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Design of a personalized water intake monitoring system using rfid-enabled smart bottle station and mobile application with target intake estimation

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Abstract. Underhydration remains common, while existing digital and sensor-based tools still depend on manual entry, single-user wearables, or fixed profile-based targets, limiting practicality and adherence in shared or institutional settings. Recent smart-bottle systems automate volume capture, but they lack reliable multi-user identification and individualized targets, so scalable, low-burden monitoring remains unmet. This research address this by designing an RFID-enabled Smart Bottle Station that pairs a load cell with user identification, a Laravel backend, and an Android app, with two-way communication over REST and WebSocket for live status and control. Each interaction is logged with weight and timestamps, then filtered into valid drinking events using weight delta, temporal coherence, and scan pairing. In a four-month deployment with three participants, the system recorded 1,747 raw entries and retained 904 valid drinking events. Functional tests confirmed weight sensing, RFID identification, data synchronization, and remote commands. Results show that the platform accurately distinguishes real intake in a multi-user setting and supports personalized logging with minimal manual input. Across users, daily intake trends increased over time, indicating consistent engagement with the system and the practical feasibility of automated, shared-use hydration monitoring.

1 Introduction

Adequate hydration is essential for maintaining physiological balance, supporting cognitive performance, cardiovascular function, metabolic processes, and general health. Recent findings have shown that even mild levels of dehydration can impair working memory, attention, and mood [1, 2]. For instance, a randomized trial involving fluid restriction in young adults demonstrated significant declines in episodic memory and cognitive speed, as well as increased fatigue and mood disturbances, effects that were reversed upon rehydration [1]. Similarly, water supplementation has been reported to enhance decision-making performance following a state of mild dehydration [2].

Despite this scientific consensus, inadequate daily fluid intake remains a persistent issue. In Indonesia, approximately 28% of adults fail to meet the recommended Total Fluid Intake (TFI), with the problem being more pronounced in certain regions such as Kalimantan where prevalence reaches 41% [3]. The gap between hydration awareness and actual behavior is especially evident in the working population. A national survey by the Indonesian Hydration Working Group (IHWG) found that 53.7% of workers did not meet

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their daily water intake needs, with many attributing this to workplace conditions such as prolonged use of face masks or the unavailability of water access during working hours [4].

In response to this challenge, various digital and sensor-based interventions have emerged. Smartphone applications that provide hydration reminders have shown measurable success in improving fluid intake adherence, particularly in structured work environments [3]. Additionally, non-invasive wearable sensors such as those based on electrodermal activity have been developed to monitor hydration status in real time [5]. However, these technologies often face limitations in usability and scalability. Many require manual input, rely on single-user interaction, or necessitate additional wearable devices, which reduce their practicality in real-world settings.

Recent advances in Internet of Things (IoT) technology have led to the development of smart bottle systems equipped with sensors such as ultrasonic detectors to automatically log fluid intake [6] . These systems offer improved accuracy in fluid volume estimation, but they generally lack personalization features and are not optimized for use in shared environments. For example, the system developed by [7] integrates waterflow sensors and user profile registration to track water consumption, however the water intake targets in their system remain largely fixed and are based on static profile information and are not dynamically adjusted.

To address these shortcomings, this study proposes a personalized water intake monitoring system that combines an RFID-enabled Smart Bottle Station with a mobile application. The system enables real-time identification of users, records weight-based drinking events, and estimates individualized water intake targets based on user demographics using established formulas such as Watson and Holliday–Segar [8], in accordance with guidelines from the Indonesian Ministry of Health [9]. It also supports two-way communication via WebSocket for dynamic updates and allows seamless operation in shared or institutional environments.

By addressing personalization, automation, and scalability, the system seeks to offer a more adaptive and context-aware solution to help individuals meet their water intake needs more effectively.

2 Literature review

2.1 Water intake needs and target intake estimation

Precise estimation of daily fluid requirements is crucial due to individual variability [10]. To address this, the proposed system estimates personalized water intake targets using established formulas and national dietary guidelines. For adults, the Watson formula calculates total body water (TBW) based on age, height, and weight, providing a foundational fluid requirement [8].

Watson for males:

$$2{,}447 - (0{,}09145 \times \textit{age}) + (0{,}1074 \times \textit{height in cm}) + (0{,}3362 \times \textit{weight in kg}) = \textit{TBW in liters} \quad (1)$$

Watson for females:

$$-2{,}097 + (0{,}1069 \times \textit{height in cm}) + (0{,}2466 \times \textit{weight in kg}) = \textit{TBW in liters} \quad (2)$$

For pediatric populations, the Holliday-Segar formula is widely used, determining daily fluid needs based on body weight, as shown on **Table 1** [8]:

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Table 1. Holliday-Segar Formula.

