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Research Article

IOT-BASED AUTOMATIC BMI MONITORING SYSTEM WITH RFID AND TRL EVALUATION

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Abstract
The increasing global prevalence of overweight and obesity, combined with limitations in conventional Body Mass Index (BMI) measurement practices, underscores the need for secure, automated, and cloud-integrated monitoring systems. Existing IoT-based BMI devices primarily focus on measurement accuracy but rarely integrate secure user authentication, longitudinal cloud tracking, usability validation, and formal technology readiness assessment within a single framework. This study aims to design, implement, and evaluate an IoT-based automatic BMI monitoring system equipped with RFID authentication and real-time cloud synchronization. The proposed system integrates an ESP32 microcontroller, ultrasonic and load-cell sensors, and an RFID PN532 module. Measurement data are transmitted to a Firebase Realtime Database and visualized via a web-based dashboard. Accuracy was evaluated using mean error analysis and linear regression (R^2). Usability was assessed using the System Usability Scale (SUS) and End-User Satisfaction (ESU) questionnaire. Technology maturity was analyzed using the Technology Readiness Level (TRL) framework. Experimental testing with 25 participants demonstrated high measurement accuracy, with mean errors of 0.38% for height ($R^2 = 0.952$) and 0.35% for weight ($R^2 = 0.9993$). BMI computation showed strong agreement with manual calculation ($R^2 = 0.9938$). The average measurement cycle required 15.2 seconds. The system achieved a SUS score of 82.5 (Excellent), ESU score of 4.6/5 (Very Satisfied), and TRL 6 classification. The novelty of this study lies in integrating secure RFID authentication, cloud-based longitudinal monitoring, dual-layer usability evaluation, and formal TRL assessment into a single IoT BMI ecosystem.

Keywords: BMI Monitoring, Cloud-based Health System, IoT Healthcare, RFID Authentication, Technology Readiness, Usability Evaluation.

INTRODUCTION

The rapid development of the digital era has significantly transformed human lifestyles, particularly in eating patterns and physical activity. Increased dependence on online food delivery services and fast-food consumption has been strongly associated with higher risks of overweight and obesity, as these platforms often promote calorie-dense meals that encourage overeating (Nazir et al., 2020; Salsabilla et al., 2025; Zou & Id, 2024). Prior studies also link fast-food intake with reduced physical activity, greater sedentary behavior, and elevated prevalence of hypertension and obesity, especially among adolescents and young adults (Kandola et al., 2019; Mahumud et al., 2021). These conditions were further intensified during the COVID-19 pandemic due to decreased mobility, increased screen time, and more frequent fast-food consumption (Lucibello et al., 2021).

Sleep disruption is another important contributor to metabolic dysregulation. Irregular or insufficient sleep has been associated with obesity, insulin resistance, type 2 diabetes, and cardiovascular disease (Markwald et al., 2013; Rudnicka et al., 2017; Wijayanti et al., 2022). Poor sleep increases hunger and energy intake, promotes unhealthy dietary choices, and exacerbates weight gain even without major changes in caloric intake (Chaput et al., 2023; Rogers et al., 2024). Combined with high-calorie diets and physical inactivity, these factors create a cumulative environment that elevates cardiometabolic risk, underscoring the need for early and continuous monitoring of weight-related indicators.

Globally, overweight and obesity have risen to unprecedented levels. The World Health Organization reported that more than 1.9 billion adults were overweight in 2022, with 650 million classified as obese (Boutari & Mantzoros, 2022; Islam et al., 2024). Recent estimates suggest even greater numbers, reaching 2.5 billion overweight adults worldwide. Since 1990, obesity prevalence has more than doubled, with the fastest increases occurring in low- and middle-income countries, particularly in Asia and Africa (Li et al., 2023). In addition to the rising prevalence of obesity and type 2 diabetes, there is growing interest in culturally adapted, holistic interventions to improve diabetes outcomes among patients with comorbid depression (Faizun et al., 2024). These trends highlight the urgent need for accessible tools to support early detection and routine monitoring of body-weight status and vascular risk among individuals with diabetes (Cahyono & Purwanti, 2019).

Body Mass Index (BMI) remains one of the most widely used indicators for assessing body composition due to its simplicity and cost-effectiveness (Flegal et al., 2014; Sweatt et al., 2024). Standardized BMI categories are routinely used for population health surveillance and clinical evaluation (Holmes & Racette, 2021; Watanabe et al., 2023). However, BMI also has notable limitations. It cannot distinguish between fat and muscle mass, fails to account for fat distribution or bone density, and may misclassify athletes or older adults (Wu et al., 2024). Ethnic variations further complicate interpretation. These limitations reinforce the need for accurate, user-friendly, and routinely accessible BMI monitoring technologies.

Rapid advancements in Internet of Things (IoT) technology provide opportunities to automate health data acquisition and visualization. IoT-based systems enable real-time measurement, cloud storage, and remote monitoring of health parameters such as heart rate, blood glucose, and physical activity (Balasundaram et al., 2023; Haghi et al., 2020; Swayamsiddha et al., 2025). While these technologies support proactive healthcare delivery (El-Deep et al., 2025; Kelly et al., 2020; Widianto et al., 2018), existing IoT health monitoring solutions still face several challenges, including limited measurement capabilities, absence of secure user authentication, and lack of long-term data tracking (Anjum et al., 2025; Gougeh & Zilic, 2024; Popoola et al., 2023; Waleed et al., 2023). Additional concerns include interoperability issues, inconsistent data quality, and privacy vulnerabilities (Emad et al., 2025; Khatun & Memon, 2023; Selvaraj & Sundaravaradhan, 2019). Although many prototypes report low error rates, large-scale validation and real-world implementation remain limited (Shafi et al., 2024).

