived behavioral control on individuals' intentions and behaviors. Noteworthy is the observed time lag and diminishing impact of external interventions, where economic, feedback, and subjective norms interventions prove more effective. This study not only contributes a theoretical framework but also provides practical insights, emphasizing the need for consistent and targeted external interventions. Practitioners, decision-makers, and stakeholders are urged to recognize the profound impact of users' psychological factors on public water-saving behavior and strategically employ interventions for sustained positive outcomes.

1. Introduction

Water, as a fundamental natural resource, is indispensable for society. However, with the growth of population, environmental pollution, and the expansion of production scale, an ever-increasing number of people are affected by water shortages (Howells et al., 2013; Ma et al., 2020). For example, China has about 22% of the world's population but only 7% of its freshwater resources, and the water resources per capita are less than 2,400 m^3, which is less than a quarter of the global average (Wang et al., 2019). According to the China Statistical Yearbook, the water usage in China was 592.02 billion m^3 (the agricultural use was 364.43 billion m^3, industrial use was 104.96 billion m^3, household consumption was 90.94 billion m^3, and ecological consumption was 31.69 billion m^3) in 2021. With the acceleration of economic development, industrialization, and urbanization, the shortage of water supply has become a major obstacle to China's social development (McGrane, 2016; Wang et al., 2020). Therefore, the government has been working on promoting water-saving in agriculture, industry, and household use through policies, regulations, engineering, and publicity (Feng et al., 2012; Kang et al., 2017; Liu et al., 2013; Tong et al., 2018; Zhong & Mol, 2010; Zhongxiang & Yi, 1991).

On the other hand, public buildings, such as office buildings, commercial centers, museums, schools, hospitals, and transportation centers, commonly have complicated functions, large energy consumption, and massive water consumption (Bohdanowicz & Martinac, 2007; Howard et al., 2012). According to the China urban-rural construction statistical yearbook, the quantity of urban water supply was 67.44 billion m^3 in 2022, among which the quantity for public service was up to 9.81 billion m^3. In order to reduce water waste in public buildings, water demand management has been implemented, incorporating three major strategies: economic, technological and behavioral (Baumann et al., 1998; Brooks, 2006; Lallana & Agency, 2001). Among these strategies, economic interventions are regarded as objective measures due to their reliance on pricing mechanisms, such as water

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tariffs, which are designed to curb consumption by imposing a financial cost on usage. The underlying assumption is that higher water costs incentivize users to reduce their consumption in order to lower expenses. However, in public buildings, this situation is altered, as water bills are typically borne by facility managers or organizations rather than individual users or visitors. This creates a disconnect between the entity responsible for paying and those responsible for consuming the water. Thus, the intended economic disincentive is diluted, as occupants do not directly experience the financial repercussions of excessive usage. This contrasts with household settings, where individuals are directly accountable for their water bills and, therefore, more responsive to price signals (Angulo et al., 2014; Nieswiadomy, 1992; Schneider & Whitlatch, 1991). In public buildings, the absence of direct financial accountability for water consumption presents significant challenges in achieving water conservation through economic measures alone. In terms of technological strategies, the design, installation, and maintenance of reuse and recycling systems or water-saving devices are objective factors, while their usage remains subjective. Evidence suggests that users may engage in offsetting behavior when they become aware of the installation of water-saving appliances (Campbell et al., 2004; Fielding et al., 2012, 2013). In contrast, subjective behavioral strategies, which represent a form of pro-environmental behavior, are generally considered more supportive of conservation efforts (Ateş, 2020; Fielding et al., 2013; Stern, 2000). Furthermore, psychological intervention has emerged as a significant area of research, with the integration of psychological concepts into water resources studies proving valuable for a deeper understanding of fluctuating water demand (Dolnicar et al., 2011; Grecksch, 2021; Russell & Fielding, 2010; Shahangian et al., 2021; Si et al., 2022; Vila-Tojo et al., 2022; Zhang et al., 2021).

From the psychological point of view, there is a complex psychological process behind the behavior, which involves a number of psychological factors (Guo et al., 2018; Valizadeh et al., 2020). The main psychological factors are attitude, belief, values, culture, subjective norms, etc. (Guo et al., 2018; Li et al., 2019). Person's behavior is influenced by psychological factors through a variety of ways. Based on the theory of multi-attribute attitude and the theory of reasoned action, a classical theory that provides theoretical support for describing this process is the theory of planned behavior (TPB) (Ajzen, 1991; Fishbein, 1963; Fishbein & Ajzen, 1975). According to the theory, actual behavior is determined by behavioral intention, which is influenced by attitude, subjective norms, and perceived behavioral control. Attitude is extent of a person's support or not support a behavior. Subjective norm (SN) refers to the social pressure that people perceives when to decide whether or not to perform a particular behavior. Perceived behavioral control (PBC) refers to the perceived ease or difficulty of performing the behavior, which encompasses both past experiences and anticipated obstacles. Accurate perception of behavioral control can reflect actual control conditions and can directly influence behavior.

There is substantial evidence supporting the TPB as an effective framework for understanding how individuals' psychological factors influence their pro-environmental behavior (Fielding et al., 2012; Gao et al., 2017; Singha et al., 2022; Yazdanpanah, Komendantova, & Ardestani, 2015). Some studies suggest that the original conceptual model can be further enhanced by incorporating additional variables, thus extending TPB into the expanded theory of planned behavior (ETPB) (Fielding et al., 2008; Kaiser, 2006; Russell & Knoeri, 2020; Wilson et al., 2018). One such variable is self-efficacy (SE), which refers to a person's belief in their ability to mobilize the motivation, cognitive resources, and behavior needed to cope with a given situation (Bandura, 2000). Past research has consistently demonstrated that self-efficacy promotes pro-environmental behavior (Lauren et al., 2016; Meinhold & Malkus, 2005; Tabernero et al., 2015; Tabernero & Hernández, 2011). These findings suggest that when individuals feel greater self-efficacy regarding pro-environmental behaviors, they are more likely to exert greater effort and persistence in engaging in these behaviors. Moreover, the literature indicates that self-efficacy and perceived behavioral control may be theoretically distinguished: items measuring perceived behavioral control assess individuals' perceptions of how much control they have over performing a behavior, whereas items measuring self-efficacy focus on their perceptions of how easy or difficult it will be for them to carry out the behavior (Bandura, 1977; Litt, 1988; Terry & O'Leary, 1995). This distinction underlies the use of self-efficacy, rather than perceived behavioral control, in predicting intentions and behavior (Armitage & Conner, 2001; de Vries et al., 1988). In this study, self-efficacy is also treated as an independent construct, considering that it specifically pertains to individuals' subjective assessment of their capability to execute a particular behavior, which may not fully overlap with the broader control beliefs encompassed by perceived behavioral control.

In the literature, interventions are primarily categorized into information (Inf), economic (Eco), and feedback (Fb) methods (Corral-Verdugo et al., 2012; Seyranian et al., 2015). Based on the ETPB, this study focuses specifically on information or educational interventions that target subjective norms, water saving attitudes, and self-efficacy. Subjective norm interventions use inclusive language (e.g., "we," "society," "nation") to align group identity with water-saving behaviors, with stronger group identification enhancing conformity to social norms (Mallett & Melchiori, 2016; Schultz et al., 2007; Seyranian et al., 2015). Water-saving attitude (WSA) interventions promoting water-saving behaviors by increasing awareness of their benefits and feasibility for further supporting of water saving behavior (Middlestadt et al., 2001; Osbaldiston & Schott, 2012; Thompson et al., 2011). Self-efficacy interventions aim to enhance individuals' self-efficacy, recognizing that belief in one's ability to perform a behavior significantly influences motivation and action. These information interventions typically employ posters, digital messages, group discussions, and social media to promote collective responsibility and reinforce water-saving norms (Corral-Verdugo et al., 2012; Seyranian et al., 2015). Economic incentives, such as water bill discounts, rebates for water-efficient devices, or monetary rewards in water-saving competitions, offer tangible motivation and aim to make water-saving practices more attractive and feasible (Corral-Verdugo et al., 2012; Maki et al., 2016). Economic interventions may affect individuals' perceived behavioral control, which reflects individuals' perceptions of the ease or difficulty of engaging in water-saving behaviors. Feedback interventions, which may primarily target subjective norms, encourage individuals to adjust their behavior based on feedback (Geller et al., 1982). High water users are prompted to reduce consumption to conform to group norms, while feedback on low usage enhances self-efficacy, reinforcing confidence in maintaining water-saving behaviors, often implemented through personalized water usage reports, facilitating social comparison with peers (Aitken et al., 1994; Fielding et al., 2013). The hypothesis of the study is that water-saving attitude, subjective norm, self-efficacy, and perceived behavioral control are likely to influence participants' water-saving intention (WSI) in public buildings. In addition, information, economic, and feedback interventions are expected to have a positive impact on water-saving behavior (WSB), with the influence diminishing as the interventions are withdrawn.