Body Weight (kg)	Fluid Needs for 24 Hours
< 10	100 mL/kgBW
10 - 20	1000 + 50 mL/kgBW for each kilogram of body weight above 10 kg
> 20	1500 + 20 mL/kgBW for each kilogram of body weight above 20 kg

These formulas are complemented by national dietary standards, such as the Angka Kecukupan Gizi (AKG) from the Indonesian Ministry of Health (Permenkes Nomor 28 Tahun 2019) [9]. Based on the data adapted from this guideline, **Table 2** shows the recommended daily water intake categorized by age and physiological status. The Age column shows the range in years. BW (Body Weight in kg) and BH (Body Height in cm) indicate median values for males and females. W (Water requirement in mL) refers to the suggested daily intake. The Category column highlights physiological states such as pregnancy and lactation, while EWA (Extra Water Allowance in mL) specifies the additional water needed in such conditions.

Table 2. Recommended Daily Water Intake.

Age Range	BW (kg)	BH (cm)	W (mL)	BW (kg)	BH (cm)	W (mL)
	Male			**Female**		
10-12	36	145	**1850**	38	147	**1850**
13-15	50	163	**2100**	48	156	**2100**
16-18	60	168	**2300**	52	159	**2150**
19-29	60	168	**2500**	55	159	**2350**
30-49	60	168	**2500**	56	158	**2350**
50-64	60	168	**2500**	56	158	**2350**
65-80	58	164	**1800**	53	157	**1550**
Category						
-	**Pregnancy**			**Lactating**		
	1st trisemester		**+300 mL**	1st 6 months		**+800 mL**
	2nd trisemester		**+300 mL**	2nd 6 months		**+650 mL**
	3rd trisemester		**+300 mL**	-		

2.2 Smart bottle systems for water intake tracking

Smart bottle systems are IoT-based solutions designed to automate hydration tracking through sensor integration and mobile feedback. By detecting drinking events and logging them in real time, these systems reduce manual input while supporting hydration adherence via reminders and personalized data visualization.

A commonly adopted approach involves ultrasonic sensors, which estimate the remaining volume of fluid inside the bottle by emitting high-frequency sound waves. For example, the SmartOne platform employs ultrasonic sensors in combination with humidity sensors, inertial measurement units (IMU), and push buttons to detect drinking events more accurately. By evaluating bottle orientation, lid status, and internal humidity variations, SmartOne distinguishes actual drinking behavior from unrelated bottle movements. It also incorporates fuzzy logic to dynamically adjust daily fluid intake targets based on user-specific parameters such as age, body mass index (BMI), and ambient temperature, thereby offering personalized recommendations [11].

In contrast, waterflow sensors focus on quantifying real-time liquid intake by measuring the volume of fluid that passes through the bottle. Akbar and Oktivasari (2019) developed a smart bottle system using a Raspberry Pi and flow sensor technology. Their system integrates with an Android application to track intake history and deliver reminders, emphasizing automation and user accessibility in daily hydration routines [7].

Other designs utilize fuzzy inference models to adapt hydration reminders based on environmental and physiological data. Wijanarko et al. (2020) proposed a smart water intake monitoring system that combines ambient temperature and water level sensors, with fuzzy logic categorizing user needs into low, medium, or high hydration levels. The system uses the Blynk IoT platform for mobile interaction and demonstrates real-time adaptation based on contextual factors [12].

While existing systems demonstrate progress in passive hydration tracking, they often lack adaptive intake targets, accurate event detection, and support for shared use. The proposed system addresses these limitations by integrating RFID-based user identification and weight-based fluid tracking, enabling personalized monitoring in multi-user environments.

2.3 RFID for user personalization in IoT systems

RFID technology enables automatic user identification in multi-user IoT settings, eliminating the need for manual logins or wearable devices. It relies on unique identifiers (UIDs) transmitted by passive RFID tags to a reader e.g. the RC522 module, which operates at 13.56 MHz and supports multiple communication protocols. Jain et al. (2021) explain how MIFARE DESFire cards, with 7-byte UIDs and AES encryption, offer secure user differentiation and memory partitioning for multi-service personalization. Their study demonstrates how this architecture supports reliable, scalable, and secure user-specific data access, making it ideal for shared applications like smart hydration stations [13].

3 Methodology

3.1 System overview

The architecture of the smart bottle monitoring system is illustrated in **Figure 1**.

