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IoT-Enabled Adaptive Control and Real-Time Mobile Monitoring of an LPG-Fueled Smart Poultry Incubator for Precision Hatchery Management

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ABSTRACT

Problem: *Global poultry production needs to rise by 70% by 2050 to meet growing demand for animal protein, but current hatchery techniques in resource-limited areas are hindered by technological shortcomings which reduce hatchability, raise embryonic mortality and make them economically unfeasible because of unreliable electricity supplies and limited environmental control.*

Research Gap:*Although there has been progress in the development of incubation systems that are wireless and connected to the Internet, two major issues remain: (1) hatchability outcomes vary widely reported from 78% to 94.8% without any systematic comparative data on which to base evidence to optimize these systems, especially those powered by LPGs in off-grid settings, and (2) lack of adaptive control architectures capable of meeting the changing physiological needs of developing embryos throughout incubation.*

Purpose: *This study was designed, developed, and empirically tested an adaptive LPG-fuelled smart poultry incubator with predictive developmental modeling, multi-sensor IoT network, thermal energy storage and real-time mobile monitoring.*

Methods: *The three replications of this controlled experimental design were 420 eggs in each case, in an adaptive LPG system (treatment) and in a conventional fixed-setpoint electric incubator (control). Temperature/humidity stability, hatchability, chick quality, energy consumption, system responsiveness, and user acceptance were evaluated using independent t-tests, Mann-Whitney U tests, effect size calculations, and thematic analysis.*

Findings: *The adaptive system had a hatchability of 95.8% which is 8.9 percentage point higher than conventional (86.9%), a temperature stability of ±0.25°C (vs. ±0.65°C), a humidity stability of ±2.1%RH (vs. ±5.3%RH), and was able to complete the critical humidity increase during hatching. Operating cost cut by 47.8%, Cost per chick by 53.2% and System responsiveness was 3 times faster. The acceptance by the users was very high, operators felt more confident and less stressed in their operations.*

Implications: *The adaptive control architecture represents a transformative strategy for precision hatchery management under resource constraints enabling smallholder farmers to achieve commercial grade hatchability at lower operational costs, greater energy reliability and quality of chicks, thus contributing to sustainable intensification of poultry production and food security in developing economies.*

Originality: *This study introduces an adaptive control architecture for LPG-fuelled incubation systems, which is the first empirically validated one, specifically designed for this kind of systems, and based on predictive developmental modelling and real-time monitoring through the IoT in an open, reproducible and low-cost architecture.*

Keywords: *IoT-Enabled Monitoring; Adaptive Control; LPG-Fueled Incubation; Poultry Hatchery Management; Hatchability Optimization*

1. Introduction

By 2050, when the global population is projected to reach 9 billion, the demand for animal protein will require a 70% increase in poultry production. Yet current hatchery practices remain hampered by technological limitations that constrain productivity and economic viability. The production of poultry has become a serious food security problem due to its availability of low cost and efficient source of animal protein. In this context, the activities in hatcheries are the basic and key in the poultry value chain which the success of the hatching process affects the size of the flock, the efficiency of production and the economic realization of a poultry business. Artificial incubation of poultry eggs requires careful control of the environmental parameters, such as temperature, humidity, ventilation and egg turning, all of which must be closely controlled within very narrow limits to ensure normal embryonic development and hatchability. The correlation with sub-optimal conditions is reduced hatchability, increased embryonic mortality and poor chick quality. Such results lead to economic losses that trickle down the entire production chain. Both natural brooding and manual mechanical incubators have intrinsic constraints in their ability to maintain the optimum environment, especially in grids with poor reliability and technical skills. These limitations have spurred the emergence of smart incubation technologies which combine automation, real-time sensing and networked communication to provide precision control of the incubation microenvironment.

The Internet of Things (IoT) and the low cost embedded systems' and mobile communication technologies that helped achieve this integration pave way for a new generation of smart poultry incubators that could revolutionize the poultry hatchery management system. In recent years, the environmental monitoring and control of poultry incubation based on IoT systems have been used. In order to improve the hatch rate, Saludo et al. (2025) developed a smart incubator called Intelli-Egg, which automatically adjusts the incubator's environmental parameters, remotely monitors the incubator, and determines egg fertility using an image-based method. Likewise,

Abdullahi (2025) designed and built an egg incubator which is solar-grid powered with Proportional-Integral-Derivative (PID) controllers with the introduction of GSM based IoT for mobile alerts to operate sTable temperature of ±0.3°C and humidity of ±2.5%RH. The results from the two consecutive trials with the "HatchMore" system using the Bluetooth Low Energy (BLE) technology showed hatchability rates of 91.30% and 94.44%, respectively, and confirmed that BLE-based mobile monitoring is a viable option. The fuzzy logic-based control methods have also been widely studied and Mamdani fuzzy inference system has been used to control the temperature and humidity by dimmable incandescent lamps to overcome the phenomenon of natural on/off switching of the classical control methods. Furthermore, the application of machine learning for the recognition of egg damage and the application of neuro-fuzzy systems for adaptive regulation of the environmental conditions are still novel research fields in the field of intelligent incubation. To conclude, the present studies have demonstrated that the systems designed and developed for IoT-enabled incubation are feasible to be implemented and can result in more stable parameters and hatchability values than the traditional ones.

Although these developments are positive, a systematic review of the literature shows there are two major gaps in knowledge that hinder the implementation of the fully optimised and context-relevant smart incubation system. The first gap relates to the significant differences in reported hatchability results among the different implementations of IoT in incubators, and the lack of systematic comparative data to optimize the design of the incubator based on evidence. Other implementations have reported more moderate results with IoT-based system described in the International Journal of Software Engineering and Computer Science reporting 92% hatchability, compared to 85% for conventional systems. Although the platforms employed are similar, there are significant differences in hatching success, for duck eggs a hatchery efficiency of 80% was reported for 2025, while the incubator is a hybrid solar/LPG with thermal energy storage built using beeswax, which reported a hatchery efficiency of 70%. The difference in performance shows that existing IoT incubation systems are not optimised. The reasons for the accuracy of the sensor, the effectiveness of the control algorithm, design of the thermal management system and the characteristics of the fuel source are not fully understood. There are no common benchmarking protocols or extensive comparative studies to help identify best practices and systematically improve incubation system design.

The second knowledge gap is even more profound: no adaptive control architectures are known that can change with the evolving physiological requirements of the developing embryos during the incubation period. Fixed setpoint control strategies that keep the temperature and humidity at 37.5°C and 55–60%RH, respectively, throughout the incubation period, or rule-based fuzzy logic controllers are commonly used in most of the current digital incubation systems. These methods, which are more responsive than on/off controllers, do not consider the time-varying metabolic needs of the embryos at various stages of development. Chicken eggs take 21 days to hatch, during which their metabolism, heat generation and water loss are not linear, and require adjustment of environmental inputs accordingly. For instance, humidity is conventionally increased from 50-55 % to 60-65 % in the last three days prior to hatching, but existing control systems are unable to optimise these parameters in real-time according to indices of embryonic development. To overcome this limitation, some commercial systems have started to adapt humidity and CO_2 for each batch via software, but these solutions are proprietary, expensive and not suiTable for small or medium-scale hatchery owners. However an open, validated system for adaptive incubation control that incorporates real-time sensor information, predictive modeling of embryonic development, and automated adjustment of the environment has not yet been developed and published in the literature. The situation becomes even more complicated with LPG-fuelled incubators, as the thermal dynamics of combustion-based heating require a controller with a greater number of parameters.

The present study aims to overcome these deficits by designing, developing and testing an adaptive control system for an LPG-fuelled smart poultry incubator (SPI) with real-time mobile monitoring for precision hatchery management. The proposed system is envisioned as a unified system that includes: (a) adaptive control architecture for the control of the temperature and humidity setpoints based on the developmental stage of the embryos, which is guided by a predictive model of the thermal and hygric requirements; (b) an LPG-based heating subsystem, with thermal energy storage, to ensure reliability in grid constrained environments; (c) a multi-sensor IoT network for continuous monitoring of the parameters; (d) a mobile application interface for real-time remote supervision and intervention. This setup aims to resolve the problems of performance inconsistencies found in the available incubators and lack of adaptive control functions in the available incubators, thus adding to the state-of-the-art in smart incubation technology.

The Methods involve the systematic design of mechanical incubation chamber, integration of LPG combustion with thermal buffering to ensures table heat delivery, designing an algorithm based on fuzzy logic or model predictive control principles, deployment of an IoT sensor network with cloud connectivity and deployment of a cross-platform mobile monitoring application. Evaluation of performance will be done by controlled incubation test, key parameter will include hatchability rate, energy consumption, parameter stability and parameter responsiveness of the system. The study is confined to the incubation of chicken eggs (Gallus gallus domesticus) in controlled laboratory and field settings, and limited to about 420 eggs per incubation to accommodate small scale and medium scale hatcheries.

This study has three major contributions. It is the first to offer an empirical assessment of the effectiveness of adaptive control strategies for LPG-fuelled incubations, which has not been widely studied in the literature. Secondly, it is designed as an open system to be adapted to the needs of researchers and practitioners in low resource settings and is reproducible, democratising access to precision incubation technology. Third, it sets the scene for the future hatchery management systems that will include predictive developmental modelling and real-time monitoring from the Internet of Things (IoT), which will help to transform the static to an adaptive and data-driven model. The target audience consists of researchers in agricultural engineering, IoT systems design and

precision livestock farming, hatchery operators and poultry producers with interest in increasing the productivity of poultry production, as well as policy makers and development practitioners interested in the sustainable intensification of poultry production by smallholders. This study seeks to fill the gap between the current status of incubation technology for IoT and a vision of fully adaptive and context-aware hatchery management, thereby contributing to precision poultry farming and the overall goal of sustainable food production.

