Iot-Based Smart Intravenous Therapy System

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ABSTRACT

The healthcare industry continues to struggle with manpower shortages, a challenge that is particularly severe in Malaysia, where only 5% of public hospitals have adequate staffing. To address this issue, researchers have explored the use of the Internet of Things (IoT) in healthcare to improve patient monitoring efficiency, yielding promising results. This study aims to design and develop an IoT-based smart intravenous (IV) therapy monitoring system to help mitigate the manpower shortage in Malaysia’s healthcare sector. The system provides real-time monitoring of IV therapy status and sends alerts to nurses remotely, reducing the need for frequent bedside visits. The study follows a machine design approach, encompassing the development of mechanical components, electrical circuits, and firmware. A three-layer cloud-based architecture, supported by the Blynk IoT platform, was implemented, with the ESP32 microcontroller enabling wireless connectivity. Cost-effective sensors and components were integrated to ensure economic feasibility. The prototype successfully streams real-time transfusion data to remote devices via the Blynk IoT platform and notifies users when intervention is needed, such as when the fluid level drops below a set threshold. In conclusion, this study successfully developed a low-cost, IoT-enabled smart IV therapy monitoring system that enhances patient monitoring efficiency while reducing the burden on healthcare staff. Future work will focus on improving system reliability, adding more features, and testing it in hospitals.

INTRODUCTION

The healthcare industry is commonly known to struggles with manpower shortage in a global scale, [1, 2]. In Malaysia, this problem is particularly acute, with only 5% of public healthcare facilities have sufficient staff to care for patients [3]. To address this manpower issue, researchers and pharmaceutical companies have been working on various solutions to reduce the dependency on human labor, and one emerging trend is the use of remote health monitoring system [4].

This remote monitoring system operates on Internet of Things (IoT) and assist medical caregivers by continuously monitoring patient’s condition, thus reducing the need for frequent patient room visits, and improving quality of patient care. For instance, the Philips IntelliVue Guardian solution (

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Figure 1) is a system that automates vital signs measurement and is proven to reduce occurrence of cardiopulmonary arrest of users by 86% [5]. While the initial capital to implement the system is astoundingly high, experts believes that IoT is a remedy for the increasing demand of manpower.

Figure 1: Philip IntelliVue Guardian Solution (Left: Machine, right: Software) [6], [7]

Despite the advantages, the implementation of IoT in healthcare industry is still minimal due to multiple reasons such as data privacy concerns, high initial capital, and unfamiliarity to new technology. To address these issues, this study proposed a design to implement IoT systems in less critical areas, such as Intravenous Drip therapy. Intravenous (IV) drip therapy is a medical technique that delivers medications, fluids, nutrients directly into a patient's vein using a needle/cannula.

The design of IV therapy is rather successful, but the administration of IV therapy involves frequent change of IV bottles. This would require constant supervision of medical staff. However, in a situation where large group of patients receive different types of IV therapy, it is difficult to perform comprehensive monitoring. Additionally, there are circumstances where patient is unable to alert the medical staff (unconscious, children, etc.) when the IV bottle needs to be changed. If the bottles are not replaced in time, the blood would backflow, causing a blocked cannula that induces inflammation, extravasation, and infection risks. The blocked cannula must be replaced with a new one, which wastes time, resources, and causes discomfort to the patient.

Objectives

The aim of this study is to design and develop an IoT-based smart intravenous (IV) therapy monitoring system for use in hospital wards. To achieve this, the study focuses on two key objectives. First, it aims to develop a system that can monitor IV therapy in real time and send alerts to nurses at remote locations, reducing the need for frequent bedside visits. This helps optimize staff efficiency while ensuring timely intervention when needed. Second, the study seeks to enhance the overall machine design by prioritizing ease of use, ease of maintenance, and cost-effectiveness. By considering these factors, the system can be more practical for hospital implementation, ensuring accessibility and long-term usability.

LITERATURE REVIEW

Application of Healthcare IoT

A group of Iran researchers [8] suggest that IoT is widely used in remote patient monitoring, wearable devices, telemedicine and smart healthcare systems. It claims that application of IoT is able to reduce hospital readmission rates by up to 20%.

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This is supported by another study from Spain [9], where it suggests that IoT applications significantly improved remote patient monitoring, reducing hospital visits by 25% and hospital stay duration by 30% due to timely intervention. Additionally, the application of IoT also led to a 20% improvement in diagnostic accuracy and 15% reduction in treatment cost.

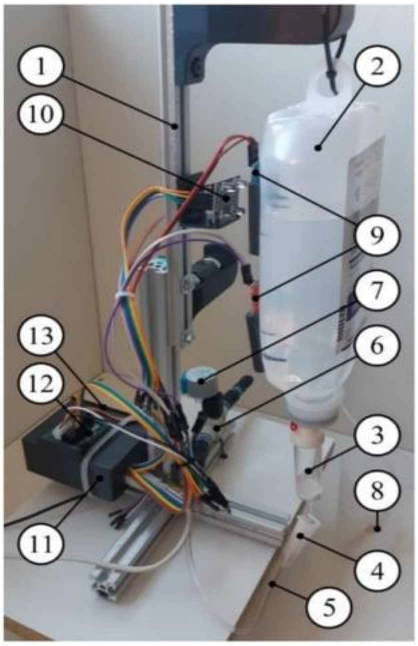
Another systematic review conducted by Aghdam Z et al. [10] identified the advancement, applications, and future challenges of Healthcare IoT (H-IoT). In general, H-IoT is able to facilitate vital signs monitoring (ECG, Blood pressure, Glucose level etc), managing chronic diseases, and ensuring medication adherence.