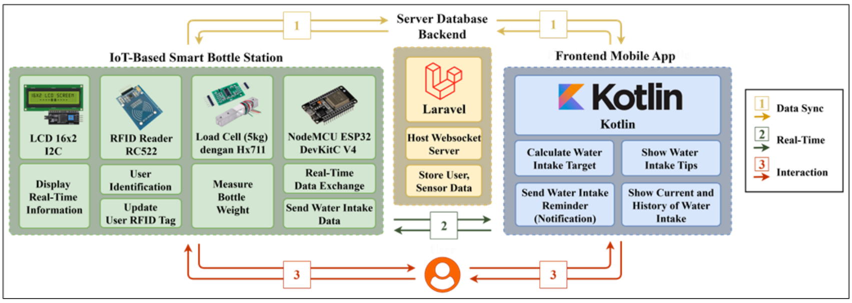

Fig. 1. System architecture of the smart bottle platform.

The system consists of three main components. The Smart Bottle Station detects user interaction via RFID tag scanning, performs water intake measurement using a load cell sensor, and transmits the data through an ESP32 module. The backend server, built with Laravel, stores user profiles and synchronizes water intake records from the device. The Kotlin mobile application calculates personalized water intake targets, displays historical and current consumption, sends hydration reminders, and provides daily hydration tips.

3.2 Hardware design of the smart bottle station

The smart bottle station integrates multiple electronic components to enable fluid intake measurement, user identification, and feedback, as shown in Figure 2.

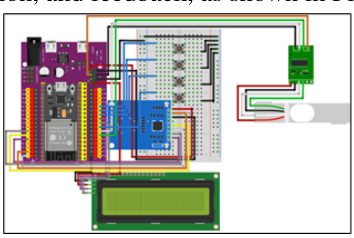

Fig. 2. Connectivity diagram of the smart bottle station.

The system consists of a NodeMCU ESP32 board that connects to an HX711 module for reading weight from a 5 kg load cell, an RC522 RFID reader for detecting user tags, and a 16x2 LCD with I2C interface for displaying real-time messages. Four push buttons are configured for operational modes such as tag registration, tare, and intake logging.

3.3 Mobile application features

The mobile application serves as the main interface for interaction between users and the hydration monitoring system. It is built using Android Kotlin and communicates with the backend through RESTful APIs for user-related operations and WebSocket for real-time data exchange. The architecture follows a modular design with responsive components for interface rendering and data handling.

Primary modules include user authentication, profile setup (name, date of birth, gender, height, and weight), and hydration goal computation. The application presents daily intake metrics and historical logs using visual components such as charts and lists. Notification routines are triggered based on stored hydration records and predicted intake patterns. Control functions for the Smart Bottle Station are also included, such as initiating RFID tag registration and tare calibration remotely. The feature breakdown is shown in **Table 3**.

Table 3. Core Mobile Application Modules.

Module	Purpose
User Authentication	Register/login; update personal data.
Target Intake Estimation	Compute daily water intake goal from profile
Real-Time Feedback Display	Visualize current water intake, RFID scans, status
Hydration History & Reminders	Track intake events; notify based on behavior patterns
Remote Station Interaction	Send control commands (e.g., reset, tare, update)

3.4 Mobile application features

The data flow of the smart bottle system outlines the interaction sequence between the hardware station, backend server, and mobile application, as shown in **Figure 3**.

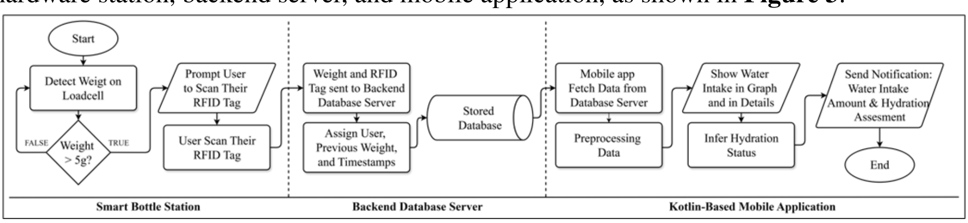

Fig. 3. Data flow and processing steps of the smart bottle system.

The process starts when the load cell detects an object placed on the platform (weight > 5g). If the system is in weighing or bottle-change mode, it prompts the user to scan their RFID tag. Once scanned, the RFID tag and current bottle weight are sent to the backend via REST API. The backend then identifies the user, retrieves the previously recorded weight, and records the timestamp. This information is stored in the water intake log database.