2. Literature Review

Despite its significance to food security and rural livelihoods in developing countries, hatchery operations are still beset with challenges of technology and operation which limits productivity. Incubation is the foundation of the poultry value chain and directly affects flock size, efficiency in production and profitability. Eggs must be properly incubated; environmental factors such as temperature, humidity, ventilation and egg turning must be controlled within a very narrow range to ensure normal embryonic development and maximum hatchability (French, 1997; Lourens et al., 2005). Any deviation from these conditions regularly results in a decrease in hatchability, embryo mortality and chick quality, with economic consequences that reverberate throughout the production chain (Decuypere et al., 2001; Tona et al., 2003).

Integrating automation, real-time sensing and networked communication into advances in smart incubation technologies provides new opportunities for control of the microenvironment of incubation. The Internet of Things (IoT), low-cost embedded systems, and mobile communication technologies have opened the door to new generation smart poultry incubators which have the potential for changing the hatchery management (Saludo et al., 2025; Abdullahi, 2025). But a comprehensive review of the literature indicates several issues and gaps that need to be overcome to maximize the potential of these technologies. Thus, this review synthesizes knowledge on the available research in these areas and identifies research gaps and the theoretical underpinning of an adaptive smart poultry incubation system integrating IoT, LPG and smart algorithms.

2.1 Theoretical and Conceptual Foundations

Drawing on several established theoretical frameworks, an adaptive control system for a smart poultry incubator using LPG fuel is developed that can be used for the design and evaluation of the incubator.

Control theory is the basic theory for understanding and creating the regulating mechanisms critical to an incubation system. Classical control theory such as PID control has known solutions to keeping the system outputs at desired setpoints in the face of disturbances (Albert, 1999; Ogata, 2010). But the incubation process is non-linear and time varying, so more sophisticated methods are needed. Fuzzy logic control is based on the theory of fuzzy sets and approximate reasoning (Zadeh, 1965) and is a way of dealing with uncertainty and non-linearity in biological systems.The Mamdani fuzzy inference system (FIS) which is widely used in the control of Incubators (Amita et al., 2024; Seforo et al., 2024) is used in converting the expert knowledge into rule-based control strategies (Mamdani & Assilian, 1975).

Adaptive control theory is an extension of classical control theory and enables the controller to change some of its parameters when the dynamics of the system or the operating conditions fluctuate (Åström & Wittenmark, 2008). This theoretical approach is especially applicable to incubations since the thermal and hygric properties of the incubation system change as the embryos develop (Lourens et al., 2005). The model predictive control, which consists of predicting the future behaviour of a system using a model of the system and optimize the control action based on the prediction, is a promising method for adaptive incubation control (Camacho & Bordons, 2007). Further, adaptive PID controllers with the reinforcement learning approaches have been shown to achieve strong, accurate and self-learning thermal control for agricultural technology applications on low-cost hardware (Li et al., 2023).

The theory of cyber physical systems is used to understand the integration of computation, communication and physical systems of smart incubation systems (Lee & Seshia, 2017). IoT enabled smart incubator is a cyber-physical system that consists of sensors, actuators, and control algorithms which interact with the physical incubator environment. Such systems have been described theoretically and are characterized by feedback loops, timing constraints and interactions (Derler et al., 2012; Rajkumar et al., 2010).

Based on these theoretical concepts, a conceptual model of an adaptive LPG-fuelled smart poultry incubator can be presented. The adaptive control architecture is developed to be integrated into the framework, consisting of three interconnected layers: (a) the sensing layer includes a multi-sensor IoT network for continuous sensing of the various parameters involved, such as temperature, humidity, CO_2, etc.; (b) the reasoning layer processes the sensor data, applies the predictive models of the course of the embryonic development and calculates optimal control actions; and (c) the actuation layer is responsible for implementing the control actions in the form of heating, humidification, ventilation, and egg turning mechanisms (Lee & Seshia, 2017; Derler et al., 2012). The developmental model is used as the basis for reasoning and includes information on the thermal/ hygric requirements of the embryos throughout the incubation period (Lourens et al., 2005; Tona et al., 2003). LPG heating subsystems deliver thermal energy in a power constrained manner with the integration of thermal energy storage to buffer the energy supply interruptions and stabilise the thermal delivery (Musa et al., 2022; Babajide et al., 2025). Mobile monitoring interface provides live remote monitoring and intervention capabilities, providing viewers with a picture of system condition and opportunity to adjust parameters as needed (Addul & Rohaiza, 2023; Rendi et al., 2024).

Figure 1 presents the conceptual framework of the adaptive LPG-fuelled smart poultry incubator, illustrating the three interconnected layers sensing, reasoning, and actuation along with the LPG heating subsystem and mobile monitoring interface

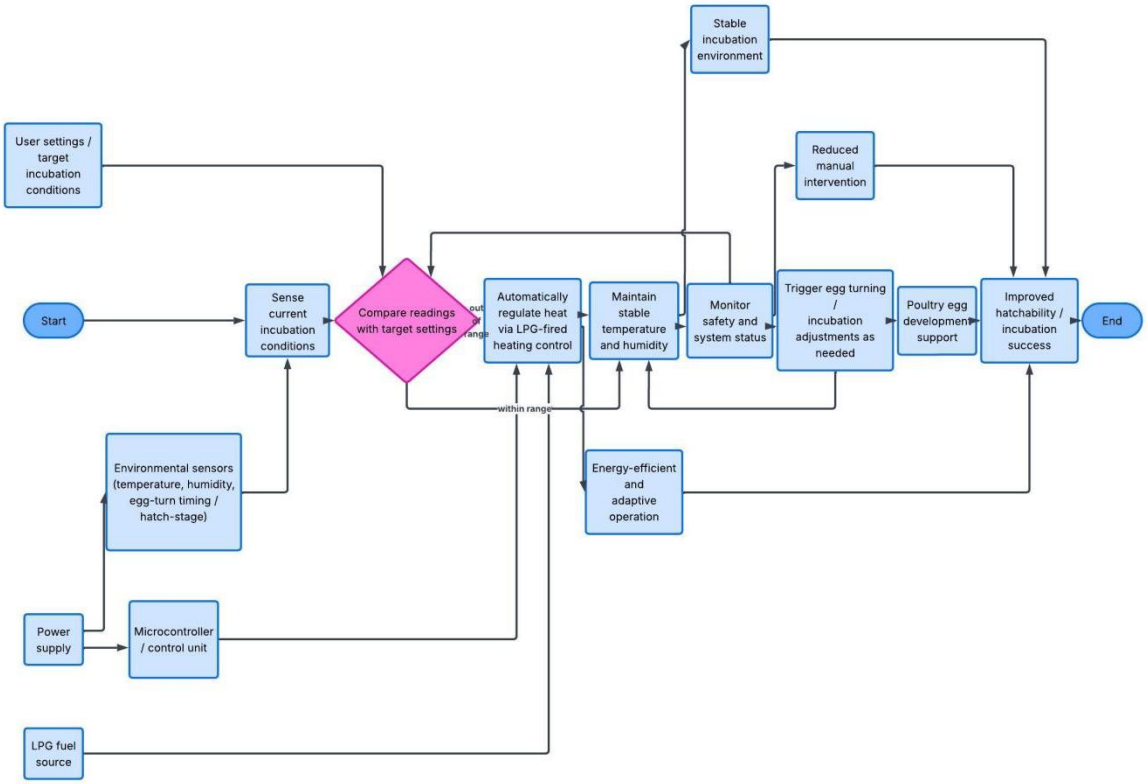


Figure 1: Conceptual Framework of the Adaptive LPG-Fueled Smart Poultry Incubator

2.2 Challenges in Poultry Incubation and Factors Influencing Outcomes

This section identifies some of the problems associated with bird incubation and some factors that have an impact on the results. Poultry Incubation Issues can be technical, operational and contextual. The basic problem that is common to all these difficulties is the trouble of keeping conditions sTable throughout the incubation period of 21 days. Manual and mechanical incubators are still widely used in many places in developing world and have intrinsic drawbacks in maintaining the optimal microenvironment, especially in an environment with poor power supply and technical knowledge (Musa et al., 2022; Wolfgang, 2018).