Fluid level Detection Method

In the work of [11], the scholars introduced an IoT system with ultrasound, temperature sensor to detect fluids levels in the IV bag. The system can be connected wirelessly by Wi-Fi/cellular systems, and it will send alert signal to the responsible medical staff through Short Messages Service (SMS). On the other hand, the article [12] proposed a similar design, which measure fluid level inside the IV bottle via NPN transistor, and alert medical staff via buzzer and messaging facility.

In volume 102 of "*Microelectronics Reliability*" written by [13], a system which involves an optical sensor with a lens for measuring the number of drops of liquid through the drip chamber is presented. The sensor will communicate via Bluetooth with a microcontroller that produces an alarm at the appropriate time.

The work conducted by [14] shows an IoT system with a combination of capacitive sensors and colour sensors to monitor the fluid level in IV bottle (see Figure 2). The capacitive sensors were used in pairs, attached to the upper side and lower side of bottle to detect MAX and MIN level of fluid. Whereas the colour sensor was used to identify the fluid colour in the bottle, indicating the type of fluid being infused. The system also incorporates a stepper motor that would turn off the infusion flow when the IV bottle is empty, to avoid backflow of blood.



No.	Part
1	pole/stand
2	saline bottle
3	drip chamber
4	roller clamp
5	IV tubing
6	valve VHK2–08f–08f
7	stepper motor 28BYJ–48
8	cannula
9	capacitive levelsensor for Arduino
10	color sensor TCS230
11	microcontroller Arduino Uno and Wi-Fi module NodeMcu ESP8266
12	motor driver 2PH64011A
13	display LCD 12864

Figure 2: System Configuration of IV Infusion dosing system [14]

Next, in the study of [15] load cell sensors were used to measure the weight of IV bottle, hence detecting the remained liquid level. The system runs on a 12V D.C. battery, with an LCD to display the status of fluid level, a buzzer to alert nurses and a 1kg load sensor. On top of that, another group of scholars from India [16] combines the use of load cell for measuring the weight of IV bottle, and a heartbeat sensor to reduce the chance of heart attack due to air embolism. The heartbeat sensor was placed before the cannula to detect the presence of embolism.

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The work above shows good examples of how different sensors could be used to achieve the same target. Yet they share the same issue where the product was not in a fully developed state, and all the results shown stops at breadboarding phase. An ideal machine should be enclosed properly to ensure the stable operation of it.

While existing studies have explored various sensor technologies such as ultrasound, optical, capacitive, and load cell sensors for IV fluid monitoring, they often focus on proof-of-concept models without extensive validation in clinical settings. Additionally, most systems lack integration with user-friendly IoT platforms, limiting their real-world deployment. This study aims to bridge this gap by developing a fully enclosed, deployable prototype with a cloud-based architecture for real-time IV fluid monitoring, improving accessibility and usability in hospital environments.

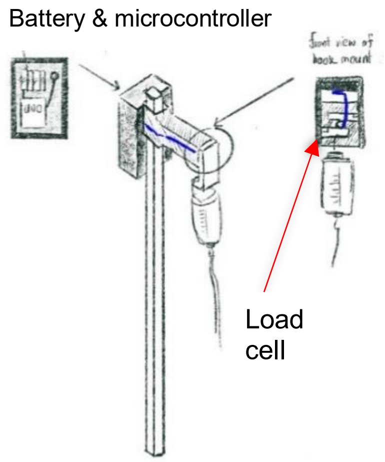
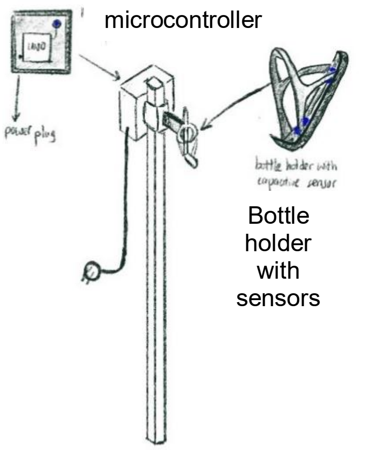
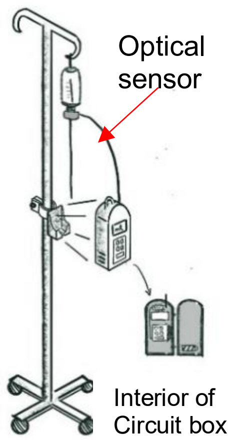
METHODOLOGY

Conceptual design

Three sketchers of the conceptual designs for the machine were designed and shown in

Table 1. The sketches were made by referencing the previous designs proposed and developed in previous articles. The crucial point in designing the machines is the choice of microcontroller, sensor, and power supply.