Furthermore, the mathematical solution of TPB usually involves calculating the structural equation model (SEM). SEM is a statistical tool in the field of psychology (Hair et al., 2010). It utilizes latent variables to articulate the concepts of TPB, connecting these variables through a structural model to thoroughly explore the relationships between them (Shahangian et al., 2021). Over the years, SEM has evolved into a robust statistical framework, facilitating the effective assessment and validation of direct and indirect relationships within ETPB, and elucidating their impacts on behavioral intentions and actions (Hair et al., 2010; Hooper et al., 2008; Nunnally, 1978; Shahangian et al., 2021). Therefore, this study conducted a questionnaire survey and applied SEM analysis to evaluate the research hypotheses. This facilitated a quantitative assessment of the linear relationship between water-saving psychology and behavior.

Nevertheless, new evidence has revealed that there could be a time delay and rebound for individuals' behavioral response to external factors, which implies that the complex psychological process behind individual behavior is not static (Fielding et al., 2013; Fu & Wu, 2016; Jorgensen et al., 2014; Saurí, 2013). Although the expanded theory of planned behavior-structural equation model (ETPB-SEM) demonstrates its capability to quantify the relationship between individuals' psychology and behavior, it falls short in illustrating the dynamic and nonlinear changes in the relationship under external interventions. In order to address this gap, the concept of control engineering was incorporated to elucidate the impact of interventions on psychology and behavior, resulting in the development of the dynamic behavior intervention model (DBIM) (Fu & Wu, 2016; Rivera et al., 2007). In DBIM, the psychological process was modeled as a dynamic inventory transfer system, representing the endogenous variables of ETPB-SEM as distinct inventories. And a fluid analogy for inventory was employed to elucidate the interaction between variables (Navarro-Barrientos et al., 2011; Rivera et al., 2007; Schwartz et al., 2006). This is instrumental in determining changes in latent variables and outcome responses, providing valuable insights for determining the timing, intervals, and extent of interventions (Navarro-Barrientos et al., 2011).

Unlike the static ETPB-SEM, which relies solely on the average scores of questionnaires for observed variable values, the evaluation of dynamic psychological and behavioral changes requires additional monitored behavioral data (Fielding et al., 2013; Inman & Jeffrey, 2006; Lee & Tansel, 2013). In this study, several field intervention experiments were conducted to obtain timely records of water-saving changes in public buildings equipped with smart water meters. Additionally, to facilitate the practical application of DBIM, a novel framework was proposed to avoid assuming parameter values in the high-order time-delay system. The framework introduces genetic algorithm (GA) to solve the multi-parameter and single-objective optimization problem, with the Pearson

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correlation coefficient as a fitting indicator. GA is a kind of global, parallel, and random search algorithm based on evolutionary theory (Holland, 1973; Srinivas & Patnaik, 1994). Because of the directed search method that uses objective functions and constraints and needs neither differential value nor other information, it has been widely used for parameter calculation in time delay system (Shin et al., 2007). Pearson correlation coefficient is regarded as a commonly used indicator in correlation analysis, employing sample product-moment correlation to measure the degree of correlation between two variables (Hedges & Olkin, 2014; Tabachnick & Fidell, 2001).

The purpose of this study is to investigate the relationship between individuals' water-saving behavior and psychology in public buildings and evaluating the dynamic change of the two under external interventions. Combining questionnaire surveys with effective intervention experiments, a typical ETPB-SEM and then an optimized DBIM were developed and analyzed to determine the dynamic relationship between individuals' psychology and behavior. Consequently, this study serves as a significant interdisciplinary contribution to water resource conservation by curbing excessive water consumption in public buildings. The methodologies, including questionnaire surveys, experiments, and the analytical framework, can be generalized for broader research on interventions targeting pro-environmental behavior. Insights into the efficacy of water-saving strategies in public buildings are pivotal for informing effective planning by water managers.

2. Methods

2.1. Sample Description

In this study, three types of buildings were carefully selected: office buildings (B1), teaching buildings (B2), and dormitories (B3), with a focus on the stability of personnel flow in public buildings. Stability here refers to whether the movement of people follows a regular and predictable pattern. For instance, locations such as shopping malls and train stations exhibit higher variability in foot traffic, whereas the selected public buildings demonstrate relatively lower mobility of personnel.

To conduct the field survey and intervention experiment, a university in Northern China was chosen as the research site due to its suitability. At this university, both office and teaching buildings exhibit stable occupancy patterns, characterized by the consistent presence of staff, faculty, and students. (a) In the office buildings, the study's participants were staff and faculty members from the same department, aged between 30 and 65 years. (b) In the teaching buildings, regular occupants included undergraduate students attending classes on specific floors and in designated classrooms, aged 18–22 years. To further ensure consistency, the building manager was contacted to obtain specific class schedules, allowing the study to track a stable pattern of public water use throughout the experiment, as class schedules are fixed each semester. (c) In the dormitory, 12 rooms were randomly selected as sample groups, based on the willingness of participants to engage. Each room housed four master's students aged 22 to 30, all with similar income levels. Following the field questionnaire survey, online chat groups were established using WeChat (an online chat app similar to WhatsApp) to facilitate participants' engagement with the intervention content. These groups were formed in person at the research site, and participants were carefully chosen based on their willingness and commitment to the study, which helped enhance the reliability of the intervention.

At the same time, to facilitate precise water usage tracking across the selected three types of public buildings, 80 smart water meters were strategically installed, each with a sampling period of five minutes, as shown in Figure S9 in Supporting Information S1. The collected data were seamlessly transferred to an online data acquisition system for analysis (Fielding et al., 2013; Willis et al., 2011, 2013). These smart water meters transmit data to a platform operated and maintained by the meter manufacturer. Users can download the recorded raw water meter readings in Excel format from this platform, with each file corresponding to the daily water usage records of a specific meter. Specifically, 36 m were placed in the 12 dormitory rooms, one in each washroom. In the office and teaching buildings, 20 and 24 m were installed, respectively, across four washrooms located on the first and second floors, with one washroom for men and one for women on each floor. As indicated in Figures S7 and S8 in Supporting Information S1, which shows the specific distribution of locations.

2.2. Procedures

As shown in Figure 1, the methodology is organized into four parts. The first part involves a pre-intervention questionnaire survey, during which both online and field questionnaires with identical content were distributed

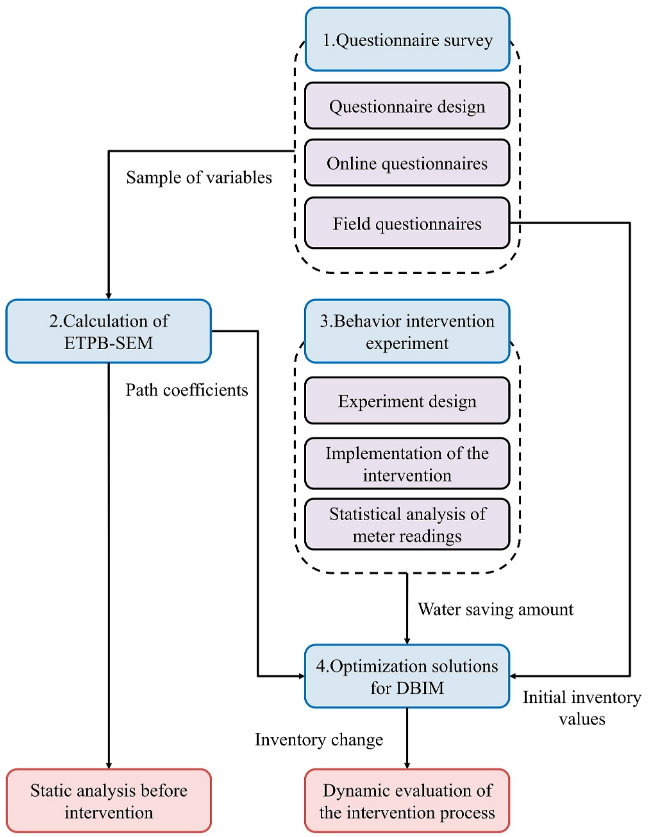

Figure 1. The procedure of the research.

to volunteers to gather a sample of relevant variables based on the questionnaire design. The second part focuses on utilizing both online and field questionnaires to calculate ETPB-SEM, calculating the static path coefficients between each two latent variables. The third part encompasses a behavioral intervention experiment, which includes the design of the experiment, implementation of the intervention, and statistical analysis of water meter readings, aiming to quantify the water savings amount during the intervention. The final part seeks to solve the DBIM by utilizing the initial inventory values obtained from the field survey, the static path coefficients derived from the ETPB-SEM analysis, and the water saving amount from the experiment, thus conducting a dynamic evaluation of the intervention process.