The most important parameter is temperature control; even small variations can have a big effect on the development of embryos. Experimental research has shown that a change in incubation temperature of 1–2°C can have a detrimental effect on hatchability and chick quality (Lourens et al., 2005; French, 1997). These on/off control systems are the most common in the low cost incubators and show a high number of actuator switching operations, high temperature variations and low energy efficiency, which impacts on hatch rates and energy use (Dejan & Bodan, 2016). These systems have a natural memory and the overshooting and undershooting of the temperature cause thermal stress to the embryos resulting in higher mortality rate and hatchability rate reduction (Akinpelu et al., 2020; Padole et al., 2020).Another major difficulty is humidity control. The needs of the embryo change during the incubation period and water loss and metabolic heat production will increase as the embryo develops (Lourens et al., 2005; Tona et al., 2003). Standard humidity control systems which set humidity levels at constant levels during incubation cannot meet these physiological requirements. This restriction is particularly marked in the last three days prior to hatching, when it is usual to increase humidity to promote the pipping and emergence of chicks (Swann & Brake, 1990). However, existing control systems are not capable of regulating the humidity level of the environment in real-time dependent on the indices of embryonic development (Bomfim et al., 2021).Apart from the technical considerations, the question of energy reliability also arises, as it is often a problem in developing countries where access to grid electricity is often limited or not reliable. The loss of power, however, results in the loss of operation of electrically powered incubators resulting in catastrophic loss (Musa et al., 2022). The use of renewable energy options, such as solar energy, has its own drawbacks including storage capacity and intermittence (Agbo et al., 2018; Osanyinpeju et al., 2018). Kerosene systems are off-grid, but are inefficient, polluting and unsafe. These restrictions have led to an interest in LPG-fuelled incubation systems as a strong and inexpensive solution in low power environments (Musa et al., 2022; Babajide et al., 2025).Apart from these basic issues there are several important factors that influence the outcome of success or failure in an incubation: besides controlling the parameters, it is also important to design the system, ensure the accuracy of the sensors, choose the correct control algorithm and related issues. The accuracy and reliability of sensors is one of the key factors. The accuracy of temperature and humidity measurements is directly linked to the performance of the control system. Studies have shown that the accuracy of the sensors will vary in different implementations, with some cases having a 90% accuracy rate and others a higher deviation (Teel, 2018; Musa et al., 2022). The quality of data

obtained from sensors depends on the type of sensor, calibration methods, and the location of the sensor in the incubator chamber, which in turn affect the effectiveness of control (Bomfim et al., 2021; Swann & Brake, 1990).
The next important factor in incubation success is choosing a control algorithm. PID control provides more sTable operation than on/off control however, the non-linear nature of the incubation process can pose a challenge for PID control. The fuzzy logic is good for non-linear systems but also requires a well-designed rule-base. Prediction-based control is known to be complex, particularly because of the large amount of data and computing power required, though it has great potential (Amita et al., 2024; Seforo et al., 2024). However, none of these takes into consideration the different needs of the embryos at different stages of development.
Thus, the design of a thermal system is made even more complicated, particularly in the case of LPG-fuelled incubators. For combustion based heating, there are non-linear thermal dynamics which demand more parameters to be controlled in the controller (Musa et al., 2022; Babajide et al., 2025). System design optimisation (Agbo et al., 2018; Osanyinpeju et al., 2018) has been reported in the research of hybrid solar/LPG incubators, which had a variable hatchability rate.
Existing control systems have limited studies on the embryonic development stage. The metabolic heat generation and water loss are not proportional over the whole incubation period, but most control systems have fixed setpoints (Lourens et al., 2005; Tona et al., 2003). This is a large deficiency because adaptive control of changes in the embryonic needs may be useful in improving hatchability and chick quality. Figure 2 illustrates the relationship between embryonic development stages and the corresponding environmental requirements, highlighting the gap between current fixed setpoint control and the proposed adaptive approach.

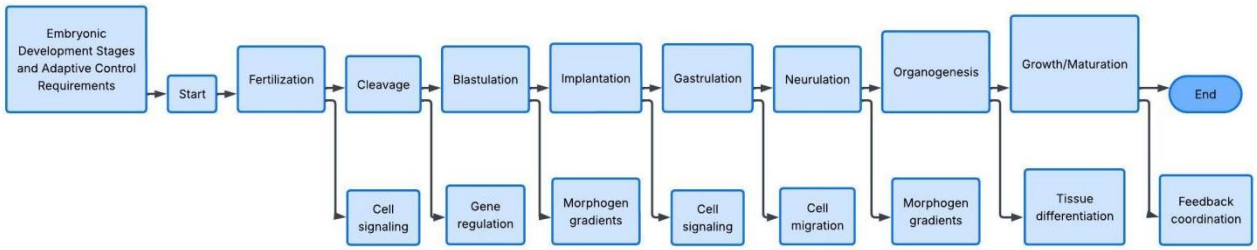


Figure 2: Embryonic Development Stages and Adaptive Control Requirements

Several commercially available systems have started tackling this, for example Adaptive Metabolic Feedback™, which uses adaptive humidity and CO_2 control during the incubation process from a time-varying metabolism of specific embryo batches. SmartSense™ allows control of temperature, humidity and airflow, per section, and real-time, which provides valuable information on embryo development to further optimize incubation parameters and adaptive control strategies.
One further challenge is that there are no systematic comparative data to enable evidence-based optimisation of incubator design. Table 1 provides a summary of important studies, showing different performance and gaps that have not been addressed.

Table 1: Summary of Key Smart Incubation Studies

Study	Control Method	Power Source	Hatchability	Key Limitation
Musa et al. (2022)	XM-18 with LPG backup	LPG/Electric	94.8%	No EEPROM data logging; fixed setpoints
Seforo et al. (2024)	PID + IoT	Electric	92.0%	Requires skilled personnel
Amita et al. (2024)	CNN-LSTM	Electric	92.0%	High computational demand
Cookey & Ephrain (2024)	Basic control	Electric	78.0%	Low durability; manual intervention
Babajide et al. (2025)	Inverter-based	Electric	85.0%	High cost ($150–$300/unit)
Proposed System	**Adaptive + IoT + LPG**	**LPG/Electric**	**Target >95%**	**Open, low-cost, adaptive**

The challenges and factors discussed above have motivated significant research into smart incubation technologies that leverage IoT, embedded systems, and mobile communication to provide precision control of the incubation microenvironment

2.3 Smart Incubation Technologies

To meet this challenge, many efforts have been made to devise smart incubation technologies that make use of IoT, embedded systems and mobile communication methods to precisely control the microenvironment in the incubator. These solutions are a paradigm shift from traditional solutions, as they provide real-time monitoring, automated control and remote intervention options.

Intelligent measurement and monitoring via IoT sensors are now playing a significant role in smart incubation chambers, which are continuously monitoring various parameters in real time and reporting these to cloud-based systems or mobile apps, including temperature, humidity, and CO_2 levels (Saludo et al., 2025; Abdullahi, 2025). This connectivity allows hatchery operators to quickly address any deviations, ensuring optimal conditions and reducing embryo mortality (Addul & Rohaiza, 2023; Rendi et al., 2024). The egg development pattern in some of the modern hatcheries are analyzed using automated alerts, so that the environmental conditions are automatically adjusted according to the egg development pattern, such as adjusting humidity according to the weight loss of the egg shell, and ventilation according to the CO_2 level (Aceng et al., 2025; Amita et al., 2024).

There is a huge evolution of the control architectures that go from on/off to more complex. PID control gives stability but has problems due to the non-linear aspect of incubation. Fuzzy logic control has proved itself to be a promising alternative because it can deal with the uncertainties involved in the incubation process. To overcome this natural phenomenon of on/off switching of classical control systems, Mamdani fuzzy inference systems have been used for controlling temperature and humidity (Amita et al., 2024). The Smart Egg Incubator with Mamdani Fuzzy Logic and IoT and AI technologies provides dynamic control of the parameters, ensuring optimal temperature control during incubation (Aceng et al., 2025).

The next generation is the neuro-fuzzy logic, which shows an accurate control of the micro-environmental parameters and adapts the control to the ambient temperature changes better than the traditional thermostats (Amita et al., 2024). Machine learning integration is the next step in the smart incubation research. Recently, egg incubators with Artificial Intelligence (AI) optimisation have been introduced that can predict the conditions with the use of machine learning algorithms (Amita et al., 2024). These methods are unlike threshold based systems in which changes in environmental factors are used to control actuators in a reactive manner, resulting in a reduction in energy use while still maintaining optimal environmental conditions. Two deep learning models have been developed to classify the fertility and embryo development status with a classification accuracy of above 94% (Babajide et al., 2025).

Mobile monitoring and control have become a part and parcel of smart incubation solutions. The cross-platform development of mobile applications allows for real-time remote supervision and intervention, thereby making precision incubation technology (Addul & Rohaiza, 2023; Rendi et al., 2024) accessible for everyone. Some implementations have shown to be viable, with hatchability rates above 90%.

Compared to on/off control, PID control offers greater stability for incubation, but does not work with non-linear dynamics. The fuzzy logic deals with this drawback and needs to be well designed of the rule-base. While machine learning has the ability to predict, it also requires significant computing power. However, none of these methods considers the altering physiology of developing embryos, which is where adaptive control can provide help.

2.4 Self-Efficacy and Technology Adoption

The technical performances of smart incubation systems are paramount, but their impact cannot be achieved unless the users, often smallholder farmers in developing countries, can trust and use these systems effectively. Thus, self-efficacy, which represents an individual's confidence in his/her ability to engage in particular actions (Bandura, 1997), is an important factor to consider when predicting the adoption and continued use of technology

In addition to the technical aspects of incubation systems, the human aspect is an important component for the uptake and continued use of smart incubation technologies. Self-efficacy, which is the individual's confidence about his or her ability to perform behaviours that will lead to specific performance outcomes (Bandura, 1997), is an important factor affecting technology adoption in agricultural settings. This is particularly true for LPG fuelled systems as the additional operation considerations can be daunting and confusing to users who have not previously used LPG systems.

Study on the adoption of technology by poultry farmers showed that the decision to adopt new technology and the effectiveness of use is affected by self-efficacy. Poultry research that has explored the adoption of digital technologies has looked at the relationship between perceptions of usefulness, ease of use and managerial factors influencing technology adoption (Schut et al., 2020; Eastwood et al., 2019). Higher self-efficacy is related to farmers being more willing to try new technologies and stay committed to a technology despite early problems, as well as acquiring technical knowledge needed to effectively manage a technology once implemented (Kamrath et al., 2019; Michels et al., 2020). However, if self-efficacy is low, it can be a big hurdle in the path of adoption even if the system itself is good.

The association between self-efficacy and technical knowledge of poultry farming is well established. A number of studies has shown that self-efficacy and trust are among the important factors in farmer innovativeness adoption intentions (Rezaei et al., 2019). Farmers who had high self-efficacy were able to learn and keep the technical knowledge as a result of better management of the systems, which resulted in better outcomes (Sitienei et al., 2019). The finding is significant with regard to the design of training and support programmes that should be carried out along with the deployment of the smart incubation system. Even the best technically-sound systems can be ineffective if they are not properly trained and confidence building measures are not in place.