Table 1: Proposed Design for Smart IV Therapy System

Design I	**Design II**	**Design III**
		
- Uses Arduino UNO - Supported by Battery - Hook-like mounting - Uses load cell sensor	- Uses Arduino UNO - Supported by Power plug - Sleeve-like mounting - Uses Capacitive sensor	- Uses Raspberry Pico - Supported by Battery - Modular mounting - Uses Optical sensor

These designs were rated with Pugh chart in **Error! Reference source not found.** to aid the decision-making p rocesses. The chart compares the designs against a set of criteria (Weight, Size factor, Mobility, Cost of fabrication, Data processing ability, Ease of fabrication, and Connectivity). The results shows that Design II has the best overall score, and it is refined with Computer Aided Design software, SOLIDWORKS.

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Table 2: Decision Matrix for Proposed Design

	Proposed Design Alternative			
Criteria	**Weightage**	**Design I**	**Design II**	**Design III**
Weight	15	-	0	-
Size factor	20	0	+	0
Mobility	20	0	-	0
Fabrication cost	15	-	0	0
Data processing ability	15	+	+	0
Ease of fabrication	10	0	0	-
Connectivity	5	0	0	+
sum of '+'		1	2	1
sum of '0'		5	3	4
sum of '-'		1	2	2
Net score		-15	0	-20

Computer Aided Design

Some modifications in design have been made to the initial design due to the concern of fabrication difficult and user experience. The modification includes relocating control panel (circuit box) to the side of device, replacing the bag holder with a saline hook.

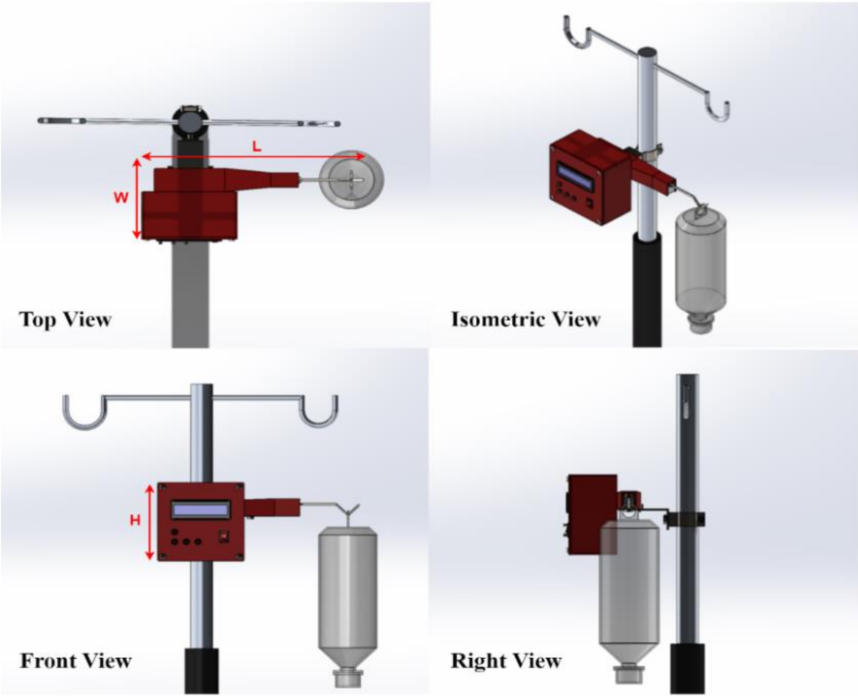

Figure 3: CAD model of the prototype

Figure 3 shows the complete design of the prototype, with a dimension of (L) 242 mm × (W) 160.4 mm × (H) 104 mm, and an estimated weight of 411.86 g (excluding miscellaneous components). The parts are mainly formed by Polylactic Acid and Mild Steel, where 3D rapid prototyping and metal working machines were used to fabricate the parts.

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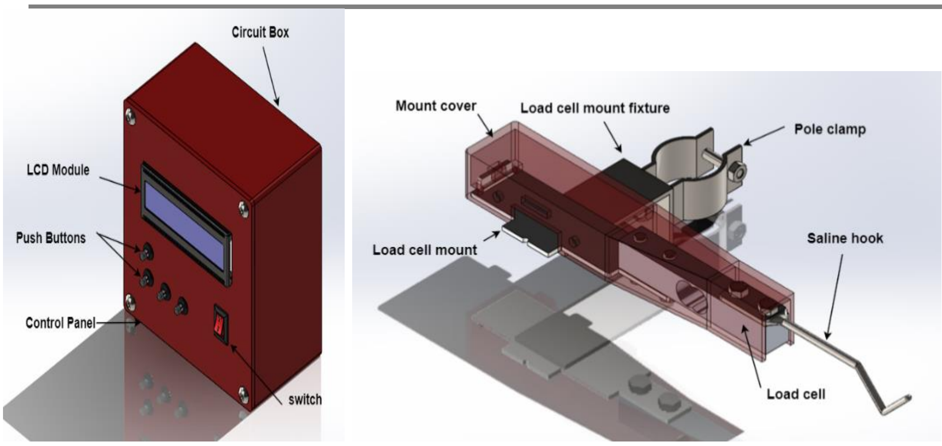

Figure 4: Subassemblies of Prototype

Figure 4 illustrates the subassemblies and the label for each part. The parts can be group into two subassemblies: the circuit box (left figure), and pole mount assemblies (right figure)

Electronic Design

Figure 5 illustrates the circuit diagram of the prototype. The initial plan was to use the Arduino UNO or Raspberry Pi Pico as the microcontroller. However, the ESP32 WROOM-32 module appeared to be a better option due to its smaller form factor, integrated WiFi feature, and lower cost. Thus, the ESP32 module was chosen as the microcontroller for this study.