The mobile application fetches this stored data and performs basic preprocessing to remove invalid or duplicate entries such as refill actions. After filtering, the application calculates the volume of water intake by subtracting the previous valid weight from the current one. This data is then visualized as cumulative daily intake tracked in real time. The system also generates personalized reminders and hydration feedback tailored to the user's needs.

In parallel with this REST-based data logging, the system maintains a continuous WebSocket connection. Through this channel, the smart bottle station transmits real-time information such as current weight, device mode, and the most recently scanned RFID tag. The backend server, built with Laravel, acts as the WebSocket message broker, enabling two-way communication that allows live status updates and interactive features between the mobile application and hardware.

4 Results & discussion

4.1 Hardware calibration and repeatability testing

Before deployment, the weighing system based on HX711 and a 5 kg load cell was calibrated and validated to ensure accuracy and consistency. Calibration was performed using certified reference weights ranging from 10 gram to 200 gram, including both single and combined loads, each tested with ten repetitions. The results showed that the scale readings were very close to the actual masses, with an average bias of –0.15 gram and maximum error of 0.4 gram (0.008% of full scale). At 100 g, the mean reading was 99.78 g with a standard deviation of 0.092 g and a coefficient of variation (CV) of 0.092%. At 200 g, the mean was 199.82 g with a standard deviation of 0.132 g and a CV of 0.066%. Linear regression analysis between nominal and measured weights yielded a slope of 0.9991 and an intercept of –0.075 g, corresponding to a span error of –0.09% and negligible zero error. The calibration procedure using certified reference weights is illustrated in **Figure 4**., whilst the statistical summary of calibration results with standard weights is presented in **Table 4**.

Table 4. Calibration test standard weights

Weight type	True weight (g)	Min (g)	Max (g)	Mean (g)	Mae (g)	SD (g)	CV (%)
10 g	10.0	9.9	10.1	10.03	0.03	0.0675	0.673
20 g	20.0	19.7	20.1	19.96	0.04	0.1174	0.588
50 g	50.0	49.6	50.0	49.85	0.15	0.1269	0.255
100 g	100.0	99.6	99.9	99.78	0.22	0.0919	0.092
150 g	150.0	149.7	150.0	149.76	0.24	0.0699	0.047
200 g	200.0	199.6	200.1	199.82	0.18	0.1317	0.066

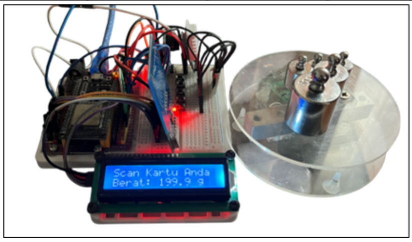

Fig. 4. Calibration test with standard weights.

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Repeatability was also tested using five bottles filled with water as practical loads under operational conditions. Each bottle was placed ten times on the scale, and the measured values were used to calculate standard deviation and CV. All bottles showed very small variations, with standard deviations below 0.14 gram and CV values below 0.12%. The testing process is illustrated in **Figure 5**, and the detailed results are summarized in **Table 5**.

Table 5. Calibration test standard weights

Bottle	Min (g)	Max (g)	Mean (g)	SD (g)	CV (%)
1	1030.6	1031.0	1030.88	0.1317	0.013
2	1025.5	1025.8	1025.68	0.1033	0.010
3	1206.1	1206.5	1206.25	0.1354	0.011
4	611.8	612.1	611.95	0.0972	0.016
5	80.7	81.0	80.79	0.0876	0.108

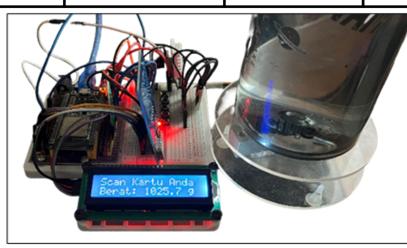

Fig. 5. Repeatability testing process using water-filled bottles.

Overall, the calibration and repeatability tests confirmed that the weighing module delivers accurate and consistent measurements, with minimal bias, high linearity, and low variability, making it reliable for recording changes in bottle weight due to drinking events.

4.2 System implementation and functional testing

To verify the overall functionality and readiness of the system, a series of scenario-based tests were conducted in a controlled deployment environment. These tests evaluated end-to-end workflows such as RFID-based user identification, weight-based intake logging, tare, mode switching, and mobile-backend synchronization. The testing approach followed a black-box methodology, focusing on input-output behaviors without accessing internal code logic.