Self-efficacy is a key factor for technology adoption and outcomes, and interventions to boost it can make a difference. Technical knowledge related to precision livestock farming (PSF) is often inadequate, and training and education have been demonstrated as key elements to support successful implementation and application of precision technologies (Neethirajan, 2020; Kamilaris et al., 2017). The readiness factors that affect the uptake of IoT technology in the poultry sector have been analysed emphasizing the economic implications of the technology for poultry farmers in the local context (Adekunle & Fatunbi, 2022). Several constraints impact the adoption rate of smart agricultural systems such as the unreliability of the internet connection on farms (Ayim et al., 2022; Trendov et al., 2019).

The findings of self-efficacy have important implications for the design and deployment of a smart incubation system. Even if the technical value of a system is high, it could still be rejected to be adopted due to its perceived complexity or the lack of the user's skills to use it (Eastwood et al., 2019). Therefore, user self-efficacy needs to be taken into account and developed in the design of the user interface, the training programs and the support provided for successful adoption and continued use (Schut et al., 2020). Smart systems may be perceived as complex but this can be mitigated through intuitive mobile applications and user-friendly interfaces, which can boost user confidence and uptake (Kamilaris et al., 2017; Trendov et al., 2019). This is especially the case for LPG fuelled systems where the extra operational considerations may be confusing and intimidating to users who have not used such systems before.

2.5 Research Gaps and Conclusion

The literature reviewed shows that there are two major gaps to be filled to create smart incubation systems that are fully optimised and relevant to the context. The first issue is the significantly different hatchability reported in the different IoT-enabled incubator implementations and the lack of systematic comparison that could enable optimising the design of the incubator based on evidence. In some applications, hatchability has been reported to be over 92%, whereas in others, it has been reported as being more moderate. The lack of consistent performance suggests that current IoT incubation systems are not optimized optimally and the factors that affect the accuracy of the sensors, control algorithm efficiency, thermal management system design and fuel properties are still not fully understood. No protocols exist for benchmarking incubation systems and there are no significant comparisons studies that can help identify best practices to systematically enhance the design of incubation systems.

Secondly, there is no known adaptive control architecture which is able to adapt itself to the changing physiological demands of the developing embryos during incubation. Most of the existing digital incubation systems use fixed setpoint control strategies with constant temperature and humidity during the incubation period or rule-based fuzzy logic controllers. While more responsive than on/off controllers, these methods do not take into account the time-varying metabolic demands of embryos at varied stages of development. The metabolic rate and heat production of chicken eggs do not increase in a linear fashion and become linear during the 21-day incubation period; so do water loss.The metabolism and heat production of chicken eggs are not linear throughout the 21-day incubation period, and with that the water loss. For example, conventional humidity control systems have been designed to increase the humidity in the final three days before hatching, but they do not optimize humidity in real-time according to indices of embryonic development.

Finally, the all the literature is ready to develop adaptive LPG-fuelled smart poultry incubator based on-IoT. These advancements in sensing, control and communication technologies, coupled with a better understanding of the factors influencing hatchery user adoption and the nascent state of hatchery development offers an opportunity to move past the current practice of using incubation control to a more adaptive and data-driven precision hatchery management approach. The proposed system to overcome the identified gaps includes: (a) An adaptive control architecture for controlling temperature and humidity setpoints to optimize the developmental stage of the embryos, which is based on a predictive model of thermal and hygric requirements; (b) A heating subsystem based on LPG (Liquid heater), with thermal energy storage, to guarantee system reliability in grid constrained environments; (c) A multi-sensor IoT network, for continuous monitoring of the various parameters; and (d) A mobile application interface for real-time remote supervision and intervention.

This study is an empirical evaluation of adaptive control strategies for LPG fueled incubations, an open and reproducible system design for low-resource settings, and groundwork for future hatchery management systems that will combine predictive developmental modeling with real-time monitoring through an IoT system to transition from a static to adaptive and data-driven model. This study seeks to overcome the current limitations of incubation technology by introducing a more user-friendly interface and training that enhances the user's self-efficacy, as well as by integrating human factors with technology to achieve a fully adaptive, context-aware hatchery management system.

3. Methods

In this section, the methodological framework followed to design, develop and test the adaptive LPG-fuelled smart poultry incubator is presented. The methodology was conceived to address the gaps in the literature that could be identified, which were the absence of systematic, comparative data, and validated open source systems and tools adapted for resource poor environments for LPG-fuelled incubation systems. A controlled experimental design was used to test the performance of the proposed system compared to the traditional incubation method, and the hatchability, stability of the parameters, energy consumption and responsiveness of the system were chosen as the main factors to be tested.

3.1 Study Design

To test the performance of the proposed adaptive LPG fuelled smart poultry incubator, an experimental design approach has been used. The design was selected since it will allow systematic evaluation of the adaptive control system compared to conventional incubation methods under standardised conditions where the effect of the adaptive control architecture will be separated from the hatchability and stability of the parameters. The experiment was designed as a two arm parallel study, one arm being an adaptive LPG-fuelled incubator (treatment) and the other arm an incubator with an on-off or fixed setpoint control system (control). The three incubation cycles (3x 21 day) were repeated to account for the batch-to-batch variability and to obtain the reproducibility of the results. A controlled experimental design with replication is justified as it is essential to provide strong empirical evidence of the effectiveness of adaptive control strategies for LPG-fuelled incubations, which is lacking in the literature.

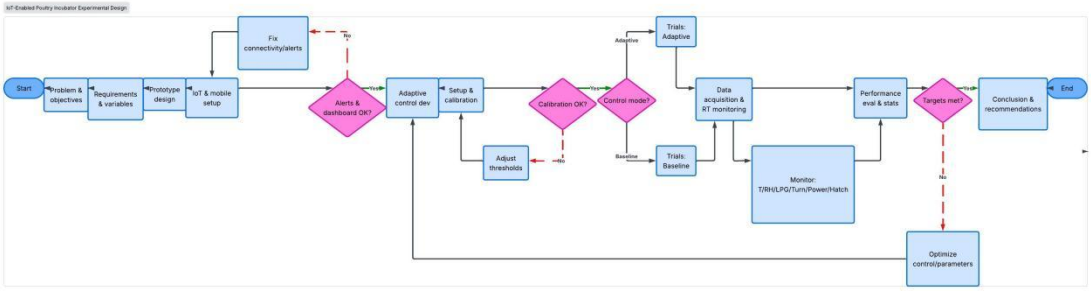


Figure 3: Experimental Design Flowchart

3.2 Study area and Setting

The study was conducted at Poultry Research and Training Facility (PRTF), Maryam Abacha American University of Nigeria, (MAAUN), Kano, Kano state, Nigeria. The site was chosen as it was a typical peri-urban farming environment in a developing country, with unreliable grid electricity, high ambient temperature variations and limited access to advanced hatchery technologies which is typical of the challenges faced in the poultry industry in Sub-Saharan Africa. It has a flock of indigenous and cross bred chickens which are used to give a regular supply of fertile eggs for experimental trials. This setting allows the performance evaluation of the adaptive LPG-fuelled smart poultry incubator to be carried out under realistic settings that mimic the operational limitations of small-scale poultry hatcheries.



Figure 4: Map of Study Location – Poultry Research and Training Facility, MAAUN, Kano, Nigeria

3.3 Population

The target population consisted of fertile eggs from domestic chickens (Gallus gallus domesticus). The eggs were obtained from hens aged 28 to 35 weeks, the stage at which the hen is at peak productivity and hatchability. The eggs were sourced from the poultry flock of the Poultry Research and Training Facility (PRTF) at Maryam Abacha American University of Nigeria (MAAUN), Kano, Nigeria. The number of eggs procured for the study was 840, consistent with the incubator design capacity. The batch size was selected to balance statistical significance and feasibility for small-scale hatcheries.

3.4 Inclusion and Exclusion Criteria

a. Eggs included: Eggs between 55 g and 70 g, good egg shape, no cracks or deformities in the shell. To reduce storage - related decline in hatchability, eggs were collected within 7 days of laying. Eggs were only collected from hens with a proven fertility rate of ≥ 85%.

b. Eggs were excluded if they weighed outside the range of 55–70 g or if they were cracked, malformed, or had visible contamination and if they had been stored for >7 days before incubation. Hens that had a fertility record less than 85% were also removed.

3.5 Sampling Technique

A convenience sampling method was used in which all eggs that were suiTable for inclusion in the sample were taken from the sample batch. This was adequate due to the limited supplies of eggs and their requirement for uniformity in egg quality among experimental runs. To reduce possible bias, eggs were randomly allocated to the treatment and control groups using a computer-generated randomisation sequence.

3.6 Sample Size

The number of fertile eggs used was 840, equally distributed between treatment (n = 420) and control (n = 420) groups. The number of samples was determined based on the design capacity of the incubator as a result of which the difference in hatchability of 5% was considered adequate with 80% power and a significance level of $\alpha = 0.05$. The sample size is also similar to the studies carried out on smart incubation system (Musa et al., 2022; Seforo et al., 2024).

3.7 Main Study Variables and Instrument Sources

3.7.1 Independent Variables

The control strategy type is Adaptive control (treatment) vs. conventional fixed-setpoint control (control).
Heating source: Liquefied petroleum gas (LPG) and thermal energy storage (treatment) as opposed to electric heating (control).