Additionally, a 3.7V Lithium-Ion rechargeable battery was added to the system to enhance the device's mobility. Furthermore, an active buzzer was included to alert patients and medical caregivers in close proximity when the transfusion fluid is running low.

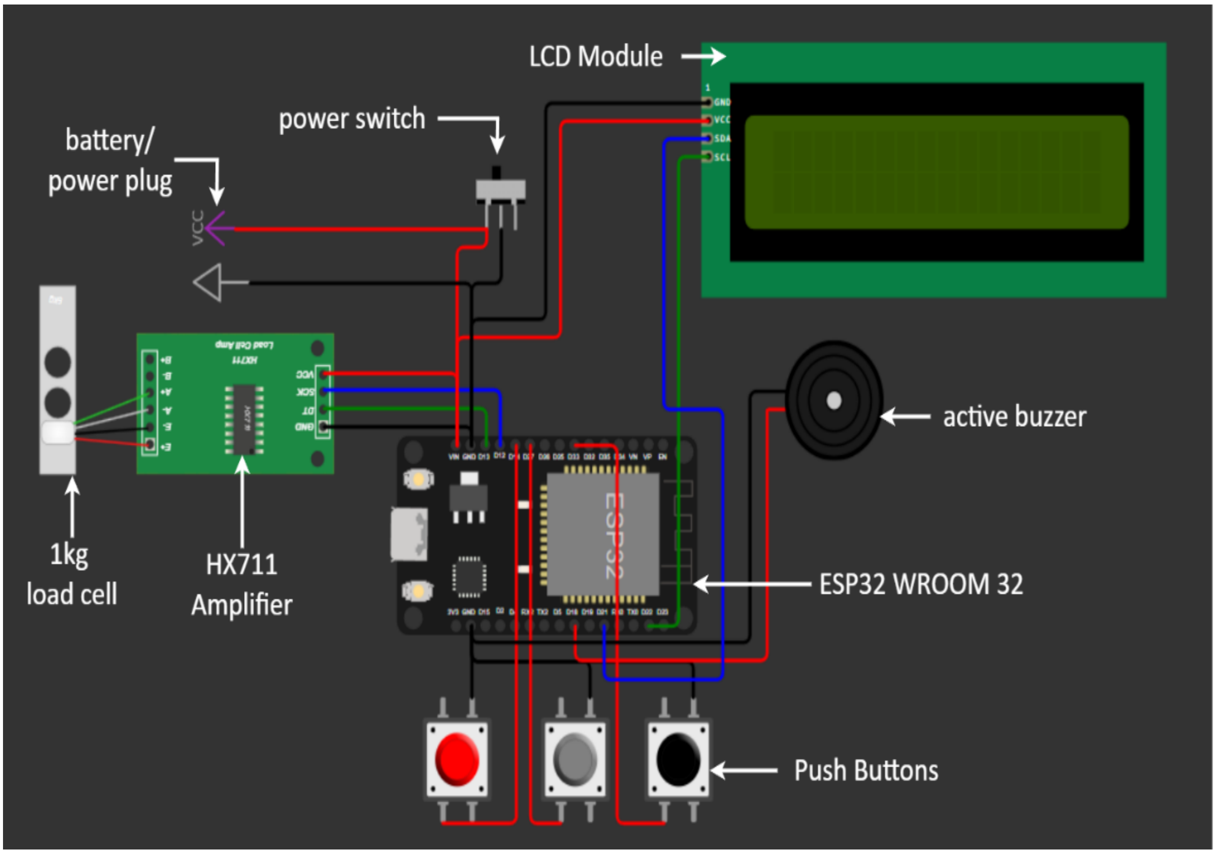

Figure 5: Proposed Circuit Diagram (Plotted with Wokwi.com)

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Three push buttons are integrated to allow the user to interact with the microcontroller. Each button has its respective function, enabling users to reset parameters (Red), select fluid variables (Gray), and confirm the selection (Black). The total cost for components and material is approximately MYR 116.20, which is considerably low, and large volume production could further compress the cost.

Firmware Development

Figure 6 depicts the flowchart of prototype firmware. The process can be divided into two stages. The first stages would connect the prototype to internet, allow user to input transfusion fluid parameters (type, flow rate). At the next stage, the prototype would transmit the measured weight of fluid continuously, and trigger notification when necessary.