This procedure aligns with the principles of acceptance testing for Internet of Things (IoT) systems, as outlined by Leotta et al. (2018). In this context, acceptance testing involves validating system behaviors from an end-user perspective within realistic operational scenarios. The focus is on ensuring that all integrated components behave as intended under typical usage, thereby confirming that the system meets its functional requirements in situationally accurate conditions [14].

All test cases were executed using the finalized prototype and observed through both the mobile application interface and backend logs to confirm expected outcomes. The results are summarized in **Table 6**.

Table 6. Testing Scenario for System

Test Case	User Action	Expected System Response	Results	Test Case	User Action	Expected System Response	Results
Connect to Stored WiFi List	Turn on the station	Successfully Connected to one of the WiFi and Display it	Success	**Store Data from Sensor and Complete it**	Place Bottle then Scan RFID	Store Data as Weight, Previous Weight, User ID, RFID Tag, and Timestamps	Success
Connect to Websocket Server	Turn on the station	Successfully Become a Publisher and Subscriber on the Websocket	Success	**Store Data from Mobile App**	Register, Update Profile, Reset Password	Successfully Store and Update User Data	Success
Tare calibration	Press Button 1	Display and Process Reset Weight	Success	**Fetch Data from Database**	Login, Home Page, History, Profile Page	Successfully Fetch User and Water Intake Data	Success
Change to Bottle Mode and Scan RFID	Press Button 2	Display Bottle Mode and Previous Weight = 0	Success	**Calculate User Water Intake Goals**	Fill Birth Date, Weight, Height, Gender	System Calculate and Shows User Water Intake Goals	Success
Change to RFID mode and change RFID	Press Button 3	Display RFID Mode and Changed User RFID Tag	Success	**Notification Based on Water Intake**	Enable Notification	Send Notification based on User Frequency	Success
Change to Weight Mode and Scan RFID	Press Button 4	Display Weight Mode and Previous Weight from last user scan	Success	**Error Handling**	No Data, Failed Login, ext…	Give Feedback and Not Crash	Success

All test cases were performed using the finalized prototype under typical usage conditions. The system's responses were observed through the mobile application interface and backend logs to confirm expected behavior. These include successful registration of water intake events, proper handling of invalid operations, and confirmation of two-way data updates via WebSocket and REST endpoints.

4.3 User interaction scenarios

Figure 6 illustrates a complete interaction sequence between a user and the water intake monitoring system. In this scenario, the load cell continuously monitors the platform. Once a bottle is placed and the detected weight exceeds 5 grams, the system prompts the user to scan their RFID tag. Upon scanning, the current weight and user ID are transmitted to the backend for logging.

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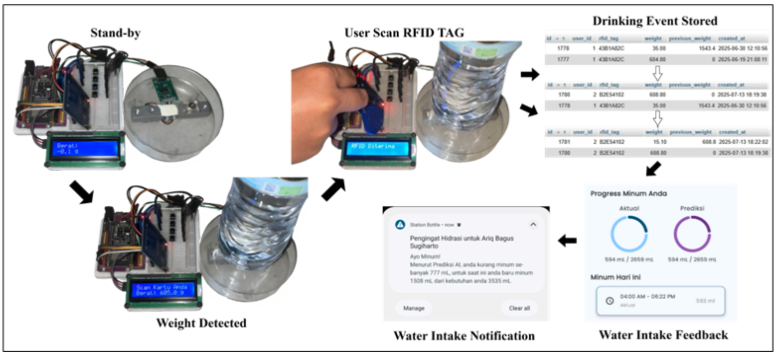

Fig. 6. Example of user interaction flow from bottle placement to mobile app water intake feedback.

After the drinking activity, the bottle is placed back on the platform. The updated weight is again recorded after the user performs another RFID scan. These values are stored along with timestamps and previous weight data, as shown in the backend logs. The mobile application subsequently fetches these entries and displays them both as cumulative intake graphs and as a detailed list of drinking events.

A hydration reminder notification is also shown in this example. The app alerts the user to drink based on previously recorded behavior and predicted needs. The rightmost section of **Figure 6** shows how the current intake status and water intake target are visualized. In this case as shown in **Figure 7**, the user profile indicates a 28-year-old female weighing 65 kg and measuring 158 cm in height, with no pregnancy or lactation status.

Fig. 7. Example of user profile information used for water intake target estimation.