2.2.1. Questionnaire Survey

In this research, printed field questionnaires were prepared and distributed to participants in the selected three types of public buildings in the university. Concurrently, volunteers who were regular visitors to the three types of public buildings were invited to complete the online questionnaire by accessing a URL or scanning a QR code. This approach broadened the sample size, improved the response rate, and reduced sampling bias. During the online questionnaire distribution, the link was also shared with classmates, friends, and family members within the research group, further encouraging dissemination and enhancing the response rate. Importantly, the content of the questionnaire remained consistent regardless of whether it was administered online or in person, ensuring uniformity in the responses. As a result, a total of 1,206 questionnaires were collected across both formats, comprising 567 from office buildings, 395 from teaching buildings, and 244 from dormitories. As indicated in Table S18 in Supporting Information S1, the majority of survey respondents were young and middle-aged individuals aged 18–40, with a monthly income below 6,000 RMB.

The relevant questions are shown in Table S19 in Supporting Information S1, which were designed according to ETPB and classified as subjective norm questions (Fielding et al., 2012; Russell & Knoeri, 2020; Yazdanpanah, Forouzani, et al., 2015; Yazdanpanah, Komendantova, & Ardestani, 2015; Yazdanpanah et al., 2014), water-saving attitude questions (Clark & Finley, 2007; Yazdanpanah, Forouzani, et al., 2015; Yazdanpanah, Komendantova, & Ardestani, 2015; Yazdanpanah et al., 2014), perceived behavioral control questions (Bozorgparvar et al., 2018; Fielding et al., 2012; Yazdanpanah et al., 2014; Yazdanpanah, Forouzani, et al., 2015), self-efficacy questions (Fu & Wu, 2016) and water-saving intention questions (Russell & Knoeri, 2020; Yazdanpanah, Forouzani, et al., 2015; Yazdanpanah et al., 2014). Besides, the seven-point Likert scale was used for option design ranging from “1” (strongly disagree/dislike) to “7” (strongly agree/like) (Finstad, 2010).

After getting the questionnaire samples, the Cronbach's α value, outer loadings, and weights of the questionnaire were calculated to assess the psychometric properties and dimensionality of the variables (Ateş, 2020). As shown in Table S20 in Supporting Information S1, the results indicate that all factors are appropriately loaded, and the Cronbach's α values exceed 0.7, affirming the reliability (Bagozzi & Yi, 1993). Additionally, composite reliability (C.R) and average variance extracted (AVE) were examined to ensure validity (Hair et al., 2010). Table S20 in Supporting Information S1 reveals that all C.R values and AVE values surpass the minimum acceptable levels of 0.7 and 0.5, respectively, confirming the internal consistency and convergent validity of the constructs. Then, as presented in Table S21 in Supporting Information S1, the correlation coefficients between every pair of constructs are all below the square root of the AVE values. This observation indicates the data meets the criteria for discriminant validity according to the Fornell-Larcker criterion (Fornell & Larcker, 1981).

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2.2.2. Intervention Experiment

As shown in Table S24 in Supporting Information S1, the experiment consisted of two 4-week rounds, each preceded by a baseline week. Interventions were applied during the first 2 weeks, followed by 2 weeks without intervention. The first round took place from 19 May to 23 June 2021, and the second from 24 November to 29 December 2021. In the field experiment, the information intervention involved displaying relevant slogans near taps, toilets, and showers. Additionally, online water-saving awareness campaigns were conducted in the dormitory every Wednesday and Saturday throughout the experiment. These campaigns featured the mentioned 12 online chat groups where participants could access water-saving videos shared. Participants were encouraged to engage with the content, and those who did not respond received personalized reminders to promote active participation. The economic intervention involved providing incentives to rooms that achieved a reduction in water consumption during the previous week. The monetary reward was calculated as five times the local water price, multiplied by the volume of water saved. The feedback intervention comprised providing participants with weekly feedback on their water consumption every Monday.

Given the variability of users in public buildings, participants in the office and teaching buildings were grouped by floor. The water consumption for each group i was calculated using the initial reading $Q_{k,s}$ and the final reading $Q_{k,e}$ from the K m in group i over the course of the week. The average daily water consumption for sample group i in week t was defined as Q_{it} (m^3/d), and for the control group as Q_{jt} (m^3/d).

$$Q_{it} = \frac{1}{7} \cdot \sum_{k}^{K} (Q_{k,s} - Q_{k,e}), k = 1, 2, \ldots K \tag{1}$$

Equation 1 calculates the total water consumption for the sample group i by summing the differences between initial and final readings from all meters within that group, providing an aggregate measure of water usage over the week. To account for the differences in basic water consumption and the number of installed smart meters between the sample group and the control group, the ratio Q_{i0}/Q_{j0} was introduced to eliminate initial errors before intervention. Subsequently, Equation 2 calculates the adjusted water consumption for the control group, $Q_{jt}{'}$, which is standardized based on this ratio. Using this adjusted value, Equation 3 then determines the actual water saving amount ΔQ_{it} for the sample group by subtracting the sample group's average consumption Q_{it} from the adjusted control group's consumption Q'_{jt}. This combined definition of water saving amount ΔQ_{it} allows for a more accurate assessment of the intervention's impact on water-saving behavior.

$$Q'_{jt} = (Q_{i0}/Q_{j0}) \cdot Q_{jt} \tag{2}$$

$$\Delta Q_{it} = Q'_{jt} - Q_{it} \tag{3}$$

In the dormitory, where smart meters recorded the total water consumption per room, each room was treated as a separate group, taking into account the number of occupants in each room (Figure S7 in Supporting Information S1). Consequently, Q_{it} represents the per capita average daily water consumption, and ΔQ_{it} denotes the per capita water-saving amount. Furthermore, Equation 4 quantifies the overall effectiveness of the intervention by calculating the percentage of total water savings (TS) over T weeks, thereby providing a robust assessment of its impact on water-saving behaviors. These statistical equations ensure a comprehensive evaluation of behavioral changes.

$$\text{TS} = 1 - \left(\sum_{0}^{T} Q_{it} \right) \Big/ \left(\sum_{0}^{T} Q'_{jt} \right) \tag{4}$$

All participants were informed, either directly or indirectly, about the purpose of the study, the voluntary nature of their participation, and their right to withdraw at any time without facing any consequences. Consent was obtained from both the university and the participants prior to the commencement of the survey and experimental procedures. Additionally, all personal information collected during the study was anonymized and used exclusively for data analysis purposes, ensuring the confidentiality and privacy of the participants.

2.3. Data Analysis of Surveys and Experiments

2.3.1. Calculation of ETPB-SEM

After conducting the questionnaire survey, ETPB-SEM was utilized to model nomological networks by expressing theoretical concepts through latent variables and connecting these variables (Byrne, 2001; Shahangian et al., 2021). SEM comprises two fundamental components: the measurement model and the structural model (Hair et al., 2010). The measurement model, based on confirmatory factor analysis, explores relationships between constructs and their indicators. In contrast, the structural model functions as a path analysis model that establishes relationships between independent and dependent variables. This relationship is represented in Equation 5:

$$\Delta = \beta\eta + \gamma\xi + \zeta \tag{5}$$

In this equation, η represents the latent or endogenous variable, ξ denotes the observed or exogenous variable, and Δ indicates the endogenous output. The parameter γ signifies the path coefficient between the exogenous and endogenous variables, while β represents the path coefficient between the endogenous variables. Finally, ζ captures the error term.