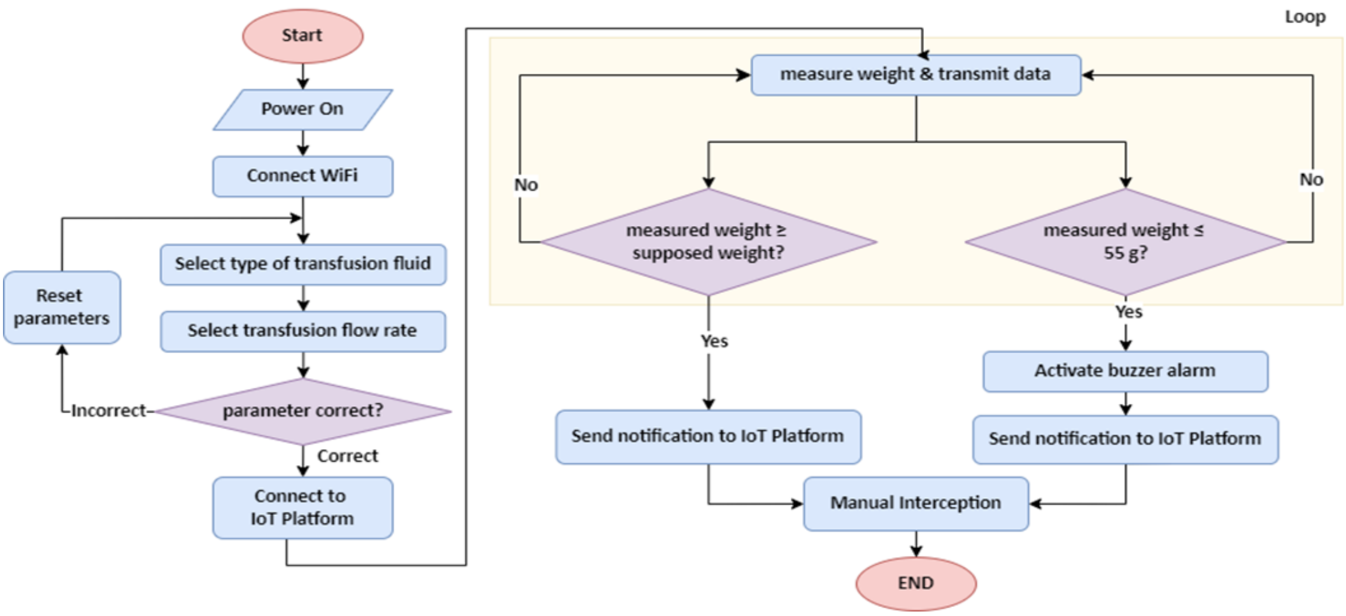

Figure 6: Flowchart of prototype firmware

When powered on, the firmware would connect to WiFi. Next, the user would be prompted to select type of transfusion fluid (i.e. blood, saline) and transfusion flow rate (i.e. 7 drop/min, 14 drop/min) through the LCD module. The selection and confirmation of variables is done by pressing the push buttons. Before moving to the next stage, the parameters would be displayed again for confirmation, and can be reset if needed.

Moving on, the firmware initiates a weight measuring loop and continuously upload weight reading to IoT cloud. The loop will then trigger a notification when the weight of transfusion fluid is lower than the threshold (i.e. 55 g), or the weight of fluid is higher than the supposed weight (implying an affected flow rate). The caregiver can then interfere and assist with the problem.

Trial run of prototype

To validate the performance of prototype, two trial run is conducted to study its accuracy and precision under different circumstances.

Single-time constant weight measurement

After measuring the weight of saline bottle with a digital coffee scale (accuracy ±0.1g), the bottle is placed on the hook of prototype, and a series of 7 data is randomly sampled over the duration of 2 minutes. The prototype is then rebooted, repeating the measuring process and obtain another group of 7 data. The data is used to calculate the accuracy and precision of prototype.

Long-term continuous weight measurement

A saline bottle is placed on the hook and punctured to allow the fluid flow in a rate of 28 drop/minute. The fluid is collected within a container and weighted with the digital coffee scale for every 5 minutes. This process is continued for a period of 60 minutes. The reading from the prototype is then compared with the coffee scale to access its performance.

RESULTS & DISCUSSION

Final assembly

Figure below shows the final assembly of prototype. The prototype has a dimension of 274×173×104 mm (L×W×H) and weight approximately 558 g.