Although several IoT-based health monitoring systems have been developed, many existing BMI devices focus primarily on measurement accuracy without incorporating secure user authentication, structured longitudinal data storage, and formal usability validation. Furthermore, few studies assess technological maturity using standardized frameworks such as Technology Readiness Level (TRL). This creates a gap between prototype development and real-world institutional deployment. Therefore, there remains a need for an integrated BMI monitoring system that combines secure identification, cloud-based tracking, comprehensive usability evaluation, and formal readiness assessment within a single platform

The objectives of this research are to design, implement, and evaluate the proposed system in terms of measurement accuracy, usability, and technological readiness. The main contributions of this study are: (1) the development of a fully integrated IoT-based BMI monitoring prototype with automated measurement and RFID-based user identification; (2) the implementation of a real-time cloud-connected dashboard for data visualization and historical tracking; (3) the evaluation of system usability using the System Usability Scale (SUS) and End-User Satisfaction (ESU) instruments; and (4) the assessment of technological maturity using the Technology Readiness Level (TRL) framework, demonstrating the system's readiness at TRL 6.

While these contributions outline the functional and evaluative scope of the proposed system, it is also important to position this work within the context of existing IoT-based health monitoring technologies. A clear distinction between what has been done in prior studies and what this research advances is necessary to emphasize the unique value and innovation offered by the developed prototype. In this regard, the following novelty statement highlights the specific aspects in which this work extends, enhances, and differentiates itself from previous approaches.

Compared with previous IoT-based BMI monitoring systems, the novelty of this work lies in the integration of secure RFID-based user authentication, real-time cloud-connected longitudinal tracking through Firebase, and a comprehensive dual-layer evaluation that includes both usability assessment (SUS and ESU) and Technology Readiness Level (TRL) analysis. These combined elements are rarely addressed simultaneously in prior studies, enabling the proposed system to offer not only automated BMI measurement but also secure identification, continuous historical monitoring, and validated readiness for real-world deployment. The remainder of this paper is organized as follows: Section 2 describes the system design, hardware configuration, and software development. Section 3 presents the experimental results, usability evaluations, and TRL analysis. Section 4 concludes the study and provides directions for future work.

RESEARCH METHOD

This study employed an experimental quantitative research design with prototype development and user-based evaluation. The research combined hardware–software engineering validation with statistical accuracy testing and usability assessment. The overall architecture of the automatic BMI monitoring system comprises three main parts: input, processing, and output, as illustrated in Figure 1. The system integrates multiple electronic components, cloud communication, and user interface modules within a single IoT framework to enable automated data collection, computation, and visualization.

The input subsystem is responsible for data acquisition and user identification. It includes: 1) an RFID PN532 module for card registration and user authentication; 2) an ultrasonic sensor (HC-SR04) for measuring body height; 3) a load-cell sensor with HX711 amplifier for weight detection; and 4) a push button used to initiate the measurement sequence. Each input component sends data signals to the ESP32 microcontroller for centralized processing.

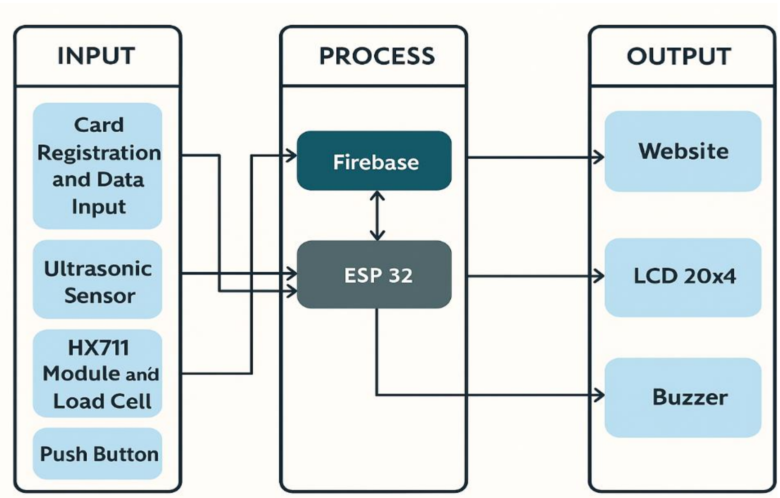


Figure 1. Block diagram of the BMI monitoring device, illustrating sensor inputs, ESP32 processing, Firebase integration, and real-time output interfaces.

The ESP32 microcontroller functions as the core processing unit. It receives data from all input sensors, computes BMI and transmits the results to the Firebase Realtime Database via Wi-Fi. The communication between ESP32 and Firebase enables real-time cloud data storage, allowing subsequent visualization on web or mobile dashboards. The output subsystem provides direct user feedback through three primary interfaces: 1) A 20×4 LCD, which presents height, weight, and BMI values immediately after measurement; 2) A buzzer, which provides an audible signal to indicate completion of measurement; 3) A web application, which retrieves and visualizes data from Firebase, displaying historical BMI trends for each registered user.

The hardware configuration of the IoT-based automatic BMI monitoring system was designed to combine structural stability, component efficiency, and user ergonomics. The physical prototype was modeled in Tinkercad before assembly, as shown in Figure 2. The device stands 195 cm tall and 45 cm wide, dimensions that are ergonomically aligned with the average stature of Indonesian adults, allowing users of various heights to be measured comfortably. The vertical frame structure serves as the main support for all components, optimizing space utilization and ensuring sensor alignment accuracy.