The analysis of the ETPB-SEM begins with data preparation, during which questionnaire data is collected and cleaned to ensure accuracy and reliability. In this study, both printed and online questionnaires are employed to gather data, with responses coded into numerical values using a Likert scale. Each latent variable is operationalized by computing composite scores derived from its observed indicators. The subsequent phase, model estimation, involves utilizing statistical software such as AMOS 21.0 and SPSS 22.0 to estimate the parameters of ETPB-SEM. The software computes path coefficients, standard errors, and significance levels, providing insights into the strength and significance of the hypothesized relationships.

In addition to conducting reliability and validity analyses, it is essential to assess the appropriateness of the structural model before discussing the results for hypothesis testing. This evaluation includes examining several fit indices, such as the comparative fit index (CFI), goodness-of-fit index (GFI), Tucker-Lewis index (TLI), normed fit index (NFI), root mean square error of approximation (RMSEA), and the ratio of chi-square to degrees of freedom (CMIN/DF) (Ateş, 2020). As shown in Table S20 in Supporting Information S1, the RMSEA values indicate the acceptable level of model specification, while the CFI, GFI, TLI, and NFI values reveal the overall fitness of the model.

2.3.2. Optimization Solutions for DBIM

Based on ETPB-SEM, DBIM was developed for the evaluation of dynamic psychological processes. Specifically, the dynamic change of each endogenous variable during intervention is represented as the accumulation of inventory (η), which is calculated as the inflow minus the outflow, in accordance with the principles of mass balance (Navarro-Barrientos et al., 2011; Schwartz et al., 2006). Thus, the inventory changes for subjective norm, water-saving attitude, self-efficacy, perceived behavioral control and water-saving intention are represented by inventories η_1–η_5, illustrated as tanks in Figure 2 and Figure S3 in Supporting Information S1.

Specifically, in DBIM, ξ represents the exogenous variable; γ denotes the transfer coefficient between the exogenous and endogenous variables or inventories; β indicates the transfer coefficient among the endogenous variables or inventories; θ represents the transfer time lag; τ is the time constant that describes the change in inventory; and ζ is the error term. Equations 6–10 illustrate the processes of the DBIM as applied in this study.

$$\tau_1 \frac{d\eta_1(t)}{dt} = \gamma_1\xi_1(t-\theta_7) - \eta_1(t) + \zeta_1(t) \tag{6}$$

$$\tau_2 \frac{d\eta_2(t)}{dt} = \gamma_2\xi_2(t-\theta_8) - \eta_2(t) + \zeta_2(t) \tag{7}$$

$$\tau_3 \frac{d\eta_3(t)}{dt} = \gamma_3\xi_3(t-\theta_9) - \eta_3(t) + \zeta_3(t) \tag{8}$$

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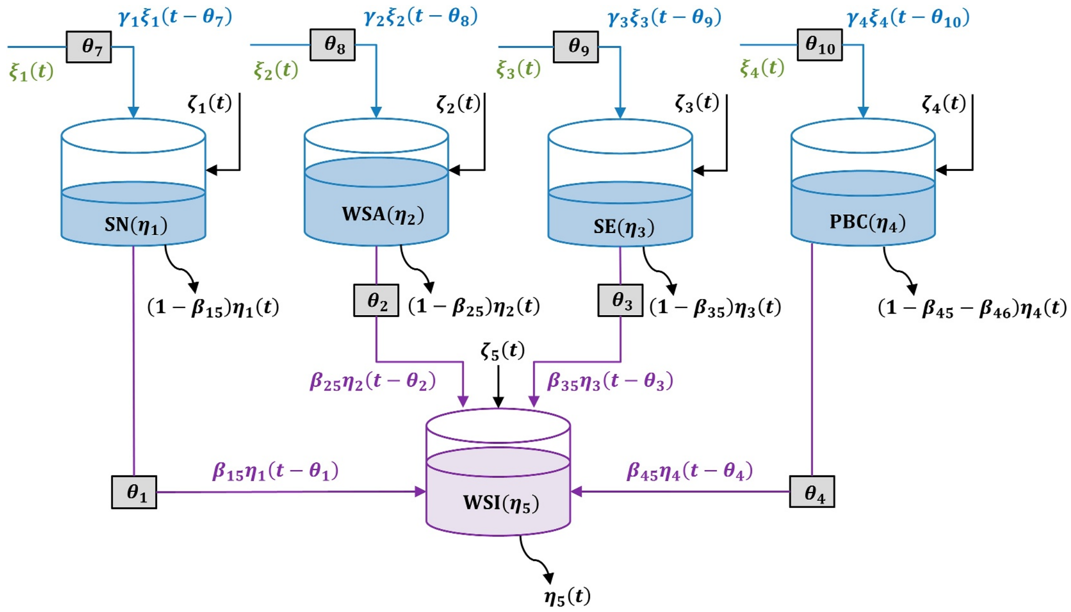

Figure 2. Schematic of the dynamic behavioral intervention model.

$$\tau_4 \frac{d\eta_4(t)}{dt} = \gamma_4\xi_4(t-\theta_{10}) - \eta_4(t) + \zeta_4(t) \tag{9}$$

$$\tau_5 \frac{d\eta_5(t)}{dt} = \beta_{15}\eta_1(t-\theta_1) + \beta_{25}\eta_2(t-\theta_2) + \beta_{35}\eta_3(t-\theta_3) + \beta_{45}\eta_4(t-\theta_4) - \eta_5(t) + \zeta_5(t) \tag{10}$$

For the calculation of DBIM, a framework is established for the optimization of parameters including time delay θ, exogenous variable ξ and time constant τ. And the Pearson correlation coefficient (r) is employed to define the fitness function as Equation 11, where Cov represents the covariance and Var is the variance. In structural equation model, the Pearson correlation coefficient serves as a statistical measure used to evaluate model fit and the linear relationships between variables (Tabachnick & Fidell, 2001). In this study, r describes the similarity between the change of water-saving intention (inventory η_5) and subjective norm, water-saving attitude, self-efficacy, perceived behavioral control and water-saving behavior (water-saving amount ΔQ_{it}), with the relationship between water-saving intention and water-saving behavior assumed to be linear.

$$r = \frac{\mathrm{Cov}(\eta_5, \Delta Q_{it})}{\sqrt{\mathrm{Var}[\eta_5]\,\mathrm{Var}[\Delta Q_{it}]}} \tag{11}$$

In the framework shown as Figure 3, or quantifying the psychological process, three mean inputs of ETPB-SEM were initialized: $\eta(t=0)$, β, and ΔQ_{it}. Before the baseline week, the mean value of each variable obtained from the printed field questionnaire survey was calculated as the initial inventory value, $\eta_1(t=0)$, $\eta_2(t=0)$, $\eta_3(t=0)$, and $\eta_4(t=0)$, based on the Likert scale, as presented in Table S23 in Supporting Information S1. To account for user variability in public buildings, participants were grouped by floor in office and teaching buildings, and by room in dormitory buildings. The average score of each group's questionnaire responses was taken as representative of the field survey results. Furthermore, given that the initial rate of change in water-saving intention inventory, $d\eta_5(t)/dt$, is zero at the outset, the initial inventory value of water-saving intention, $\eta_5(t=0)$, can be derived from Equation 10.