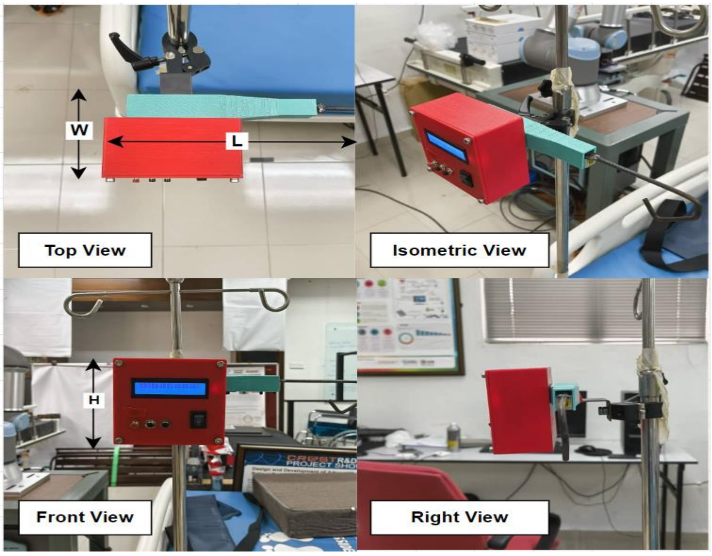

Figure 7: Final Assembly of Prototype on IV pole

IoT Architecture

Figure 8 depicts the IoT architecture implemented on the prototype. It is a fundamental three-layer Cloud-based architecture. When the prototype is turned on, the microcontroller would connect to WiFi, and then transmit the transfusion parameters (weight reading, transfusion type, transfusion rate) to Blynk IoT Platform via Internet and Blynk Cloud. Each parameter would require a data channel to transmit.

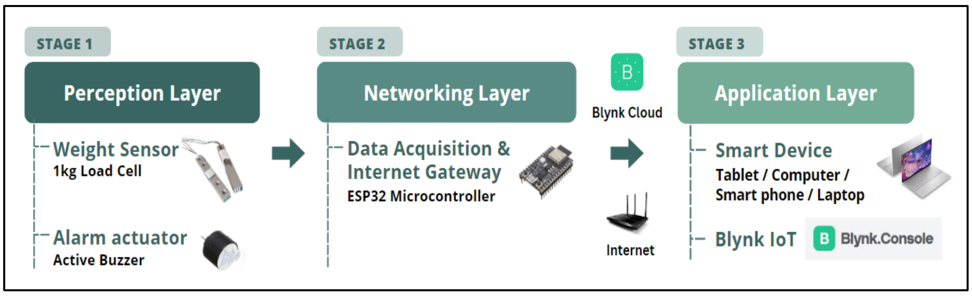

Figure 8: Proposed Cloud-based IoT Architecture

Figure 9 illustrates the outcome of IoT Architecture on Blynk Application. As shown in figure (a), the user would be able to monitor real-time weight level and other fluid parameters. Additionally, when the saline bottle is removed, and the weight stopped changing the prototype would trigger a notification through application and email (figure b, c)

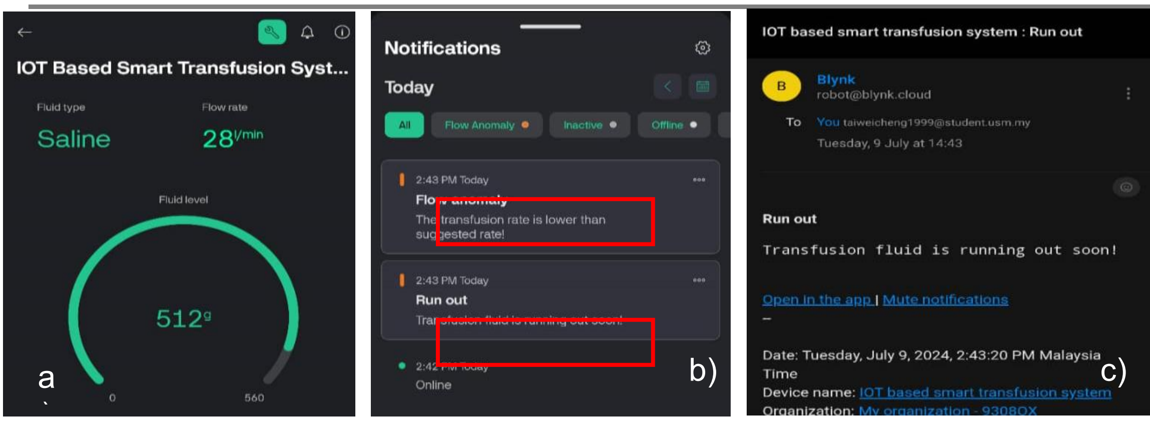

Figure 9: Outcome of IoT Architecture

(a) Real-time weight level, (b) Notifications of fluid run out & flow anomaly, (c) Email notification

Performance Validation

Table 3 shows the accuracy of trial run discussed in pg.2541. The result shows that the deviation between reading falls in a range of ± 0.25g, and the average accuracy of the measurement is 99.998%. Additionally, the coefficient of deviation is extremely low (0.01287%). This result indicates a highly accurate and precise performance.

Table 3: Results of Single-time constant weight measurement

Reading	Weight (g)	Actual Weight (g)	$Accuracy_i$ (%)
1	555.11	555.2	99.984
2	555.15	555.2	99.991
3	555.18	555.2	99.996
4	555.19	555.2	99.998
5	555.24	555.2	99.993
6	555.21	555.2	99.998
7	555.29	555.2	99.984
8	555.35	555.2	99.973
9	555.25	555.2	99.991
10	555.28	555.2	99.986
11	555.36	555.2	99.971
12	555.18	555.2	99.996
13	555.31	555.2	99.980
14	555.22	555.2	99.996
	Average Accuracy (%)		**99.988**

For the second trial run, the weight reading from the prototype (W_{ptp}) and digital coffee scale (W_{cs}) is tabulated in **Error! Reference source not found.**. Additionally, a few metrics are added to evaluate the measurements error during trial run:

$$\text{Weight difference of prototype, } \Delta W_{ptp} = W_{ptp,i} - W_{ptp,i-1}$$

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Weight difference of digital coffee scale, $\Delta W_{cs} = W_{cs,i} - W_{cs,i-1}$

Measurement Error $= \Delta W_{ptp} - \Delta W_{cs}$

With the equations above, the performance is calculated and visualized in Figure 10 and Figure11.