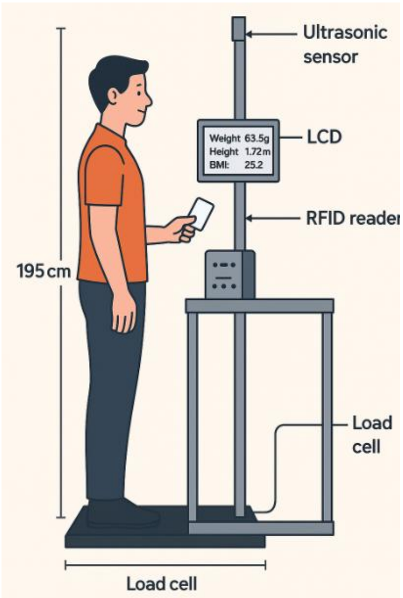
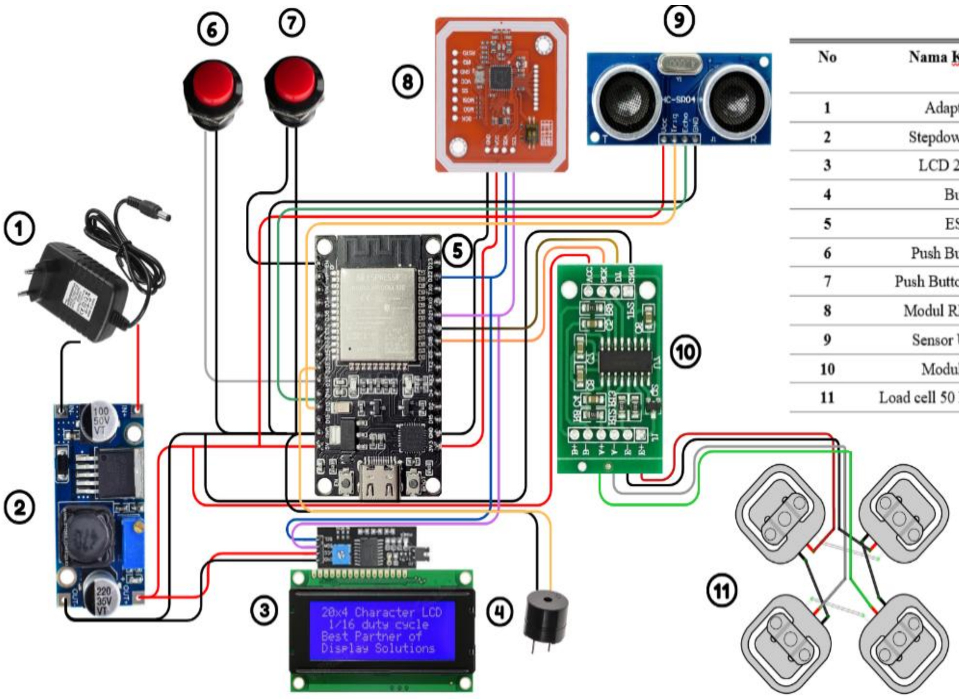


Figure 2. Illustration of a user operating the automatic BMI measurement device.

At the top of the frame, an HC-SR04 ultrasonic sensor is mounted to measure the user's height by detecting the distance to the top of the head. The load cell platform at the base serves as the weight-measuring section, converting mechanical force into electrical signals via the HX711 amplifier. In the central portion of the frame, an electronic component box houses the ESP32 microcontroller, power regulator, and signal interfaces. A 20×4 I²C LCD mounted on the front side shows height, weight, and BMI results in real time.

On the right side of the frame, two push buttons are provided—one to initiate measurement and another to reset the system. An RFID PN532 reader is positioned near the control box to enable user identification prior to measurement. The entire hardware layout is designed to minimize cabling complexity and provide a safe, practical, and user-friendly configuration suitable for routine use in clinics, schools, or public health facilities. The prototype emphasizes modularity and maintainability. Each sensor and peripheral module can be easily replaced or recalibrated without dismantling the main structure, thereby supporting long-term reliability and future scalability for additional health-parameter integration. The electronic circuit of the automatic BMI monitoring device was designed to ensure reliable signal acquisition, stable power distribution, and effective data communication among all components. The detailed wiring configuration is shown in Figure 3. The system uses the ESP32 microcontroller as the central processing unit, connecting various sensors and modules through both analog and digital interfaces. A 12 V adapter supplies power to the circuit, which is then regulated by an XL4005 step-down module to provide a stable 5 V for the sensors and peripherals.



No	Nama Komponen
1	Adapter 12 V
2	Stepdown XL4005
3	LCD 20X4 I2C
4	Buzzer
5	ESP32
6	Push Button Ukur
7	Push Button Reset ESP
8	Modul RFID PN532
9	Sensor Ultrasonic
10	Modul HX711
11	Load cell 50 Kg Half Bridge

Figure 3. Wiring diagram of the IoT-based BMI system.

The HX711 amplifier module is connected to the load-cell sensor to amplify and convert the analog weight signal into a digital format readable by the ESP32. The ultrasonic sensor (HC-SR04) transmits and receives distance signals to measure body height. The RFID PN532 module communicates with the ESP32 through the serial interface to perform user identification. Two push buttons are integrated—one for initiating measurement and another for system reset—providing manual control during testing or recalibration.

The LCD 20×4 I²C display is connected via the SDA and SCL pins to show height, weight, and BMI values in real time. A buzzer is incorporated to emit a short tone upon completion of measurement, signaling that data have been successfully recorded and transmitted to the Firebase database. Proper grounding and short-wire routing are maintained to reduce signal interference and ensure measurement accuracy. This configuration allows simultaneous data collection and processing with minimal latency while maintaining electrical stability. The modular wiring setup also facilitates easy maintenance and component replacement, ensuring long-term system reliability.