Subsequently, the transfer coefficient β in DBIM is equal to the path coefficient in ETPB-SEM, and the water-saving amount ΔQ_{it} is calculated by Equation 3. The initialization of parameters including the inflow of exogenous variable ξ, time delay θ, and time constant τ. If the Pearson correlation coefficient (r) does not meet the termination criteria, the genetic algorithm (GA) is employed to generate the optimal output, utilizing stopping

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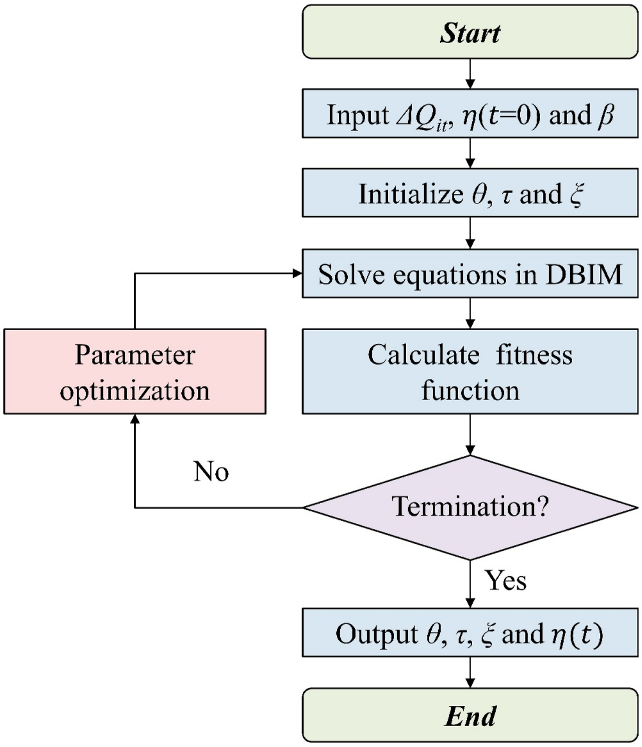

Figure 3. The parameter optimization framework.

criteria such as fitness function tolerance, maximum iterations, or maximum function evaluations. Specifically, GA starts with a population of potential solutions encoded as individuals, and iteratively evolves these solutions to reach optimal or near-optimal solutions. This iterative evolution involves the application of genetic operators such as selection, crossover, and mutation to mimic the mechanisms of natural selection, genetic recombination, and mutation (Shin et al., 2007; Srinivas & Patnaik, 1994). More details can be found in Figure S4 in Supporting Information S1.

3. Results and Discussion

3.1. Questionnaire Analysis

Based on the previous examination, the calculated standardized correlation coefficients (Con), standardized path coefficients (β) between every two latent variables with the corresponding R squared (R^2) are depicted in Figure 4, generated in SPSS and AMOS. The results suggest that subjective norm, water-saving attitude, self-efficacy and perceived behavioral control have a combined effect on water-saving intention and the effect varies in different public buildings. Specifically, in B1, self-efficacy and perceived behavioral control have a great impact on users' water-saving intention; in B2, water-saving attitude and perceived behavioral control show more effectiveness on for individuals' water-saving intention; in B3, self-efficacy and water-saving attitude effect participates' water-saving intention more than other variables. And despite the varying degrees of influence on water-saving intention observed in these different latent variables, the path coefficient values for these variables are remarkably similar.

The result aligns with findings from other studies on pro-environmental behavior. First, attitude has a positive effect on individuals' intentions to save water (Si et al., 2022). When individuals perceive value in water-saving behaviors, they are more likely to express intentions to engage in these practices. Second, perceived behavioral control serves as a significant factor influencing intention (Yazdanpanah, Komendantova, & Ardestani, 2015). Individuals who view water-saving behaviors as more manageable, or who possess higher levels of confidence and control in adopting these practices, are more inclined to express intentions to implement them (Shahangian et al., 2021). Third, self-efficacy

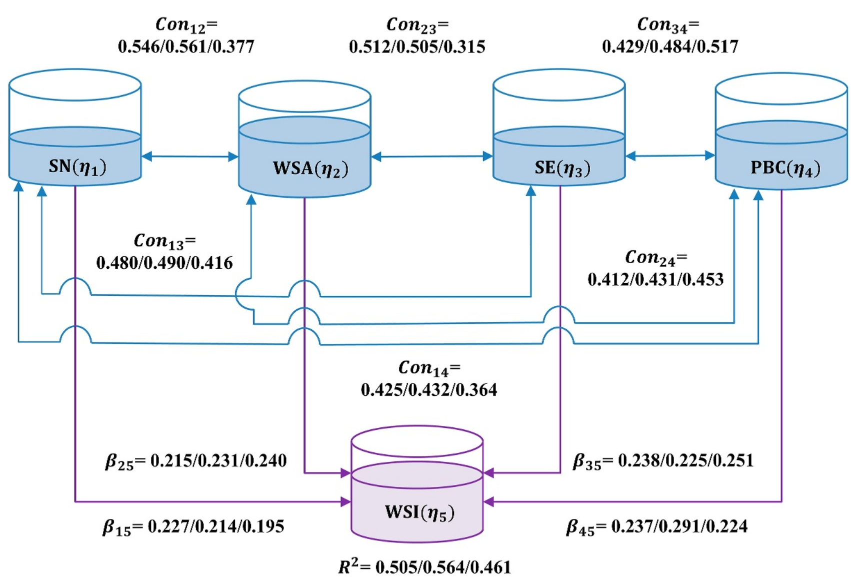

Figure 4. Results of ETPB-SEM. Notes: The values in B1/B2/B3 are delimited by slashes.

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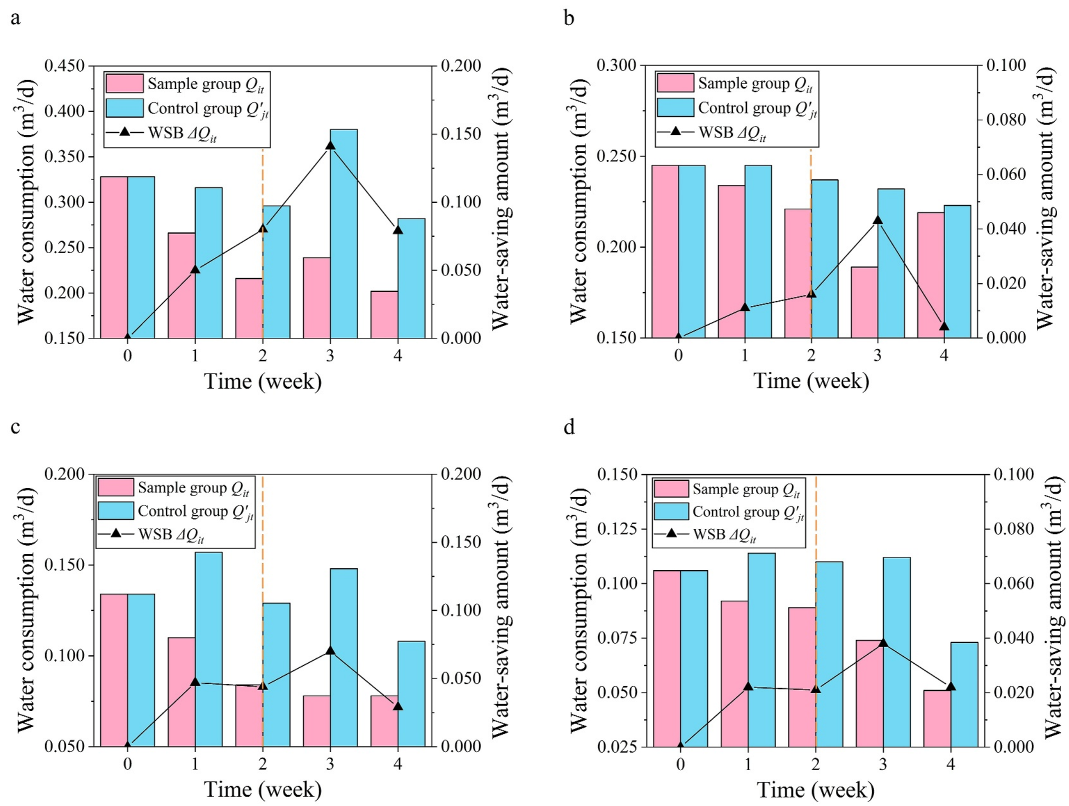

Figure 5. The actual patterns of behavior in the office building and teaching building. Notes: The orange dashed line indicates the dividing line between the intervention phase and the cessation of the intervention. (a, b) Show the water consumption and water-saving behavior of users in B1 under subjective norm and water-saving attitude intervention in the first 2 weeks and the withdrawal of the intervention in the second 2 weeks. (c, d) Show those in B2 under subjective norm and water-saving attitude intervention.

plays a crucial role in influencing individuals' water-saving behaviors through subjective evaluations (Fu & Wu, 2016). Additionally, subjective norms significantly impact individuals' water-saving intentions; a shared ideology within closely knit communities, such as among friends, classmates, and colleagues, substantially influences behavioral outcomes (Jiang et al., 2019; Si et al., 2022).