The total body water (TBW) was calculated using the Watson formula for females [8]:

$$TBW = -2.097 + (0.1069 \times 158) + (0.2466 \times 65) \approx 30.81 \text{ liters}$$

The total daily hydration target is computed using:

$$(30.81 \times 0.023 \times 1000) + (65 \times 30) = 708.7 + 1950 \approx 2659 \text{ mL}$$

In addition to the user-facing interaction flow described above, a real-time system interface is provided for monitoring device status. As shown in **Figure 8**, the mobile application displays active sensor connectivity, operational mode, load cell readings, and RFID scanning prompts. These elements are transmitted via WebSocket, which maintains a continuous data stream between the hardware and application. The interface updates in response to backend messages and reflects the current state of the station without requiring manual page interaction.

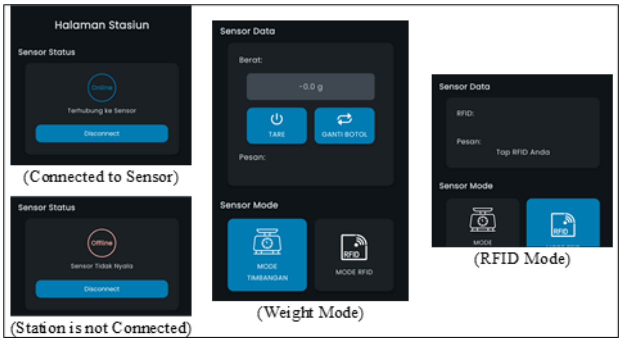

Fig. 8. Real-time mobile application system monitoring with WebSocket for device control & sensor feedback.

4.4 Data collection outcome and log validation

The collected dataset spans a deployment period from 10 February 2025 to 7 June 2025, during which the smart bottle station recorded 1,747 raw log entries across all user sessions. These entries, automatically transmitted to the backend database, included time-stamped RFID scans and corresponding weight readings from the load cell sensor.

The data were gathered from three users with differing demographic characteristics to reflect a range of physiological hydration needs. The participants consisted of a 21-year-old male weighing 83 kg and measuring 173 cm in height, a 28-year-old female weighing 65 kg and 158 cm tall, and a 47-year-old female with a body weight of 73 kg and height of 154 cm. All participants were non-pregnant and non-lactating throughout the evaluation period. This demographic diversity allowed the system to be evaluated under varying usage behaviors and target hydration requirements.

Although all entries were automatically recorded by the system, not all corresponded to actual water intake. Several logs originated from bottle refills, mode changes, or erroneous weight readings unrelated to drinking activity. **Table 7** illustrates examples of such non-consumption events. To extract valid drinking records, a multi-step filtering procedure was applied. Log entries were retained only if they met the following criteria: the previous weight was non-zero and greater than the current reading; the resulting drink volume exceeded 20 mL; and the entry was not a duplicate of a previously recorded event.

Table 7. Example of non-consumption logs

User ID	UID (RFID Tag)	weight (g)	prev weight (g)	timestamp	drink amount (mL)
User Refilled Their Bottle					
6	058B255D023200	2048.2	16.00	2/19/2025 9:03	-2032.2
User Changed Bottle (from Change Bottle Mode)					
2	B2E54102	225.00	0.00	2/28/2025 12:11	-225.00

Water Intake < 20 mL					
2	B2E54102	14.00	22.50	2/28/2025 12:10	8.50
Duplicate Data					
2	B2E54102	507.80	577.50	2/12/2025 18:16	69.70
2	B2E54102	507.80	577.50	2/12/2025 18:16	69.70

After filtering, a total of 904 entries (approximately 51.7% of the raw logs) were confirmed as valid drinking events. The data segmentation and impact of each filtering step are visualized in **Figure 9**.

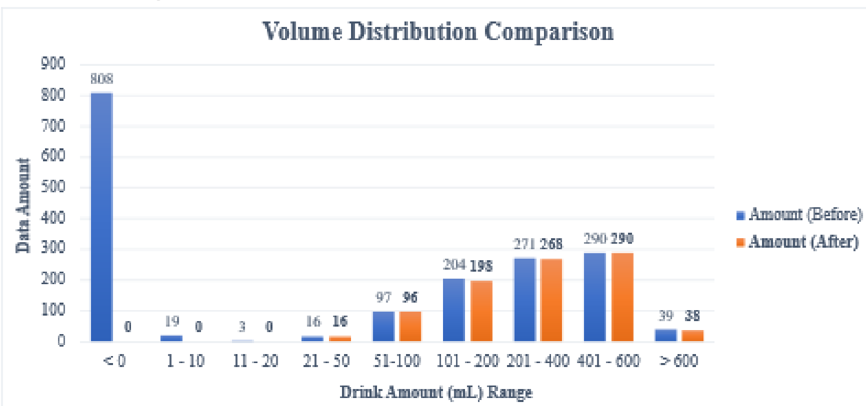

Fig. 9. Data amount before and after filtering process.