The software component of the automatic BMI monitoring system governs data processing, hardware control, and cloud communication. Development was carried out using several integrated tools to ensure efficient programming, visualization, and system stability. The Arduino IDE was used to program the ESP32 microcontroller that coordinates all sensors and peripheral modules. The Arduino environment employs a simplified form of C/C++, specifically designed for embedded systems, enabling straightforward integration of sensor libraries and serial communication functions (Papoutsidakis, 2018). Through this platform, the ultrasonic sensor, load-cell module, and RFID PN532 were configured to acquire measurement data, calculate the Body Mass Index (BMI), and transmit results to the Firebase Realtime Database via Wi-Fi (Suruso et al., 2023).

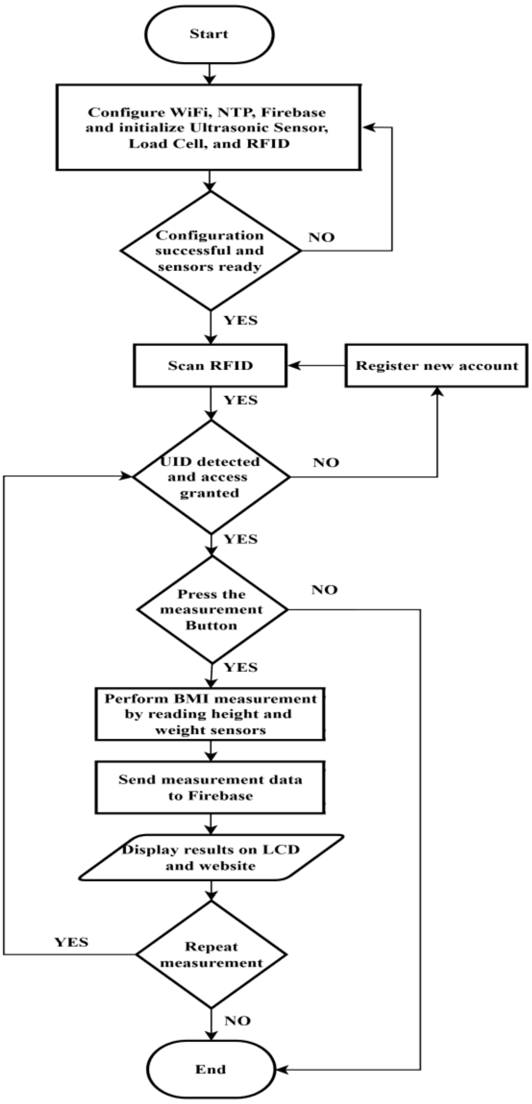


Figure 4. Flowchart of the automatic BMI measurement process implemented using ESP32 and Firebase cloud integration

The Visual Studio Code environment was utilized to design and implement the web-based interface, providing real-time visualization of measurement results, secure user authentication, and graphical trend analysis of BMI data retrieved directly from Firebase. This interface enables users to track their health parameters through any device connected to the Internet. To support circuit design, EasyEDA Editor was employed to create the schematic and Printed Circuit Board (PCB) layout. This tool facilitates schematic capture, signal routing optimization, and voltage stability during electronic assembly (Kelly et al., 2020). Additionally, the Tinkercad 3D Design Editor was used for virtual prototyping and structural modeling of the BMI device, validating component placement, ergonomics, and assembly feasibility prior to fabrication (El-Deep et al., 2025).

The overall workflow of the system software is illustrated in Figure 4, showing the logical process from initialization to result visualization. At startup, the ESP32 initializes Wi-Fi, Firebase, and sensor modules. After RFID authentication, the user presses the “Measure” button to initiate the height and weight measurement processes. The ESP32 calculates the BMI, uploads the result and metadata (user ID, timestamp, raw data) to Firebase, and displays the result on the LCD 20×4. A buzzer provides an audible signal indicating completion, and the program returns to standby mode, ready for the next user.

The study involved 25 participants selected using purposive sampling. Participants were adults who met the inclusion criteria of being physically able to stand independently during measurement. The sample size was considered adequate for prototype validation and usability testing based on prior SUS benchmarking studies, where 12–30 participants are generally sufficient to obtain stable usability estimates. Although the sample size of 25 participants is modest, it is consistent with usability testing standards, which suggest that 15–30 users are sufficient to detect major usability issues with high confidence. For measurement validation, repeated measures (three trials per participant) increased data robustness, resulting in 75 height and weight observations, enhancing statistical reliability.

The research instruments consisted of three main categories: (1) the developed prototype as the primary measurement instrument, (2) reference instruments for accuracy validation, and (3) standardized evaluation instruments for usability and technology readiness assessment. The primary research instrument was the developed IoT-based automatic BMI monitoring prototype integrating an ESP32 microcontroller, HC-SR04 ultrasonic sensor for height measurement, load-cell sensor with HX711 amplifier for weight measurement, and RFID PN532 module for user authentication. The system automatically calculates BMI using embedded firmware and transmits data to the Firebase Realtime Database. To validate measurement accuracy, two calibrated reference instruments were used: A calibrated digital weighing scale (accuracy ±0.1 kg); A manual stadiometer (accuracy ±0.1 cm); Both instruments were calibrated prior to data collection to ensure measurement reliability.