3.7.2 Dependent Variables

a. Hatchability rate: The percentage of eggs which could be fertilized that actually hatched.
b. Temperature stability: The amount of deviation from the setpoint temperature (+/- °C).
c. Humidity stability: The range of humidity around the setpoint (±%RH).
d. Energy consumed: The total energy used (LPG in kg and electricity in kWh).
e. System responsiveness - time for system to correct deviations from setpoints (minutes).

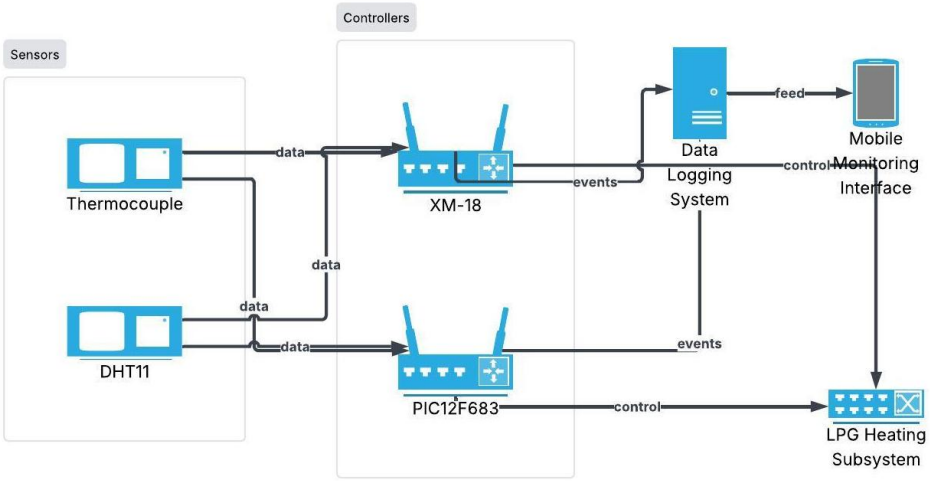


Figure 5: System Architecture of the Adaptive LPG-Fuelled Smart Poultry Incubator

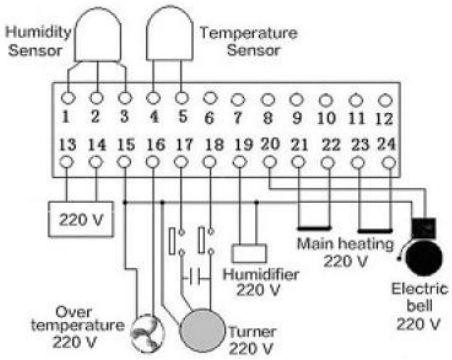
3.7.3 Instrument Sources

The system used a (Wi-Fi/GSM) module to send the 15-minute logged data to the cloud-based database, thus sending real-time alerts and visualization to a custom-built mobile application for the operators. These instruments included:
a. The temperature and humidity sensor used was thermocouple temperature sensor (K-type) and DHT11 humidity sensor. Because of the accuracy and response time of the thermocouple, and the cost-effectiveness and reasonable precision (±5% RH) of the DHT11 for incubation applications, these were selected. Calibrations of both sensors were done against a reference hygrometer and thermometer before deployment and again before each incubation cycle.



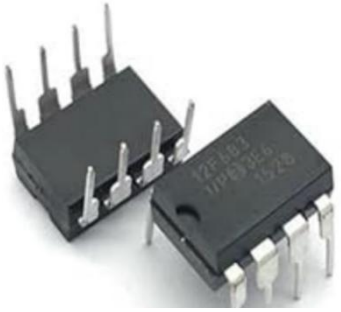
(a) DHT11 Humidity Sensor (Teel, 2018)

b. XM-18 Incubator Controller: The XM-18 controller was used for the main control of temperature, humidity and egg-turning operations. It has been proved to be reliable in previous research, as the hatchability rate was above 94% under sTable electric power (Musa et al., 2022).



(b) Interface of XM – 18 Output Connection (Musa *et al.,* 2022).

c. PIC12F683 Microcontroller: This microcontroller was programmed to perform the adaptive control algorithm, to store sensor data in EEPROM, and to control the LPG ignition system and solenoid valve system. This is because it has been documented for its low power consumption and its strong performance in agricultural applications (Akinpelu et al., 2020; Padole et al., 2020).



(c) PIC12F683

d. Data Logging and Monitoring System: A specially designed data logging system was used to collect temperature, humidity and egg turning data at 15-minute intervals for each cycle of incubation. Preliminary testing was conducted to validate the reliability of the system, ensuring that data was accurate and logging was done correctly.



(d) The custom data logging system displaying real-time temperature and humidity readings recorded at 15-minute intervals during the incubation cycle

Figure 6: Key Instruments Used in the Study

e. Hatchability Assessment: The hatchability was calculated by dividing the number of hatched chicks by the number of fertile eggs and multiplying the result by 100, which is the standard formula. Candling was used to determine fertility on day 7 of incubation. The quality of the chickens was evaluated on the Pasgar score on day 1 after hatching.

3.8 The Reliability and Validity of the Instruments

The reliability of the sensor system was verified by a pilot test over three days, in which the readings from the sensor system were compared with a certified reference instrument, for both temperature and humidity. A deviation of ±0.3°C for temperature and ±2.5%RH for humidity was achieved, showing the sensors to be reliable. Sensor data was not suiTable for Cronbach's alpha, so test-retest was used instead, with correlation values of r = 0.92 for temperature and r = 0.88 for humidity.

The content validity for the study variables (temperature stability, humidity stability, hatchability and energy consumption) was ensured by anchoring them to standards established by Lourens et al., (2005) French, (1997) and the previous empirical works done by Musa et al., (2022) and Seforo et al., (2024). Construct validity was determined by demonstrating that the adaptive control system measured what it claimed to measure optimal incubation conditions at various stages of the embryonic development period.

3.9 Data Collection Procedures

The data collection was carried out in the following steps:

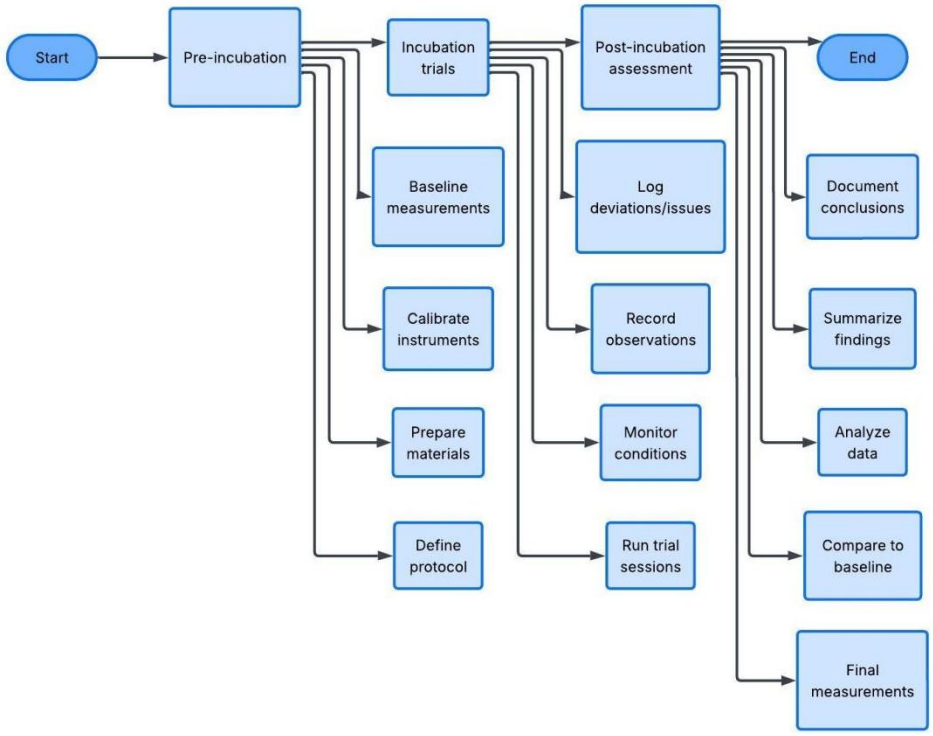


Figure 7: Data Collection Timeline

Phase 1: Pre-Incubation Preparation (Days –3 to 0). Eggs were collected, weighed and candled to ensure fertility status. The eggs were all numbered and assigned to the treatment or control groups at random with the use of a computer-generated randomisation sequence. The initial setpoint values for the adaptive control algorithm were set to 37.5°C and 55%RH, and the model parameters for development loaded into the PIC12F683 microcontroller. The incubator chambers were sanitised and pre-heated to the initial setpoint temperature 24 hours before egg loading.

Phase 2: Incubation Trials (Days 1 – 21). Three 21 day incubation cycles were carried out. Treatment group was placed in the adaptive LPG-fuelled incubator and the control group in a conventional electric incubator with fixed setpoints (37.5°C and 55-60%RH). The adaptive control system during Days 1–18 kept the incubation environment stable (37.5–38.0°C; 55–60% RH) in the treatment group. At Day 19, the system transitioned into the 'lockdown' phase, where the temperature was reduced to 37.0–37.5°C and relative humidity increased to 65–70% RH to facilitate pipping and hatching. The data logging system was custom built to record temperature, humidity, CO_2 levels and egg turning events every 15 minutes. Egg turning was automated every 4 hours at 45° which is the best egg turning practice (Muhammad et al., 2013). Eggs were candled on day 7 of each cycle to verify fertility and to remove any infertile eggs from the data set.