Following the validation process, **Figure 10** – **Figure 12** was generated to present the total daily water intake (in milliliters) per user over time. Linear trendlines were fitted to each user's time series to highlight changes in hydration patterns.

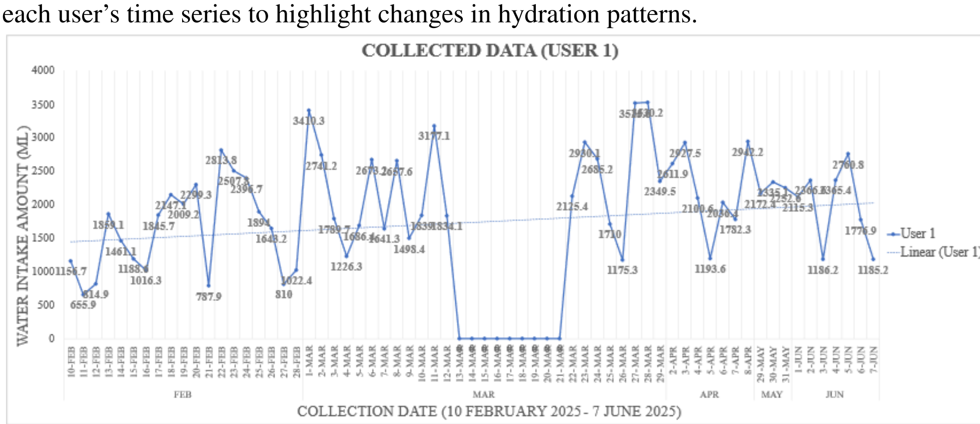

Fig. 10. Cumulative water intake logs (user 1) with fitted linear trendlines over deployment period.

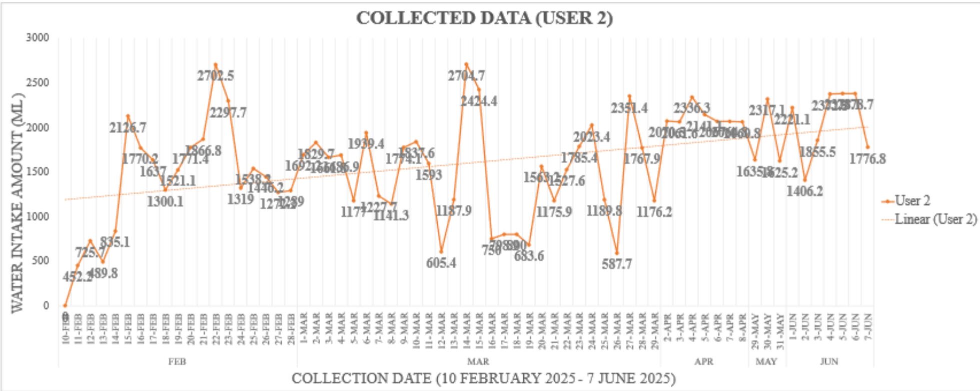

Fig. 11. Cumulative water intake logs (user 2) with fitted linear trendlines over deployment period.

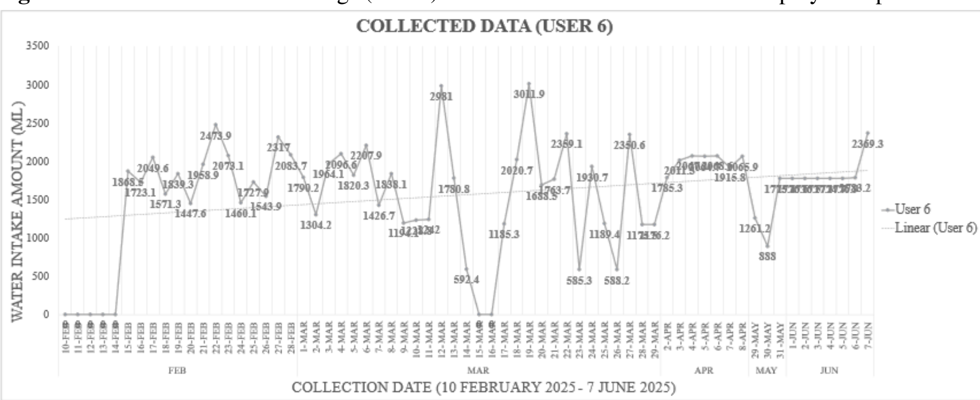

Fig. 12. Cumulative water intake logs (user 6) with fitted linear trendlines over deployment period.