Usability evaluation was conducted using the System Usability Scale (SUS), a standardized 10-item questionnaire rated on a 5-point Likert scale, producing a composite score between 0 and 100 (Gohari et al., 2022; Gronier & Baudet, 2021; Hyzy et al., 2022). SUS has been widely validated in digital health applications and provides a reliable benchmark for system usability classification. End-User Satisfaction (ESU) was measured using a structured six-indicator questionnaire assessing functionality, ease of use, performance, clarity of information, aesthetic design, and overall satisfaction. The ESU framework was adapted from established usability and health information system evaluation models (Almasi et al., 2023). Technology maturity was assessed using a structured Technology Readiness Level (TRL) checklist, based on the nine-level framework defined by NASA and adopted by the U.S. Department of Energy and the European Space Agency (Carmack et al., 2017; Héder, 2017; Jansen-kosterink, 2022; Salvador-carulla et al., 2024). This checklist evaluates progression from conceptual validation to prototype demonstration in a relevant environment.

Data collection was conducted through experimental testing, observational measurement, and structured questionnaire administration. Height and weight measurements were obtained using a repeated-measures procedure in which each of the 25 participants performed three consecutive trials. Ultrasonic sensor readings were compared with manual stadiometer values, while load-cell measurements were validated against a calibrated digital weighing scale. Measurement accuracy was analyzed using Mean Absolute Error (MAE), percentage deviation, and linear regression (R^2) to determine linearity and precision. BMI validation was performed by comparing system-generated BMI values with manually calculated BMI derived from reference height and weight measurements. RFID performance was evaluated using seven RFID cards, including both registered and unregistered tags, by recording authentication success rate, rejection accuracy, and response stability. Operational performance was further assessed by measuring task completion time across five sequential activities: RFID login, weight measurement, height measurement, LCD display, and website visualization, with timing recorded through direct observation. Following system interaction, all participants completed the System Usability Scale (SUS) and End-User Satisfaction (ESU) questionnaires using a 5-point Likert scale. SUS scoring followed the standardized conversion procedure to produce a usability score ranging from 0 to 100 (Hyzy et al., 2022; Gronier & Baudet, 2021), while ESU responses were summarized using mean Likert values for each evaluation indicator (Almasi et al., 2023; Gohari et al., 2022). Technology readiness data were collected using a structured TRL checklist assessing compliance with criteria from TRL 1 to TRL 6, supported by laboratory testing results, user trials, system integration documentation, and usability findings (Carmack et al., 2017; Héder, 2017; Miceli et al., 2023; Salvador-carulla et al., 2024). To ensure systematic alignment between research variables, instruments, and analytical techniques, Table 1 presents the data collection instrument grid.

Table 1. Instrument and Data Collection Grid

Research Variable	Indicator	Instrument used	Data Collection Technique	Data Analysis
Height Accuracy	Measurement deviation	Ultrasonic sensor vs stadiometer	Direct measurement (3 trials per participant)	MAE, % error, regression (R^2)
Weight Accuracy	Measurement deviation	Load-cell vs digital scale	Direct measurement (3 trials per participant)	MAE, % error, regression (R^2)
BMI Validity	BMI computation difference	ESP32 automated BMI algorithm	System vs manual calculation comparison	Mean deviation, regression
Authentication Reliability	UID recognition accuracy	RFID PN532 module	Registered vs unregistered card testing	Accuracy percentage
System Responsiveness	Task completion time	Stopwatch observation	Sequential task timing	Mean completion time
Usability	Perceived usability	SUS questionnaire	Post-use survey	SUS score (0–100)
User Satisfaction	Satisfaction indicators	ESU questionnaire	Post-use survey	Mean Likert score
Technology Readiness	TRL compliance	TRL checklist	Structured assessment documentation	TRL level classification

Statistical analysis was conducted using descriptive statistics and linear regression analysis. Mean Absolute Error (MAE) and mean percentage deviation were calculated to evaluate measurement accuracy. The coefficient of determination (R^2) was used to assess linear correlation between sensor measurements and reference instruments. Usability scores were analyzed according to standard SUS scoring procedures, while ESU scores were summarized using mean Likert values. All analyses were performed using spreadsheet-based statistical computation. Internal consistency of the SUS and ESU questionnaires was assessed using Cronbach's alpha coefficient.