Considering the age distribution, the majority of visitors in office buildings are middle-aged, while young people predominantly occupy teaching buildings and dormitories. This suggests that the attitudes of youth are critical determinants of their water-saving behavior. In contrast, office staff tend to focus more on the evaluation of water-saving conditions in public facilities, reflecting a pragmatic approach to resource management. Additionally, the findings illustrate the importance of environmental literacy and awareness, particularly among younger individuals, who may be more responsive to educational interventions aimed at fostering sustainable practices. Overall, the results corroborate the original hypotheses and indicate that the ETPB-SEM constructed in this paper is a valuable model for conducting further dynamic analyses.

3.2. Psychological and Behavioral Changes of Water-Saving

3.2.1. Behavioral Change of Users in B1 and B2

As shown in the bar chart, the water consumption of the sample group gradually decreases in the first two or 3 weeks but rebounds with the withdrawal of psychological interventions, compared to the control group in Figures 5a–5c. The dot-line chart illustrates that the water-saving amount of each case significantly increases in the first 3 weeks, reaching the maximum value (0.141, 0.043, 0.070, and 0.038 m^3/d) in the third week, followed by a notable decline in the fourth week. Although water consumption of sample group keeps decreasing in the fourth week in Figure 5d, the degree of reduction in the sample group is relatively small compared to the control

Table 1
The Results of Parameters ξ, θ, and τ in the Office Building and Teaching Building

Places	Variables	Parameters	Range	Results
B1	SN	ξ_1	(4.30, 7.00)	6.13
	WSA	ξ_2	(4.95, 7.00)	6.55
B2	SN	ξ_1	(4.17, 7.00)	6.51
	WSA	ξ_2	(4.89, 7.00)	5.21
B1	SN	θ_1	[1, 14]	11(Integer)
	WSA	θ_2		5(Integer)
B2	SN	θ_1		3(Integer)
	WSA	θ_2		8(Integer)
B1	SN	τ_1 and τ_5	(0, 1) (Reciprocal of τ)	3 and 1(Integer)
	WSA	τ_2 and τ_5		1 and 7(Integer)
B2	SN	τ_1 and τ_5		5 and 4(Integer)
	WSA	τ_2 and τ_5		13 and 4(Integer)

group, resulting in a decline in the water-saving amount. The similar patterns of water consumption in B1 and B2 under different interventions suggest that the effect of intervention has a time lag and decays over time.

Meanwhile, calculated as Equation 4, the subsample group saves an average of 21.80% water under subjective norm intervention and 6.26% under water-saving attitude intervention in B1 compared to the control group. As for B2, the subsample group saves 28.10% water under subjective norm intervention and 20.00% under water-saving attitude intervention. The observed phenomenon may stem from the fact that subjective norms may exert a stronger influence than attitude in the public buildings. The reason may be that users are embedded in visible social networks (e.g., colleagues, classmates, and teachers), where expectations from peers are more pronounced. When interventions highlight collective water-saving norms, individuals are more likely to align their behavior with these norms to avoid social disapproval or gain approval. TPB posits that normative beliefs pertain to the likelihood that important referent individuals or groups will approve or disapprove of performing a given behavior (Ajzen, 1991). Observing peers' water-saving behaviors in public places likely reinforces perceived social expectations, thereby amplifying the influence of subjective norms on behavioral intentions.

At the same time, it is worth noting that the maximum water-saving amount suggests a stronger effect of subjective norm intervention compared to water-saving attitude intervention in both B1 and B2. This finding diverges slightly from the results depicted in Figure 4 of the ETPB-SEM ($\beta_{15} = 0.214 < \beta_{25} = 0.231$). The observed difference implies that external interventions may primarily function as inputs to the system, rather than directly influencing the internal path coefficients. In this context, interventions that primarily provide external stimuli, such as information or reminders, may not translate into sustained behavior change unless they are reinforced by internal cognitive processes.

3.2.2. Psychological Change of Users in B1 and B2

After the optimization calculation of DBIM, the optimized parameters results of ξ_1, θ_1, τ_1, and τ_5 are presented in Table 1. These parameters represent the optimized values of the well-fitted model parameters. By utilizing these parameters, the model's calculations yield results that closely align with the actual observed values.

In Figure 6, the dot-line chart illustrates the simulated patterns of inventories, depicting the dynamic changes of variables under different interventions in different public buildings. The r values are 0.939, 0.785, 0.845, and 0.909, corresponding to Figure 6Sa–6Sd, with 69, 81, 72, and 331 iterations of GA. The optimization results align with the expected range in Table 1, as the correlation coefficients are close to 1, and the dynamic change trend of $\eta_5(t)$ in Figure 6 aligns with that of water-saving behavior in Figure 5. These results indicate that the dynamic changes in individuals' water-saving psychology under intervention were successfully quantified by DBIM with GA.

Meanwhile, in the first 2 weeks, the optimized input ξ_1 increases by 42.65% for B1 under subjective norm intervention in Figure 6Sa; ξ_2 increases by 32.28% for B1 under water-saving attitude intervention in Figure 6Sb; ξ_1 increases by 56.13% for B2 under subjective norm intervention in Figure 6Sc; ξ_2 increases by 6.61% for B2 under water-saving attitude intervention in Figure 6Sd. The results are not only consistent with the actual water-saving amount in Figure 5, where the effect of subjective norm intervention is stronger than that of water-saving attitude intervention, but also reveals the dynamic change of inventory over time.

Besides, as shown in Table 1 and Figure 6, the time delay θ_1 in B1 is higher than that in B2 under subjective norm intervention, while, on the contrary, for time delay θ_2 under water-saving attitude intervention. The time constant τ_1 in B1 and τ_2 in B2 under subjective norm intervention are lower than those under water-saving attitude intervention. According to previous research, time delay and time constant describe individuals' response toward external interventions (Navarro-Barrientos et al., 2011). Moreover, it is the time delay that describes the horizontal characteristic of the curve or response speed, and the time constant describes the shape of the curve or response gradient, as shown in Equations 6–10. As seen in Figure 6, η_5 begins to increase in B1 under subjective

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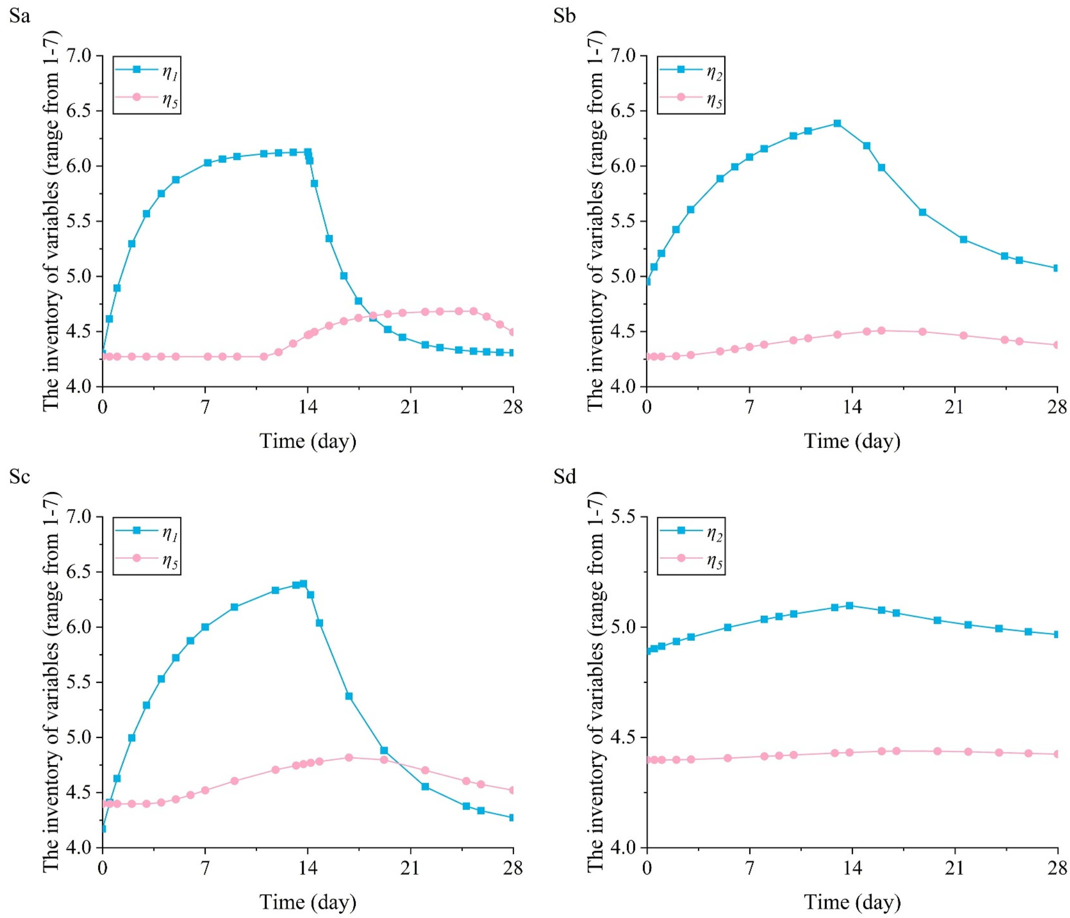