Table 4: Outcome of long-term continuous weight measurement

Time (min)	W_{ptp} (g)	W_{cs} (g)	ΔW_{ptp} (g)	ΔW_{cs} (g)	Error (g)
0	527.5	527.5	0	0	0
5	521.1	521.2	6.4	6.3	0.1
10	514.5	515.0	6.6	6.2	0.4
15	508.2	508.8	6.3	6.2	0.1
20	501.9	502.6	6.3	6.2	0.1
25	495.4	496.4	6.5	6.2	0.3
30	489.0	490.2	6.4	6.2	0.2
35	483.1	484.0	5.9	6.2	0.3
40	476.7	477.7	6.4	6.3	0.1
45	470.3	471.5	6.4	6.2	0.2
50	464.0	465.3	6.3	6.2	0.1
55	457.5	459.1	6.5	6.2	0.3
60	451.2	452.9	6.3	6.2	0.1

The linear graph in Figure 10 implies that the measured weight change for both devices is consistent. However, a closer examination of Table 4 reveals that the prototype has lower precision. The readings of coffee scale only vary in a range of 0.1g, but the reading of protype varies in a range of 0.7g.

Moreover, there is a 0.4% difference between the final readings. By extrapolating this difference ($difference \times operating\ hours$), it is possible that the difference would scale up to 4.8% after a 12-hour transfusion. This would lead to a negative 26.65g (556.2g × 4.8%) weight difference, implying that the prototype might falsely trigger the 'Run out' notification upon long period of operation.

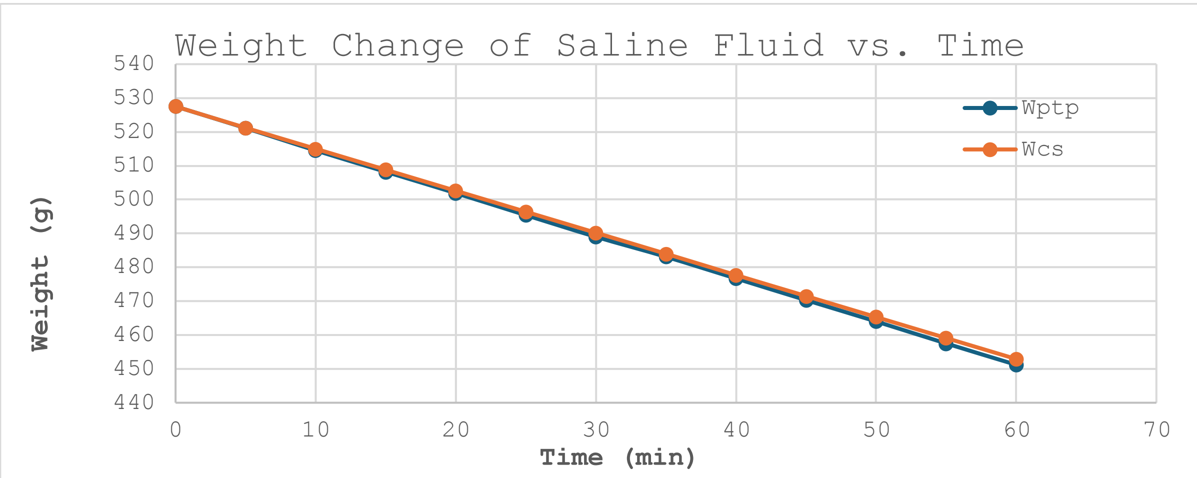

Figure 10: Weight Change of Saline Fluid vs. Time (Prototype & Coffee scale)

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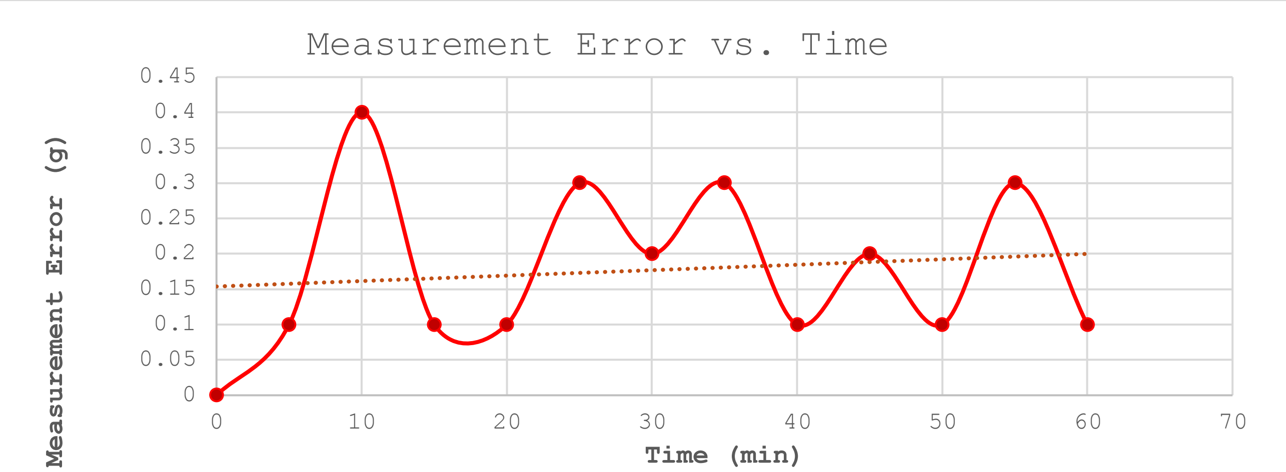
Additionally, a fluctuation in measurement error is observed. Figure11 shows that the errors are constantly ≥ 0.1g, half of the error is above 0.2g and a maximum error of 0.4g were recorded.