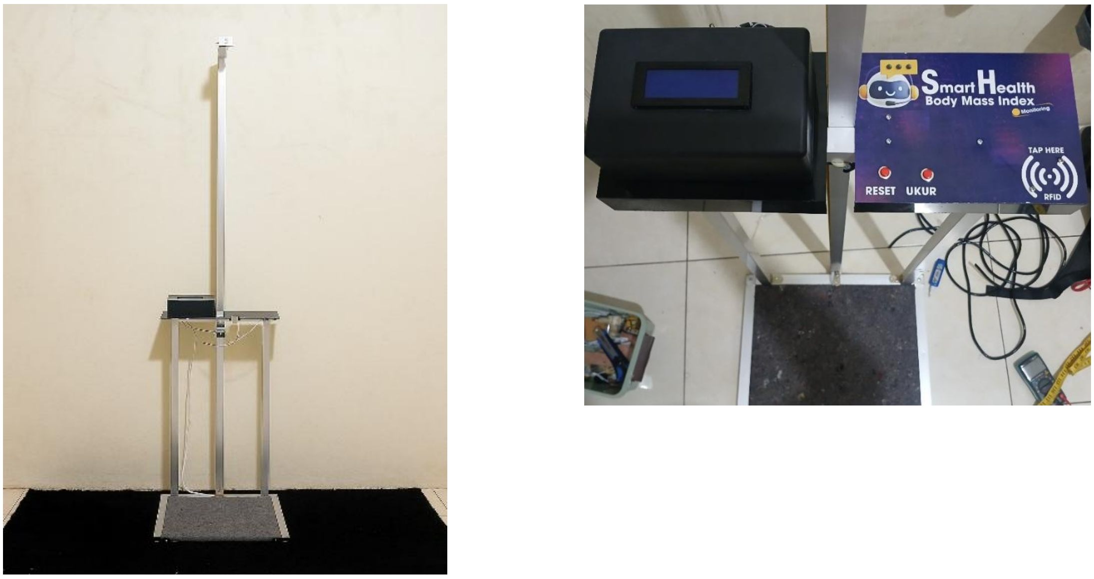
RESULTS AND DISCUSSION

Hardware and Interface Implementation

The developed automatic BMI measurement device has a total height of 195 cm and a width of 45 cm, designed according to average adult anthropometric dimensions in Indonesia to ensure user comfort and accessibility. The system frame is constructed using 2.5 × 2.5 cm hollow steel, providing mechanical stability during operation. The load-cell sensor is mounted on a triblock base with an additional 3D-printed support frame made of PLA+ filament to enhance structural rigidity and maintain sensor alignment during repeated use.

An electronic box, fabricated from 3D-printed polymer, serves as the housing for the ESP32 microcontroller, HX711 amplifier, and RFID PN532 module, as illustrated in Figure 5. The RFID module is intentionally positioned on the front of the electronic box to facilitate user access during registration and measurement without assistance, ensuring ergonomic operation and intuitive system interaction. The complete electronic configuration inside the control box is shown in Figure 6, which illustrates the integration between the microcontroller, sensor modules, and ribbon-cable communication system. The internal layout allows organized wiring, stable voltage regulation, and simplified maintenance.

A web-based monitoring dashboard was developed using HTML, CSS, and JavaScript and integrated with the Firebase Realtime Database to enable automatic data synchronization. Users can access their personal records through RFID-based authentication or manual UID entry. After each measurement session, the dashboard updates the height, weight, BMI value, and BMI classification within approximately two seconds under stable network conditions, although delays of up to ten seconds may occur during poor connectivity.



(a) Front view (b) Top view

Figure 5. Front and top view of the automatic BMI monitoring device showing electronic module placement

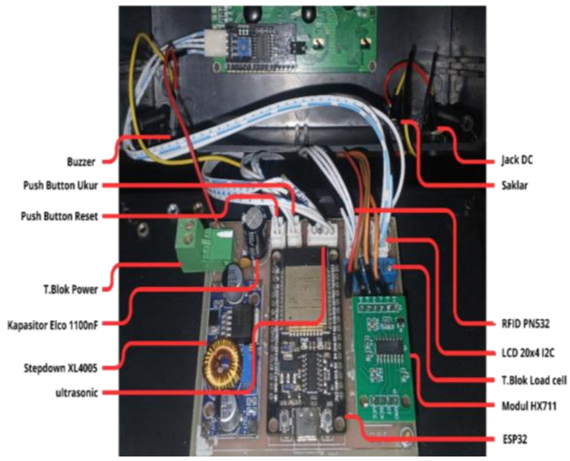


Figure 6. Internal electronic arrangement of the automatic BMI measurement system

This integration demonstrates that the system not only performs physical measurements reliably but also provides an interactive and cloud-connected experience, enabling continuous health monitoring from any Internet-enabled device. The seamless communication between the ESP32 firmware, Firebase cloud service, and web interface confirms that the prototype achieves a fully operational IoT ecosystem ready for broader deployment.

Experimental Testing and Performance Evaluation

Experimental testing was carried out to evaluate the accuracy, responsiveness, and reliability of the developed automatic BMI monitoring system. The prototype was tested using real users in a controlled environment to ensure each subsystem—height and weight measurement, BMI calculation, RFID authentication, and web-based data visualization—functioned according to its design objectives. As summarized in Table 2, all subsystems met or exceeded the performance standards for accuracy and responsiveness. The integration of ESP32 and Firebase enabled seamless data flow from measurement to visualization, supporting reliable and real-time BMI monitoring.

Table 2. Summary of Experimental Testing and Performance Evaluation Results

No.	Evaluated component	Parameter	Results	Remarks
1	Ultrasonic Sensor	Mean Absolute Error	0.38 %	High accuracy; strong linearity (R^2 = 0.952) with manual measurement
2	Load Cell Module	Mean Deviation	0.35 %	Excellent precision; nearly perfect correlation (R^2 = 0.9993)
3	BMI Computation	Mean Difference vs Manual BMI	1.06 %	Algorithm validated; consistent real-time computation (R^2 = 0.9938)
4	RFID PN532 Module	Authentication Accuracy	100 %	All registered UIDs accepted; unregistered UIDs correctly rejected
5	Web Visualization	Data Update Delay	< 2 s (average) – 10 s (max)	Real-time cloud synchronization; minor delay under weak Wi-Fi
6	Overall System Performance	Functional Accuracy	≥ 97 % (mean across modules)	Stable and precise operation within ±5 % standard tolerance

The ultrasonic sensor and load-cell module were evaluated by comparing their outputs with reference instruments. The ultrasonic sensor showed a strong linear relationship with manual height measurements, achieving a mean absolute error of 0.38% and a coefficient of determination (R^2) of 0.952, indicating high accuracy and consistency in distance detection. Similarly, the load-cell module exhibited an average deviation of only 0.35% from a calibrated digital weighing scale, with an (R^2) value of 0.9993, confirming excellent precision and stable load reading performance. Both sensors maintain error levels below the accepted ±5% threshold for consumer-grade health monitoring systems, validating the effectiveness of their calibration and data-processing algorithms.