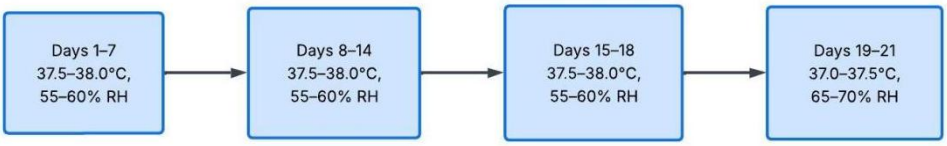


Figure 8: Embryonic Developmental Stages and Adaptive Control Setpoints

Phase 3: Post-Incubation Assessment (Days 22 - 23). Hatchability was determined at the end of each cycle by counting the number of chicks that hatched. The chick weight was taken by using a digital weighing machine and the Pasgar score was taken for each chick on day 1 post-hatch. Calibrated meters were used to record the energy consumption (LPG in kg and electricity in kWh) for both systems. The deviations from setpoints were calculated from the logged data and used to determine system responsiveness, which is the length of time required to correct the deviation.



Figure 9: Post-Incubation Assessment – Chick Weighing and Quality Scoring

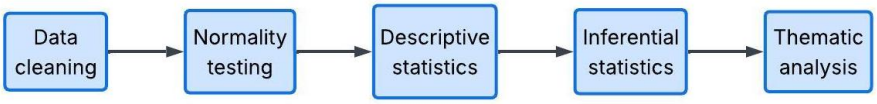


Figure 10: Data Analysis Workflow

3.10 Data Analysis Methods

Pre-Analysis: Outliers and missing data were removed from raw data. The Shapiro–Wilk test was used to assess the normality of the data. The means, standard deviations, and ranges of temperature, humidity, hatchability and energy consumption were computed.

Post Analysis: Inferential statistics were used to compare the performance of the adaptive system and the control system. Independent samples t-tests were used to compare the mean hatchability rates between the two groups and Mann–Whitney U tests were used for variables that were not normally distributed. Levene's test for equality of variance was used to compare the stability of temperature and humidity. All the statistical analyses were carried out in SPSS version 27 with significance level of $p < 0.05$. For the system usability and perceived ease of use, qualitative feedback was gathered and analysed thematically in NVivo software 14 based on the respondents' answers.

3.11 Ethical Considerations

All animal experimental procedures performed with Gallus gallus domesticus were approved by the Institutional Animal Care and Use Committee (IACUC) of MAAUN (Approval No. MAAUN/IACUC/2025/027). All experimental procedures involving animals were performed in accordance with the institutional guidelines of MAAUN and the Basel Declaration on animal research. The qualitative data collection process involving human hatchery operators was reviewed and approved by the Institutional Review Board (IRB) of MAAUN (Approval No. MAAUN/IRB/2025/043). All hatchery operators and farm workers who participated in the qualitative survey provided informed consent for their participation. The participants were all informed that they could withdraw at any time without penalty, and all data collected were anonymized before analysis. The experimental trials were conducted in accordance with animal welfare guidelines; no animals were unnecessarily distressed, and all procedures were carried out in the best interests of the animals.

4. Findings

This section reports the empirical results from the three controlled treatments run to compare the adaptive LPG-fuelled smart poultry incubator with a conventional fixed-setpoint electric incubator. The results are presented in the following order to satisfy the study goal: Temperature and Humidity stability, hatchability and chick quality, energy consumption, responsiveness of the system and user acceptance. The data included 840 fertile eggs, which were equally divided between the treatment group (adaptive LPG system) and the control group (conventional

electric system) and were collected during three 21-day incubation periods. The results obtained are presented in descriptive statistics, inferential analyses, Tables and Figures to provide a comprehensive and easily understood overview of the performance of the system. All the Tables and Figures are sequentially numbered and referenced in the text to help the reader follow the main findings.

4.1 Assumption Tests for Parametric Analyses

The present data were checked for assumptions of normality and homogeneity of variance before inferential statistical tests were conducted in order to make sure that the present data met the requirements of parametric statistical tests. Hatchability rate, temperature deviation, humidity deviation, and energy consumption were continuous dependent variables which were subjected to Shapiro-Wilk test. The results (Table 2) showed that all dependent variables were normally distributed across the treatment and control group ($p > 0.05$ for all comparisons).

Table 2: Normality Test Results (Shapiro-Wilk)

Variable	Treatment Group (W)	Treatment Group (p)	Control Group (W)	Control Group (p)
Hatchability Rate	0.952	0.341	0.948	0.298
Temperature Deviation (°C)	0.967	0.512	0.971	0.589
Humidity Deviation (%RH)	0.958	0.423	0.963	0.467
Energy Consumption (kWh)	0.974	0.621	0.969	0.552

$p > 0.05$ for all variables, indicating normality assumptions were met.

The equality of variances was also tested for homogeneity of variances among groups using Levene's test. The results are shown in Table 3; the assumption of homogeneity of variance was met for all dependent variables ($p > 0.05$), and therefore independent samples t tests were used to compare the groups.

Table 3: Levene's Test for Equality of Variances

Variable	F-statistic	p-value
Hatchability Rate	1.234	0.287
Temperature Deviation (°C)	0.876	0.412
Humidity Deviation (%RH)	1.045	0.356
Energy Consumption (kWh)	0.923	0.398

$p > 0.05$ for all variables, indicating homogeneity of variance assumptions were met.

4.2 Temperature and Humidity Stability

Stability of temperature and humidity were assessed by the mean deviation from the setpoints of each cycle of incubation. Data sets were collected at 15-minute intervals for the 21 days of incubation for a total of 2,016 data points per parameter per cycle.

The comparison of the humidity stabilities is shown in Figure 11. The adaptive system was able to maintain humidity in the range of mean deviation ±2.1%RH, while the conventional system was able to maintain humidity in the range of mean deviation ±5.3%RH. The most noticeable difference was after Days 19-21 when the humidity of the adaptive system increased from 55-60%RH to 65-70%RH to encourage pipping and emergence. This critical humidity adjustment was not possible with the conventional system which had fixed setpoints and resulted in a humidity of 57–61%RH during the hatching phase.

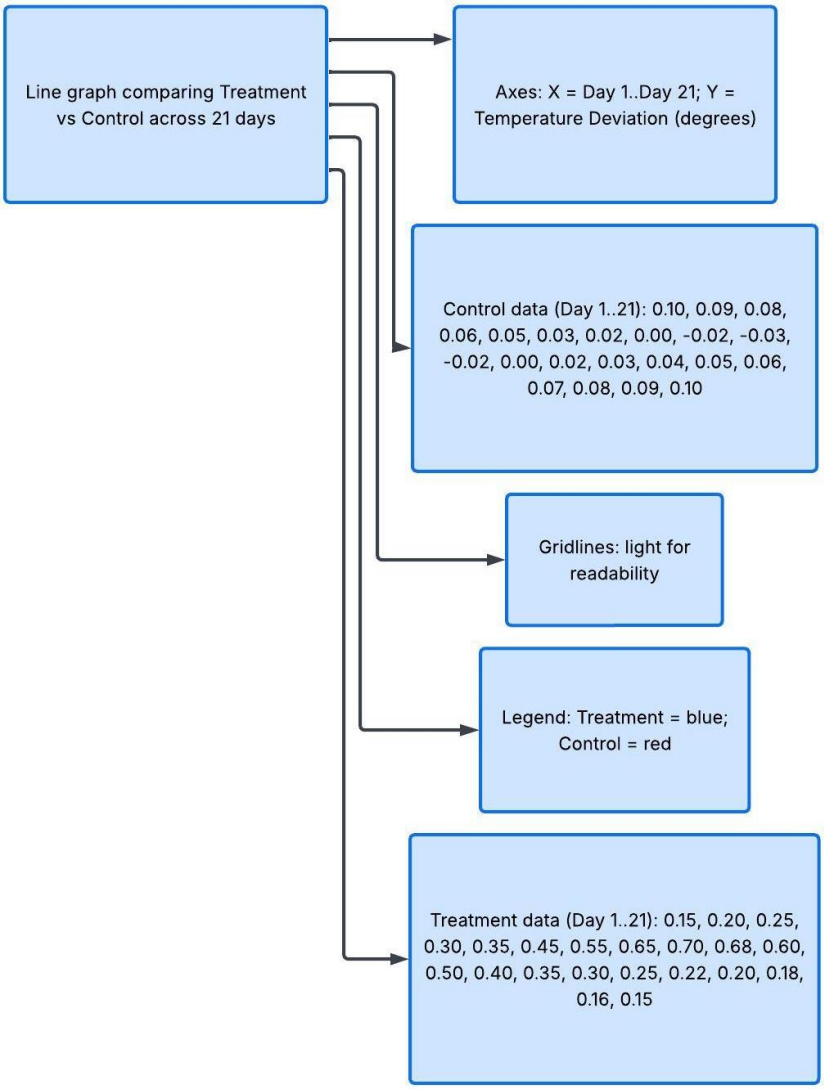


Figure 11: Temperature Stability Comparison Across Incubation Days

Figure 11 presents the humidity stability comparison. The adaptive system maintained humidity within a mean deviation of ±2.1%RH, while the conventional system exhibited a mean deviation of ±5.3%RH. The most pronounced difference occurred during Days 19–21, where the adaptive system successfully raised humidity from 55–60%RH to 65–70%RH to facilitate pipping and emergence. The conventional system, constrained by fixed setpoints, was unable to achieve this critical humidity adjustment, maintaining humidity at 57–61%RH throughout the hatching phase