Figure 6. The simulation patterns of inventories in the office building and teaching building. Notes: (Sa, Sc) show the dynamic change of subjective norm inventory (η_1) and water-saving intention inventory (η_5) under subjective norm intervention in B1 and B2, while (Sb, Sd) show those of water-saving attitude inventory (η_2) and water-saving intention inventory (η_5) under water-saving attitude intervention in B1 and B2.

norm intervention from the eleventh day, which is later than in other cases, and the shape of the curves varies in different cases. Thus, to some extent, it can be inferred from the results of time delay that participants in B1 become more sensitive to water-saving attitude intervention, while those in B2 become more sensitive to subjective norm intervention. At the same time, from the results of time constant, it can be inferred that the accumulation of the effect for subjective norm intervention in inventory is stronger in both B1 and B2 compared to water-saving attitude intervention.

3.2.3. Behavioral Change of Users in B3

As shown in the bar chart in Figure 7, there is a significant reduction in the water consumption of the sample groups in the first or first 2 weeks, followed by a rebound similar to the situation in B1 and B2. The effect of external intervention accumulates as a continuous influence and varies abruptly. This timeliness aligns with the DBIM that considers external intervention as a step-input in the simulation part and is consistent with previous research (Fu & Wu, 2016). Meanwhile, in the dot-line chart, the water-saving amount for each case reaches its maximum value at 0.00317, 0.00301, and 0.00431 m^3/d in the third, fifth, and fifth week, respectively, confirming the time lag and weakening of the effect with the withdrawal of the intervention.

Moreover, in comparison to the control group, the subsample group achieves total water savings of 5.92% under information intervention, 8.32% under feedback intervention, and 10.68% under economic intervention in B3. This demonstrates that the effects of economic and feedback interventions are stronger than information intervention in the experiment. Considering the results in B1 and B2, despite variations in the impact of different

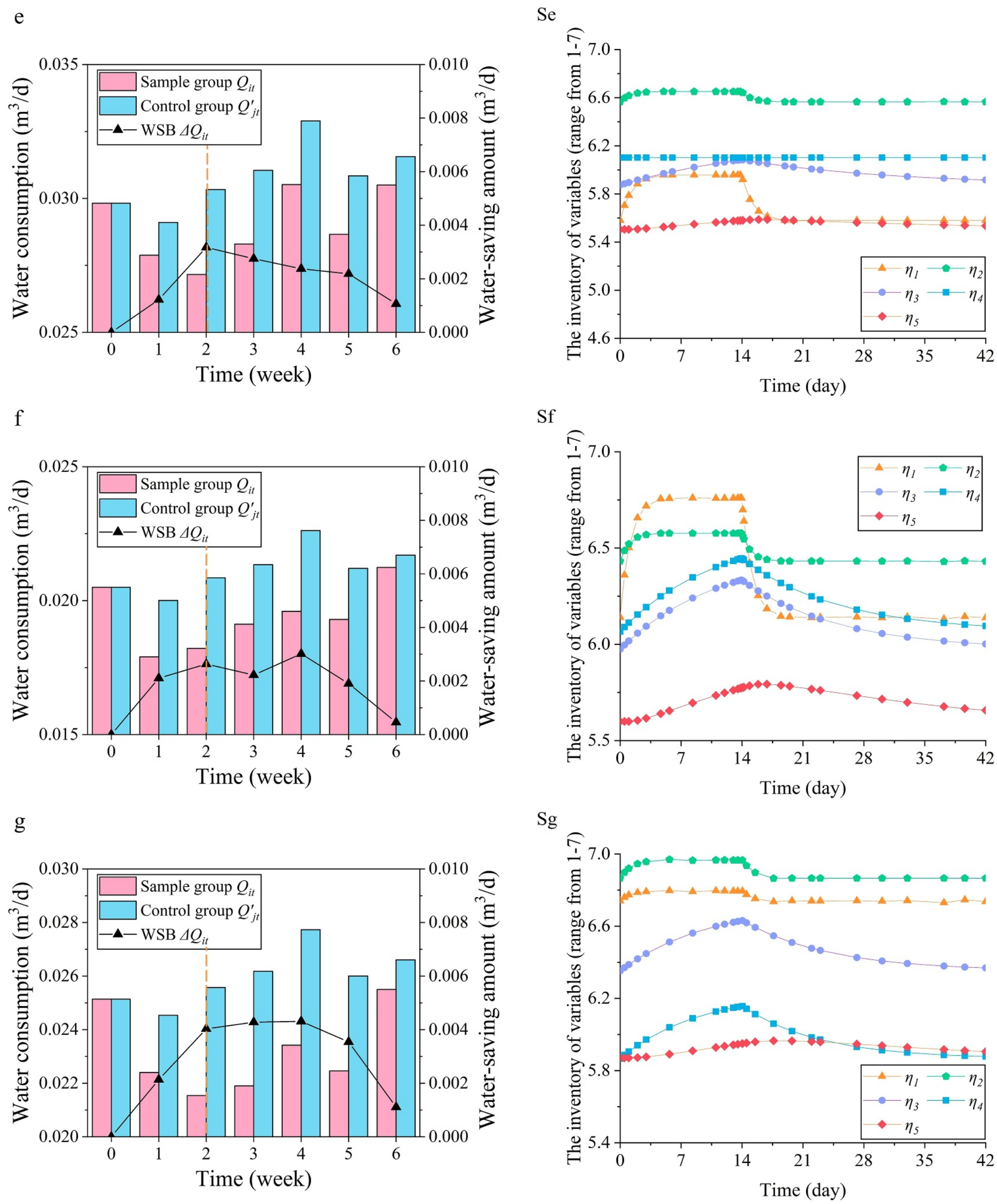

Figure 7. The actual patterns of behavior and simulation patterns of inventories in the dormitory. Notes: The orange dashed line indicates the dividing line between the intervention phase and the cessation of the intervention. (e) Shows the water consumption and water-saving behavior of users in B3 under information intervention in the first 2 weeks and the withdrawal of the intervention in the next 4 weeks. (f, g) Show those in B3 under feedback and economic interventions. (Se) Shows the dynamic change of subjective norm inventory (η_1), water-saving attitude inventory (η_2), self-efficacy inventory (η_3), perceived behavioral control inventory (η_4) and water-saving intention inventory (η_5) under information intervention in B3, while (Sf, Sg) show those in B3 under feedback and economic interventions.

interventions across different types of public buildings, it is evident that the interventions indeed alter users' water-saving psychology and behavior. This aligns with previous research indicating that economic and feedback interventions influence users' pro-environmental behavior (Fielding et al., 2013; Fishbein & Ajzen, 1975). Economic intervention enhances perceived behavioral control by introducing economic incentives, which mitigate perceived barriers to engaging in water-saving behaviors. By offering tangible rewards, individuals are motivated to adopt these practices, reinforcing the notion that their actions are both feasible and beneficial.