All three users demonstrated an upward trajectory in daily water intake over the deployment period. The increasing trends suggest that users consistently engaged with the system and maintained or improved their water intake behavior across time. Given the passive and personalized nature of the system, this observation reinforces the system's suitability for long-term monitoring and its potential influence on hydration adherence.

The overall results validate the system’s ability to accurately capture and differentiate real drinking events from unrelated interactions in a multi-user environment. Moreover, the consistent data quality and behavioral trends observed across diverse participants support the scalability of the proposed platform in real-world usage contexts.

4.5 Limitations

Although the proposed system successfully demonstrates automatic logging of water intake and individualized hydration target estimation, several limitations remain that may affect its overall reliability and scalability in real-world applications:

a. Potential for Intentional Misreporting

The system assumes that every interaction on the load cell involves a genuine drinking action. However, users could intentionally manipulate the system by placing unrelated lightweight items (e.g., small objects) instead of actual bottles to simulate water intake. Since the system relies solely on weight difference, it cannot distinguish between legitimate and falsified input, which may lead to inaccurate hydration tracking.

b. Lack of Real-Time Physical Feedback at the Station

While the mobile application provides real-time updates and notifications, the smart bottle station itself does not include any direct alert mechanisms such as buzzers or LED indicators. This means that users who are not actively viewing the app may not receive immediate feedback when incorrect actions occur (e.g., forgetting to scan, placing the wrong bottle), potentially reducing system usability and user adherence.

c. Inability to Confirm Actual Water Consumption

The system interprets a decrease in bottle weight after an RFID scan as a drinking event. However, it cannot confirm whether the water was genuinely consumed by the user, spilled, or given to someone else. This limitation is inherent to non-invasive, passive tracking systems and may introduce uncertainty into the intake data.

d. No Consideration for Environmental or Physiological Context

The current hydration target estimation is based only on static user profile data (age, weight, height, and gender). It does not account for dynamic environmental or physiological factors such as ambient temperature, physical activity, or illness, all of which significantly affect hydration needs. As a result, the estimated targets may not always reflect the user's true fluid requirements.

e. Scalability Limitations in Shared Environments

The system is designed for sequential, individual use and does not yet support features required in larger-scale or public settings. For example, it does not support multi-user queuing, which refers to the ability to handle several users waiting to use the system in sequence, or concurrent identification, which would allow detecting and managing multiple users interacting with the system at the same time. This limits its practicality in high-traffic environments like schools or clinics.

f. Dependence on Proper User Behavior

The system's accuracy relies heavily on user compliance with its operational protocol, specifically, scanning the RFID before and after placing the bottle. If users forget to scan or interrupt the expected sequence, the log entries may be incomplete, misleading, or entirely absent. Such behavior-dependent operation can reduce the completeness and quality of the collected data.

5 Conclusion and future scopes

This study presented a personalized water intake monitoring system integrating an RFID-enabled smart bottle station with a mobile application. The platform was designed to operate in shared environments and tailored individual water intake targets based on demographic data. Calibration and repeatability tests of the HX711-based weighing module confirmed high accuracy and consistency, with a maximum error of 0.4 g (0.008% of full scale), a slope of 0.9991, and coefficients of variation below 0.12%, ensuring reliable detection of drinking events.

During a four-month deployment, the system recorded 1,747 raw log entries, of which 904 (51.7%) were validated as genuine drinking events through multi-step filtering. The data, collected from three participants with varying demographic profiles, showed consistent engagement and an upward trajectory in daily intake. Across the observation period, daily intake fluctuated, yet average values in later months were higher than at the beginning. In February, mean daily intake was approximately 1,570 mL for User 1, 1,430 mL for User 2, and 1,730 mL for User 6, while in June the averages rose to about 2,130 mL, 2,100 mL, and 1,940 mL, respectively. This upward shift explains the positive slopes of the linear trendlines and reflects gradual improvement in drinking behavior supported by automated monitoring.

Functional and scenario-based tests demonstrated that the system reliably logged drinking events, maintained real-time synchronization, and provided personalized feedback. While these findings validate the feasibility of scalable, shared-use hydration monitoring, limitations remain in terms of lack of onboard feedback, potential user misuse, and the absence of dynamic adjustment to environmental or physiological factors.

Future work will address these limitations by incorporating real-time feedback mechanisms, extending intake recommendations with contextual parameters such as activity and health status, and expanding the architecture to support queuing and concurrent use in high-density environments. These developments aim to enhance system reliability, contextual accuracy, and scalability for broader adoption in real-world settings.

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