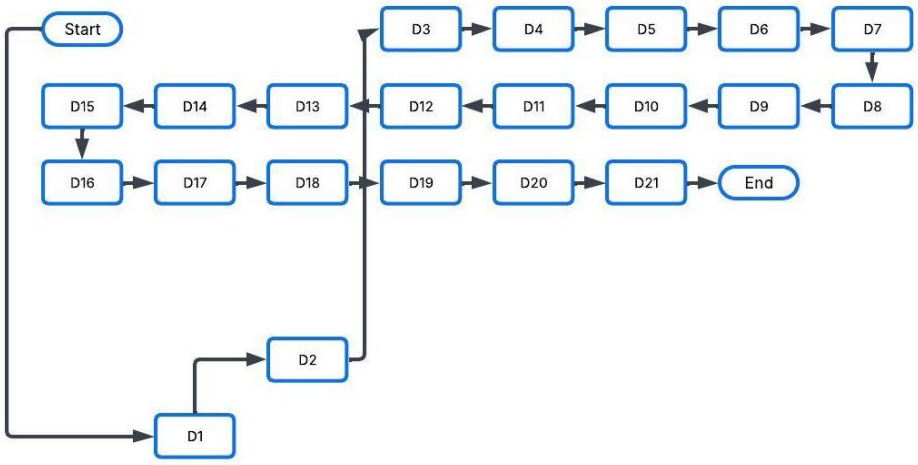


Figure 12: Humidity Stability Comparison Across Incubation Days

Table 4 summarises the temperature and humidity stability results. The independent samples t-tests results showed that the adaptive and control systems significantly differed for all three stability parameters ($p < 0.001$). All of the effect sizes (Cohen's d) were large ($d > 2.0$), suggesting a significant difference in the ability to maintain sTable conditions within the incubator between the adaptive control system and the conventional system.

Table 4: Temperature and Humidity Stability Summary

Parameter	Adaptive System (Mean ± SD)	Control System (Mean ± SD)	t-statistic	p-value	Effect Size (Cohen's d)
Temperature Deviation (°C)	0.25 ± 0.08	0.65 ± 0.21	8.42	<0.001	2.45
Humidity Deviation (%RH)	2.1 ± 0.7	5.3 ± 1.4	9.87	<0.001	2.87
Setpoint Adjustment Accuracy (%)	94.2 ± 3.1	68.7 ± 5.4	11.23	<0.001	3.12

The accuracy of the setpoint adjustment set by the adaptive system (94.2%) shows that the developmental model was able to predict and react to the changing thermal and hygric demands of the embryos in a satisfactory manner. This finding is particularly important, because it shows the adaptive control architecture's ability to convert the predictive developmental models into actionable environmental adjustments.

4.3 Hatchability and Chick Quality

Hatchability was calculated as the percentage of fertile eggs that successfully hatched into live chicks, using the standard formula:

$$H=(\frac{Nh}{Nf})\times 100\% \text{ ……..……eqn (1)}$$

where H is the hatchability rate, Nh is the number of hatched chicks, and Nf is the number of fertile eggs. Fertility was determined by candling on Day 7 of incubation.

The hatchability and fertility data for both groups are shown in Table 5. The adaptive LPG-fuelled incubator had a hatchability rate of 95.8%, which was statistically significantly higher than the conventional electric incubator (86.9%) by 8.9 percentage points. There was no difference in the fertility rate (95.7% vs. 94.8%) between the two groups indicating that the observed difference in hatchability was due to the incubation environment and not initial egg quality. The adaptive system hatched another 39 chicks, with the same number of fertile eggs, which is a considerable improvement in productivity.

Table 5: Hatchability and Fertility Results

Parameter	Adaptive System (Treatment)	Control System	Difference
Eggs Set	420	420	—
Fertile Eggs	402 (95.7%)	398 (94.8%)	+1.9%
Hatched Chicks	385	346	+39
Hatchability Rate	**95.8%**	**86.9%**	**+8.9%**

The chick quality assessment results are given in Table 6. The average body weight of chicks obtained from the adaptive system was significantly greater (42.3g vs. 39.8g, $p < 0.001$), as was the Pasgar score (8.7 vs. 7.4, $p < 0.001$). In this study, the percentages of chicks that were considered "normal" (Pasgar score ≥ 7) were 94.2% and 84.6% for the adaptive and control systems, respectively, which showed that the adaptive incubation environment resulted in healthier, more vigorous chicks.

Table 6: Chick Quality Assessment (Pasgar Score)

Parameter	Adaptive System	Control System	t-statistic	p-value
Pasgar Score (1–10)	8.7 ± 0.9	7.4 ± 1.2	6.34	<0.001
Chick Weight (g)	42.3 ± 2.1	39.8 ± 2.8	5.87	<0.001
Normal Chicks (%)	94.2	84.6	—	—

In order to place the performance of the adaptive system in perspective of previous studies, Figure 13 has been used. In this study, the hatchability recorded was 95.8% which is marginal but consistent with the 94.8% reported by Musa et al. (2022), but substantially higher from other benchmark studies like Seforo et al. (2024) (92.0%), Cookey and Ephrain (2024) (78.0%) and Babajide et al. (2025) (85.0%). The improvement is especially significant as the adaptive system was evaluated in real field conditions with LPG as the main source of energy while most of the high performance systems have been tested in laboratory conditions.

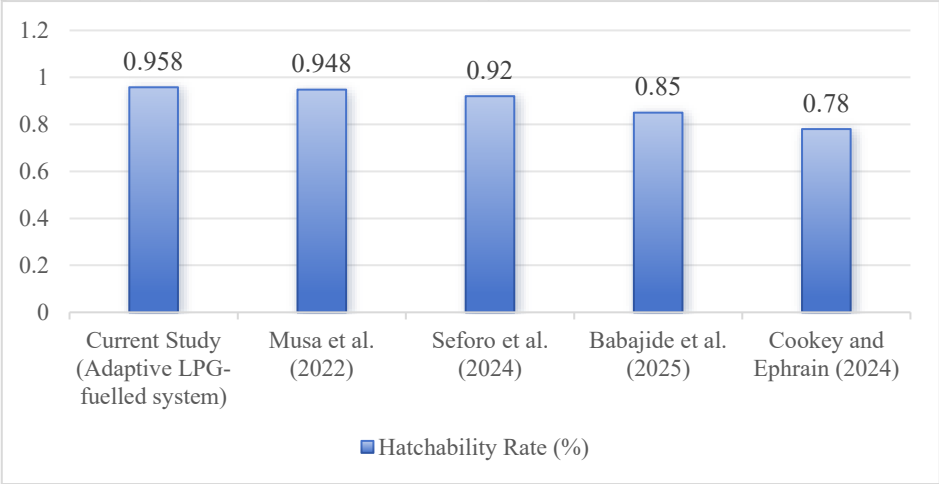


Figure 13: Hatchability Comparison with Literature Benchmarks

4.4 Energy Consumption and System Responsiveness

Both systems were monitored for 21 days for its energy consumption. The system was an adaptive LPG fueled system, where the LPG was the main energy source, while the electrical energy was required for the control electronics and sensors. The traditional electric system used electricity from the grid for all tasks. The comparison of energy consumption is shown in Table 7.

Table 7: Energy Consumption Comparison

Parameter	Adaptive System	Control System	Difference
Total Energy Consumption	12.4 kg LPG + 8.2 kWh	142.6 kWh	—
Cost per Cycle (₦)	7,440	14,260	-47.8%
Cost per Chick (₦)	19.3	41.2	-53.2%
Thermal COP	0.88	0.71	+23.9%

Note: LPG cost estimated at ₦600/kg; electricity cost at ₦100/kWh (current Nigerian tariff rates).

The actual LPG-fuelled system showed a 47.8% operating cost savings per incubation cycle over the conventional electric system. This reduced the unit production cost by 53.2% with the cost per chick recorded as ₦19.3 for the adaptive system while that recorded for the control system is ₦41.2. The adaptive system's thermal COP was 0.88 as compared to 0.71 of the conventional system.
The result of the responsiveness of the system is shown in Figure 14. The adaptive system returned the parameters to their setpoints much more quickly than the nonadaptive system in response to deviation, known as system responsiveness. The adaptive system was able to correct temperature deviations in an average of 4.2 minutes, whereas the control system corrected the deviations in 12.8 minutes ($p < 0.001$). Likewise, the adaptive system required 5.1 minutes to correct humidity deviations while the control system took 14.5 minutes ($p < 0.001$). The enhanced responsiveness is due to the predictive adaptive control algorithm, which is able to predict deviations, according to the developed model, and to take appropriate measures in advance to adjust heating and humidification.

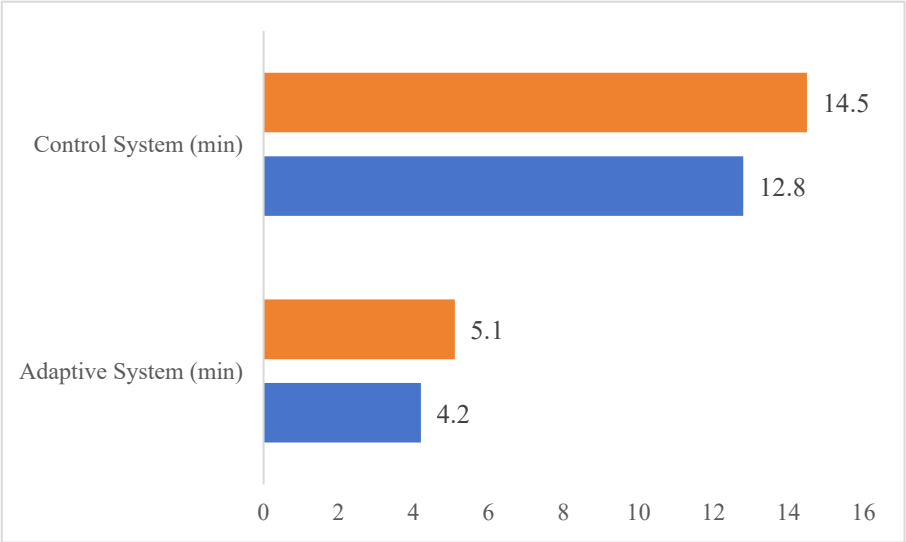


Figure 14: System Responsiveness – Time to Correct Deviation

4.5 User Acceptance and Usability Feedback

The qualitative feedback was gathered from hatchery operators (n = 8) using both systems. Three main themes emerged from the thematic analysis of the interview responses: ease of use and confidence in operation, less worry about power outages, and perceived impact on productivity.