The RFID PN532 module functioned as the primary access and identification component. Tests using seven RFID cards confirmed consistent tag reading before and after registration. Prior to registration, all unrecognized tags were correctly denied access, while registered users were accurately authenticated and allowed to continue the measurement process. This confirmed that the authentication logic—comprising user verification and data association with individual Firebase accounts—operated effectively and securely. The web-based visualization system, developed using Visual Studio Code and connected to Firebase, successfully displayed all uploaded data in real time. The interface automatically updated BMI, weight, and height values immediately after each measurement session, providing a clear user dashboard with historical tracking. The delay between Firebase upload and website display averaged less than two seconds, except in cases of network instability where latency reached up to ten seconds. Overall, the synchronization between hardware, firmware, and cloud services demonstrated high system reliability.

The BMI calculation process was verified by comparing system-generated BMI values with manually computed results from reference data. The mean difference was 1.06%, and regression analysis yielded an (R^2) of 0.9938, confirming the reliability of the embedded formula and the accuracy of real-time BMI computation in the ESP32 firmware. These findings collectively confirm that the automatic BMI monitoring system achieves a high degree of functional accuracy, operational stability, and data integrity. The strong correlation between measured and reference values indicates that the prototype is well-calibrated for practical applications. The integration of ESP32, Firebase cloud services, and RFID authentication ensures secure, real-time data management—marking a significant advancement toward efficient and automated health monitoring solutions.

Task Performance and Responsiveness

The task performance test was conducted with 25 participants to evaluate system responsiveness and operational efficiency during real-time use. Each participant performed a complete measurement cycle consisting of five sequential activities: RFID login, weight measurement, height measurement, BMI display on LCD, and website visualization. The time for each task was recorded, and qualitative observations were documented to identify potential usability issues.

Table 3. Summary of average completion time and task observations

No.	Task	Mean Time(s)	Remarks
1	RFID Login	1.9	Minor delay in some trials due to improper card placement
2	Weight Measurement	3.0	Stable readings achieved within 2–3 seconds
3	Height Measurement	3.1	Slight variation (±2 cm) caused by user posture differences
4	LCD Display	3.0	Display latency consistently below one second
5	Website Visualization	4.2	Delay increased under unstable Wi-Fi conditions

Average total task completion time per participant: 15.2 seconds

The results shown in Table 3 indicate that the system performed efficiently, completing the entire measurement and data synchronization process in less than 20 seconds. The RFID module responded rapidly, with only minor misalignment delays observed in a few participants. Both weight and height measurements stabilized within three seconds, and the LCD module displayed results immediately after processing. The longest task occurred during website visualization, where latency occasionally increased to ten seconds under poor network conditions. However, this did not affect data accuracy or system stability. The cloud synchronization via Firebase remained consistent, ensuring that all BMI data were transmitted successfully and displayed in real time.

The consistent task success rate of 100% across 25 users demonstrates that the prototype functions reliably under repeated use. Minor variations observed were due to external factors such as user position or network connectivity, not software or hardware malfunction. These findings confirm that the system's operational workflow is stable, user-friendly, and responsive, meeting the functional requirements for small-scale deployment in public or institutional health settings.

Usability and User Satisfaction Evaluation

Usability testing was conducted to assess user experience, ease of use, and system satisfaction after multiple trials of the BMI monitoring process. Two standard evaluation tools were used: the System Usability Scale (SUS) and the End-User Satisfaction (ESU) questionnaire. Both assessments involved the same 25 participants who completed the device testing session.

The SUS instrument provides a quantitative measure of overall usability through 10 statements rated on a 5-point Likert scale (Hyzy et al., 2022; Sulistiyono et al., 2023). The results, summarized in Table 4, show that the system achieved an average score of 82.5, which falls within the "Excellent" usability category (Maudina et al., 2024; Nugraha et al., 2025). This indicates that participants found the device easy to operate, reliable, and intuitive to use repeatedly. The lowest-rated aspect was related to system complexity (mean score 3.9), while the highest-rated item was ease of use (mean score 4.7). These findings suggest that the system effectively supports seamless user interaction with minimal learning effort.

Table 4. Summary of System Usability Scale (SUS) results

No.	Evaluation aspect	Mean Score (0 - 100)	Interpretation
1	Overall SUS Score	82.5	Excellent usability
2	Perceived Ease of Use	4.7 / 5	Users found the device highly intuitive
3	System Complexity	3.9 / 5	Minor adjustment required for first-time users
4	Learnability & Confidence	4.5 / 5	Users quickly learned and trusted system operation

The ESU questionnaire further evaluated user satisfaction across six key indicators: functionality, ease of use, performance, information clarity, aesthetic design, and overall satisfaction. As summarized in Table 5, the mean score across all indicators was 4.6 out of 5, categorized as "Very Satisfied." The highest scores were recorded for performance (4.7) and information clarity (4.8), reflecting strong user appreciation for the device's responsiveness and the clarity of displayed data. Aesthetic design scored slightly lower (4.3), suggesting opportunities for improving the interface's visual appeal and ergonomics (Abolghasemi et al., 2021; Ameen et al., 2024; Ihsan & Kurniadi, 2025).

Table 5. Summary of End-User Satisfaction (ESU) Results

No.	Indicator	Mean Score (1 - 5)	Interpretation
1	Functionality	4.5	Very Satisfied
2	Ease of Use	4.6	Very Satisfied
3	Performance	4.7	Very Satisfied
4	Information Clarity	4.8	Very Satisfied
5	Aesthetic Design	4.3	Satisfied
6	Overall Satisfaction	4.6	Very Satisfied

The combined results of the SUS and ESU evaluations confirm that the BMI monitoring system is highly usable and well-received by users. The overall user feedback emphasizes ease of operation, quick response, and clear data presentation, validating the design's effectiveness in supporting real-time health monitoring activities. Minor improvements could focus on refining the visual layout to enhance long-term user engagement.