Table 2
The Calculation Results of Parameters ξ, θ, and τ in the Dormitory

Variables	Parameters	Range	Results
Inf	ξ_1–ξ_3	(5.58, 7.00), (6.57, 7.00), (5.87, 7.00)	5.96, 6.65, and 6.26
	θ_1–θ_3	[1, 14]	1, 11, and 11 (Integer)
	τ_1–τ_3 and τ_5	(0, 1) (Reciprocal of τ)	1, 1, 17, and 13 (Integer)
FB	ξ_1–ξ_4	(6.14, 7.00), (6.43, 7.00), (5.97, 7.00), (6.07, 7.00)	6.76, 6.58, 6.47, and 6.59
	θ_1–θ_4	[1, 14]	1, 11, 11, and 11 (Integer)
	τ_1–τ_4 and τ_5	(0, 1) (Reciprocal of τ)	1, 1, 11, 11, and 12 (Integer)
Eco	ξ_1–ξ_4	(6.74, 7.00), (6.87, 7.00), (6.35, 7.00), (5.87, 7.00)	6.79, 6.97, 6.72, and 6.23
	θ_1–θ_4	[1, 14]	1, 11, 11, and 11 (Integer)
	τ_1–τ_4 and τ_5	(0, 1) (Reciprocal of τ)	1, 1, 10, 9, and 13 (Integer)

Meanwhile, the feedback intervention leverages subjective norms by providing feedback on individual water usage, fostering social comparison processes. Individuals who see their consumption in relation to their peers are likely to adjust their behavior to align with group norms, either by reducing excessive usage or maintaining low consumption levels. This feedback not only enhances self-efficacy for low water users but also encourages those with higher consumption to adopt pro-environmental behaviors through normative pressure. Therefore, economic and feedback interventions are recommended as primary options, particularly in public buildings where individuals have long-term residence. The subjective norm information intervention can serve as a secondary proposal in public buildings with high social mobility.

3.2.4. Psychological Change of Users in B3

Like the simulations in B1 and B2, DBIM was also applied to B3. However, the optimized parameters differed, including ξ_1–ξ_3, θ_1–θ_3, τ_1–τ_3, and τ_5 for information intervention, and ξ_1–ξ_4, θ_1–θ_4, τ_1–τ_4, and τ_5 for economic and feedback interventions, taking into account the influence on four inventories η_1–η_4. The results, with r values of 0.989, 0.889, and 0.970 from Figures 7Se–7Sg and GA program iterations of 117, 326, and 383, respectively, confirm the good fitness of the model.

From Table 2, the optimized time constant τ_3 under information intervention is higher than τ_1 and τ_2, indicating that self-efficacy inventory η_3 is influenced more than subjective norm inventory η_1 and water-saving attitude inventory η_2. Meanwhile, compared with the weeks without intervention, the optimized step-input values of ξ_1–ξ_3 in the first 2 weeks increased by 6.80%, 1.23%, and 6.58%, respectively, under information intervention. Thus, it can be asserted that, in B3, subjective norm intervention and self-efficacy intervention, rather than water-saving attitude intervention, play a more crucial role in influencing students' water-saving psychology. This finding is consistent with the results in B1 and B2. However, it diverges from the questionnaire analysis in the dormitory, where individuals' self-efficacy and water-saving attitude are found to impact water-saving intention more than other variables. Combining this with the similar situation in B1 and B2, it can be confirmed that external interventions affected users' water-saving intention more as an input rather than directly changing the internal path coefficients. Additionally, the effects of time lag and time constant may be intricately linked to individuals' socio-demographic characteristics, which vary across different groups.

What is more, the optimized step-input values of ξ_1–ξ_4 increase 10.08%, 2.27%, 8.42%, and 8.62% under feedback intervention in the first 2 weeks, and they increase by 0.80%, 1.46%, 5.84%, and 6.15% under economic intervention. This phenomenon suggests that feedback intervention affects the individual's subjective norm and self-efficacy, which ultimately affect water-saving intention, while economic intervention mainly affects the individual's perceived behavioral control and self-efficacy. The reason may be that individuals with high water consumption tend to save more water under the influence of normative behavior, and those with low water consumption are influenced by self-efficacy through feedback, motivating them to maintain the behavior. As for economic intervention, it may be the financial support that reduces the practical difficulties or risk of water-saving perceived by individuals and improves their confidence in this behavior to some extent, but not the effect coming from the normative behavior of society.

In summary, unlike the ETPB-SEM, which relies solely on data from questionnaire surveys, solving the DBIM requires data from experimental trials to estimate parameter coefficients and validate the framework (Navarro-Barrientos et al., 2011). In this study, the initial inventory $\eta(t=0)$ was obtained from the field questionnaires, the transfer coefficient β was generated by ETPB-SEM, and the water-saving amount ΔQ_{it} came from the actual water consumption records that support the simulation. Therefore, the effect of different interventions and the dynamic water-saving psychology over time could be quantified. The application of GA ensures that the results were generated elaborately for comparison, which was beyond the reach of ETPB-SEM. Furthermore, by testing the effect of intervention on outcomes over time, the aspects of the intervention, such as the ordering and strength of the components, can be optimally decided.

4. Policy Recommendations

Following the in-depth analysis of the questionnaire survey, it is evident that the variables subjective norm, water-saving attitude, self-efficacy, and perceived behavioral control exert varying degrees of influence on water-saving intention. Despite these differences, comparable path coefficient values indicate a synergistic effectiveness. The results from DBIM enable a dynamic comparison of three intervention types, providing decision-makers with valuable insights. Recommendations encompass the formulation of strategies for economic and feedback interventions, with feedback on users' water consumption behavior shown to be conducive to conservation.

While challenges exist in controlling extra water consumption through pricing, economic intervention proves impactful. Direct economic interventions, such as cost reduction or incentive systems in public buildings, are viable options. Additionally, creating a feedback platform disseminating information on water-saving activities in public buildings is suggested. Although not as impactful as economic and feedback interventions, information interventions like strategically placed slogans have proven effective. Proper information interventions are crucial, particularly since not all public buildings may seamlessly implement interventions. Furthermore, integrating subjective norm interventions into public building management represents a promising strategy for promoting pro-environmental behaviors.

Furthermore, the findings caution against relying solely on path coefficients generated by ETPB-SEM for assessing individuals' water-saving psychology. External interventions play a vital role but may not directly influence path coefficients, and their impact decays over time. Decision-makers are advised to conduct small-scale pilot experiments before formal intervention to evaluate attenuation effects. The questionnaire survey remains highly significant, and in practice, conducting it alongside pilot experiments is advisable.

Leveraging online communication through the Internet and mobile phones can enhance the speed and effectiveness of information dissemination. Integrating online and offline information publicity is suggested for a comprehensive and long-term intervention approach. Governments, enterprises, and social organizations are encouraged to implement long-term information interventions focused on disseminating knowledge and policies related to water-saving behavior. These efforts should be complemented by tracking and evaluation measures to ensure intervention efficacy.

5. Conclusions and Perspective

In conclusion, this study aimed to explore the nuanced relationship between water-saving psychology and behavior in public buildings, emphasizing the impact of external interventions. A novel theoretical model of water-saving intention was developed, extending self-efficacy to the theory of planned behavior. Survey data validated the expanded model, revealing that subjective norms, water-saving attitude, perceived behavioral control, and self-efficacy collectively influence water-saving intention, with variations observed across different public building types.

A psychological experiment across three building types, uncovering a significant time lag in intervention impact and emphasizing the effectiveness of subjective norms intervention in office buildings and teaching buildings. Economic and feedback interventions proved more effective than information interventions in dormitories. The study introduced a dynamic behavior intervention model, utilizing a genetic algorithm for parameter optimization, validating practical experiment analyzes, and elucidating time lag and decline in intervention effect.

External interventions were found to impact users' water-saving intention as an input without directly altering internal path coefficients. Practical recommendations were provided for water management departments to enhance resident participation in water-saving. However, limitations include the complexity of decision-making in water-saving behavior and the need for larger sample sizes in future research. Multigroup analysis considering sociodemographic characteristics and diverse building types is suggested, along with further exploration of intervention model parameters and their influence on path coefficients. Extending studies to diverse regions can assess the dynamic behavior intervention model's applicability in different contexts.

Data Availability Statement

All data and code generated in this study are available (Duan, 2024).

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