Figure11:Weight Change of Saline Fluid vs. Time



Discussion on Performance

The comparison between the performances of trial runs is rather paradoxical. The first trial run implied that the prototype has excellent performance when measuring constant weight, but the second trial run indicates the prototype is unreliable in long-term measuring, with fluctuating measurement error.

To explain this contradicting performance, several studies of related topic have been reviewed. The review infer that long-term continuous weight measurements often have higher errors than single-time measurements due to factors such as dynamic effects on the weight sensor, environmental influences, and propagation of uncertainty.

Dynamic effects on weight sensors are mainly caused by the physical movement of the materials being weighed, environmental influences, and the inherent characteristics of the sensors. In the study of Mansur and Pershin [17], the effect of dynamic motion to continuous weight measuring is examined, and the researchers conclude that dynamic motion would introduce vibration or fluctuation that disturbs sensor reading, leading to inaccurate measurement. In a hindsight, the experiment was conducted in a windy circumstance where the saline bottle would occasionally sway. This probably causes the inconsistent measurements, as the saline hook is more susceptible to the effect of dynamic motion, while digital coffee scale is not.

On the other hand, propagation of uncertainty is a common problem in continuous measurement. As human error, environmental issue, and inherent uncertainties of sensor induced measurement errors. the errors would compound in continuous measurement and led to a cumulative inaccuracy [18].

In summary, continuous measurements are more susceptible to reliability and uncertainty issues, where cumulative errors can be induced by environmental conditions and sensor characteristics. This risk was overlooked throughout the study development, and expertise in control feedback systems would be needed to address this issue, which future research should explore.

Regulatory and Ethical Considerations

The adoption of IoT-based medical devices in healthcare is subject to various regulatory and ethical considerations. Compliance with medical device regulations, such as Malaysia's Medical Device Act 2012 (Act 737) and international standards like ISO 13485 for medical device quality management, is crucial to ensure patient safety and data security. Additionally, IoT systems handling patient data must adhere to health data privacy laws, such as Malaysia's Personal Data Protection Act (PDPA), to prevent unauthorized access and data breaches.

From an ethical standpoint, IoT-driven healthcare solutions or devices might raise concerns regarding patient consent, data ownership, and reliance on automated monitoring. Ensuring that medical staff retain decision-making authority and that IoT integration does not replace but rather complements human oversight is critical for ethical implementation. Future work should focus on addressing these challenges by incorporating robust cybersecurity measures, encryption protocols, and transparent patient data handling policies to facilitate regulatory approval and ethical acceptance in healthcare settings.

CONCLUSION

This study developed an IoT-based smart IV therapy monitoring system that allows nurses to monitor the real-time weight level of transfusion fluid through a low-code IoT platform (Blynk IoT). This platform can be accessed via computer, laptop, and smartphone, which significantly improves data accessibility. Moreover, the system can alert nurses through an integrated buzzer and push notification, email, or SMS when the transfusion fluid reaches the lowest threshold, or when the transfusion flow rate is abnormal (slower than predetermined transfusion rate). This system reduces the need for frequent supervision, allowing the hospital to reallocate human resources for other critical activities.

Additionally, the prototype is low-cost, mobile, and easy to set up. The accuracy of prototype in long-term continuous weight measurement needs to be improved by using higher-quality sensors and modifying the

electrical wiring to prevent noise in signal feedback.

While the proposed IoT-based smart IV therapy system has demonstrated feasibility in controlled environments, future research should focus on enhancing its capabilities through machine learning (ML) integration. By leveraging ML algorithms, the system could predict IV fluid depletion rates, detect anomalous infusion patterns, and optimize sensor calibration to improve accuracy over extended use. Predictive analytics could also help healthcare providers preemptively schedule IV replacements, further reducing the burden on medical staff.

Moreover, real-world pilot testing in hospital settings is crucial to validate the system's performance under practical conditions. Conducting clinical trials across multiple hospital wards would provide insights into operational challenges, usability issues, and system reliability in diverse healthcare environments. Such testing would also facilitate regulatory approval and foster adoption within existing hospital infrastructure.

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