Technology Readiness Level (TRL) Evaluation

The prototype's readiness was analyzed using the Technology Readiness Level (TRL) framework to assess its maturity stage in the product development process. As summarized in Table 6, each TRL criterion from basic concept formulation to prototype demonstration—was systematically validated through laboratory and field testing (Koo & Jeong, 2024). The TRL framework, as defined by the U.S. Department of Energy (DOE) and the European Space Agency (ESA), provides a structured measure of how close a technology is to real-world deployment Levels range from initial conceptualization (TRL 1) to a fully operational system (TRL 9) (Olechowski et al., 2015).

Based on the results of experimental validation, user trials, and usability testing, the developed IoT-based automatic BMI monitoring system achieved TRL 6, classified as "prototype demonstrated in a relevant environment." This level indicates that all core subsystems—hardware, firmware, and cloud-based software have been successfully integrated and verified under realistic operating conditions. Testing with 25 participants confirmed reliable sensor accuracy (< 3 % error), stable cloud connectivity via Firebase, and excellent usability (SUS = 82.5; ESU = 4.6). These outcomes collectively validate the system's technical robustness and readiness for small-scale deployment in institutional or public health environments.

Table 6. Summary of TRL assessment criteria and status

No.	TRL Level	Description	Project status
1	TRL 1	Literature review and concept formulation	Completed
2	TRL 2	Functional design and system architecture defined	Completed
3	TRL 3	Hardware–software integration tested in laboratory	Completed
4	TRL 4	Sensor and RFID modules tested individually	Completed
5	TRL 5	All modules operated together under controlled conditions	Completed
6	TRL 6	Field-tested with 25 users; stable data transmission and high usability	Achieved
7	TRL 7–9	Requires industrial-grade packaging and clinical certification	Next Stage

The measurement accuracy obtained in this study (<1% mean error) is comparable or superior to several previous IoT-based health monitoring prototypes that reported error ranges between 1–5%. The integration of RFID authentication addresses security limitations identified in earlier systems that relied solely on manual login. Additionally, the incorporation of TRL assessment strengthens the transition from laboratory validation to institutional feasibility, a component rarely discussed in prior BMI monitoring studies. These findings suggest that combining hardware validation, usability testing, and readiness evaluation provides a more comprehensive framework for IoT healthcare device development.

Despite the strong performance demonstrated in sensor accuracy, system responsiveness, and user acceptance, several limitations should be acknowledged to guide future refinement and large-scale implementation. Sensitivity to Environmental and User-Related Factors. The ultrasonic height measurement still exhibits sensitivity to posture variations, head orientation, and hair volume (e.g., hijab, thick hair). Environmental conditions such as ceiling height, sound reflections, and sensor mounting angle may also influence measurement stability. These factors suggest the need for adaptive calibration or alternative height-sensing modalities. Dependence on Internet Connectivity for Real-Time Synchronization. Because the system relies on Wi-Fi to upload measurement data to Firebase, unstable network conditions can introduce noticeable delays in dashboard updates. Although this does not affect measurement accuracy, it may reduce usability in settings with limited or inconsistent connectivity. Incorporating local data buffering or hybrid offline–online synchronization mechanisms would enhance system robustness. Prototype-Grade Structural Durability. The current prototype employs research-scale materials such as hollow steel profiles and 3D-printed housings, which, while functional for controlled testing, may not yet withstand long-term or high-frequency public use. Transitioning to industrial-grade enclosures, reinforced sensor mounts, and weather-resistant materials will be essential for deployment at TRL 7–8. These limitations highlight important opportunities for future development to further improve measurement reliability, environmental robustness, and long-term operational performance.

CONCLUSION

This study successfully developed and validated an IoT-based automatic BMI monitoring system integrating RFID authentication and cloud-based data storage. The system demonstrated high measurement accuracy, excellent usability (SUS = 82.5), strong user satisfaction (ESU = 4.6), and achieved TRL 6 classification. The integration of secure identification, real-time cloud tracking, and formal readiness evaluation represents the primary contribution of this work. The findings indicate that the system is technically reliable and suitable for small-scale institutional deployment. Future development should focus on industrial-grade refinement and clinical validation to advance toward higher TRL levels.

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AUTHOR CONTRIBUTIONS

Conceptualization, Ratnasari Nur Rohmah; Formal Analysis, Ratnasari Nur Rohmah; Writing, Ratnasari Nur Rohmah; Editing, Ratnasari Nur Rohmah; Hardware, Catur Putra Aprilianto; Software, Catur Putra Aprilianto; Testing, Catur Putra Aprilianto and Ratnasari Nur Rohmah; Methodology, Catur Putra Aprilianto and Ratnasari Nur Rohmah; Validation, Aris Budiman; Visualization, Aris Budiman; Resources, Mohammad Nasrul Mubin; Investigation, Mokhamad Arfan Wicaksono and Nurokhim; Data Curation, Mokhamad Arfan Wicaksono and Nurokhim.

CONFLICTS OF INTEREST

The author(s) declare no conflict of interest.

USE OF ARTIFICIAL INTELLIGENCE (AI)-ASSISTED TECHNOLOGY

The authors declare that no artificial intelligence (AI) tools were used in the generation, analysis, or writing of this manuscript. All aspects of the research, including data collection, interpretation, and manuscript preparation, were carried out entirely by the authors without the assistance of AI-based technologies.

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