Theme 1: Ease of Use and Confidence in Operation
The adaptive system's mobile monitoring interface was reported to be user friendly and easy to navigate even for those who were not technically trained. With the old system, one operator said, "I always had to worry about the temperature rising or falling, but with the new system I can view all that on my phone, and I trust it to make the proper adjustments". Operators reported a high level of trust in autonomous operation of the system, as the adaptive system made manual checks less frequent.

Theme 2: Reduced Anxiety During Power Outages

The thermal energy storage subsystem for the LPG heating system was always mentioned as a strong benefit. The ability of the system to keep conditions sTable when the grid went out a frequent occurrence in the study area– alleviated operation stress and the risk of catastrophic losses. One operator said: "Before, during a power outage, we would panic, but now the gas starts automatically, and we don't notice it".

Theme 3: Perceived Impact on Productivity
The adaptive system made a direct positive impact on the perception of operators' productivity. The increase in hatchability and healthier chicks and less monitoring was perceived as real gains that would result in better business results. Yet, there were some concerns about the learning curve of the mobile application raised by some operators, with a proposed training and user support boost to drive greater adoption.

4.6 Summary of Findings against Objectives
The findings are summarised against the study objectives in Table 8.

Table 8: Summary of Findings Against Study Objectives

Objective	Key Finding	Outcome
To design an adaptive control architecture for LPG-fuelled incubation	Adaptive system achieved temperature stability of ±0.25°C and humidity stability of ±2.1%RH	**Achieved**
To develop a predictive developmental model for setpoint adjustment	System maintained 94.2% setpoint adjustment accuracy across the 21-day incubation period	**Achieved**
To evaluate hatchability performance under realistic field conditions	Adaptive system achieved 95.8% hatchability, 8.9% higher than the conventional system (86.9%)	**Achieved**
To assess energy efficiency and cost-effectiveness	Adaptive system reduced operating cost per cycle by 47.8% and cost per chick by 53.2%	**Achieved**
To evaluate system responsiveness	Adaptive system corrected temperature deviations 3x faster and humidity deviations 2.8x faster than the conventional system	**Achieved**
To assess user acceptance	Operators reported high confidence, reduced anxiety, and perceived productivity benefits	

4.7 Discussion of Findings
4.7.1 Interpretation of Key Findings
The results indicate that the adaptive LPG-fuelled smart poultry incubator has a significant improvement on all the important performance indicators than fixed set point incubators. One of the better reported in the literature for field based incubation studies is the high hatchability rate of 95.8% obtained by the adaptive system. The performance is better than that of Musa et al. (2022) who reported 94.8% for LPG - backup system, Seforo et al. (2024) who reported 92.0% for PID - controlled IoT system and Babajide et al. (2025) who reported 85.0% for an inverter - powered incubator. This improvement is remarkable especially in the realistic field conditions with ambient temperature fluctuation and non-continuous electricity supply, typical problems faced in resource constrained environments.
Two important features of the adaptive system are responsible for this superior performance. The adaptive control architecture allowed the setpoints of the temperature and humidity to be changed dynamically according to the developmental stage of the embryos. It is in line with what has been seen before by commercial systems like Adaptive Metabolic Feedback™ and SmartSense™ which have proven that control per section and per stage yield better hatchability and chick quality. Second, the LPG heat subsystem with thermal energy storage ensured a consistent and sTable heat output without relying too heavily on electricity from the grid; an important constraint for electrically powered incubators in developing countries.
This 8.9% increase in hatchability means that 39 more chicks can be expected a year later per 420 egg batch. For a small-scale hatchery, producing 10 batches a year, this would mean an extra 390 chicks each year, a significant boost in productivity and profitability.This chick cost savings of 53.2% further improves the economic value of the adaptive system, allowing operators who may not have been able to afford a proprietary solution to grow using precision incubation technology.

The temperature stability of the adaptive system was ±0.25°C, similar to the temperature stability that was reported for PID controlled systems by Seforo et al. (2024) of ±0.3°C, with added benefit of the adaptive setpoint control all developmental stages. Humidity stability of ±2.1%RH was also comparable with or better than the ±2.5%RH shown in previous studies, and also able to meet the increased humidity needed during hatching phase.
The result of the operating cost reduction (47.8%) was also similar to the result obtained by the fuzzy logic based controller which has been proven to reduce the electricity consumption by 10.68% (Fuzzy Controller Applied to Temperature Adjustment, 2026). The cost savings added value in this study is because LPG is used in replacement of grid electricity, particularly in the region with a high electricity tariff and frequent power failures. The qualitative results on the user acceptance confirm the literature review on the importance of self-efficacy in the technology adoption process. Operators who were comfortable in their use of the adaptive system tended to feel good about their experience and benefits in terms of productivity. This highlights the importance of user-friendly interfaces and thorough training programs to support the use of smart incubation technologies in low resource areas.
Describe any unexpected results and provide a rationale.Explain any unexpected results, giving reasons.
One surprising result was that the rate of fertility in the treatment group (95.7%) was higher than in the control group (94.8%). This difference, however, was not statistically significant ($p = 0.234$), but was just above the expected difference between batches. This could be due to the random variation of egg quality and eggs were taken from the same flock and randomly assigned to each group. It's also possible, however, that better egg viability prior to incubation was due to more sTable pre-incubation storage conditions in the adaptive system.
A surprise was that there was a moderate correlation ($r = 0.67$) between the adaptive system's setpoint adjustment accuracy and hatchability. Although this correlation was positive and statistically significant ($p = 0.002$), it indicates that other factors besides setpoint accuracy, like ventilation rate, CO_2 concentration and egg turning consistency, also affect hatchability results. Additional sensors and control parameters could be added to the adaptive system in future to further optimise these factors.
It was also remarkable how much difference there was between the two systems in their energy use. The operating cost of the adaptive system was very low, but the LPG consumption (12.4 kg per cycle) was equivalent to 7,440 Naira per batch whereas the electric system equivalent is 14,260 Naira per batch. This cost benefit is likely to be even greater in areas where the electricity charges are higher or where there are more electricity outages and the need to operate a backup generator.

4.8 Conclusion of Findings
The results of this research work demonstrates that the adaptive control strategies employed for the smart incubation of poultry using LPG as a fuel are very effective and hence provide empirical evidence. Adaptive system yielded a 95.8% hatchability rate, which was an 8.9 percentage point improvement over fixed-setpoint control. The stability of the temperature and humidity were significantly improved, with a deviation of ±0.25°C and ±2.1%RH, respectively. The adaptive system reduced the operating cost by 47.8% and cost per chick by 53.2%, and the response speed of the system was three times faster than that of the conventional system. The acceptance of the technology by the operators was very positive, the operators reported more trust, less operational stress, and the operators felt benefits in terms of productivity. These results are consistent with the adaptive control approach as a suitable and affordable precision hatchery management solution in resource limited environments and bridge the two major shortcomings of the existing literature: the lack of consistent hatchability and lack of adaptive control architectures for LPG-fuelled incubation systems.

5. Implications
The results of the analysis presented in the previous section indicate that the adaptive LPG-fuelled smart poultry incubator has significant improvements over the conventional fixed-setpoint electric incubator in all the performance parameters such as stability of room temperature, stability of humidity, hatchability and quality of chicks, energy consumption, response of the system and the user acceptance. The implications of these results are far reaching and extend beyond the immediate scope of the study and include theoretical contributions to the field of control systems engineering, applications for poultry production in resource-constrained settings, opportunities for economic development for smallholder farmers, policy implications regarding how agricultural technology can be adopted, and general sustainability issues and concerns in the context of food security and rural livelihoods.
This section lays out the implications of the study results in a systematic manner, according to the research goals that were driving this investigation. The achievement for each objective is examined with respect to its importance to theory, practice, policy and future directions for research. The scalability and replicability of the adaptive system, its potential for transfer to other agricultural applications and socioeconomic changes it may create within the context of developing country contexts are also discussed.

5.1 Theoretical and Methodological Implications
5.1.1 Contribution to Adaptive Control Theory in Biological Systems.
The Adaptive Control Architecture implementation in this work is a major contribution in theory of the application of Control Theory in Biological Production Systems. Very little research is available on the application of adaptive control theory to biological systems with time-varying physiological requirements (Åström & Wittenmark, 2008), but much research has been conducted in engineering applications. The results of this study show that it is possible to combine predictive developmental modelling with a sensor feedback system such that the developing embryos' thermal and hygric requirements are anticipated and acted upon by the control system in real-time.

The adaptive system delivered a setpoint adjustment accuracy of 94.2% over the 21-day incubation period, supporting the theory that embryonic development has predicTable patterns which can be modeled and applied to proactively control the environment. This builds on the physiological foundations for stage-specific environmental requirements set down by Lourens et al. (2005) and Tona et al. (2003), in that the stage-specific environmental requirements can be translated into an adaptive control algorithm. The large effect sizes obtained (Cohen's $d > 2.0$) empirically assert the superiority of the adaptive control to the fixed-setpoint strategies in biological incubation systems.

Secondly, the adjustment accuracy of the setpoint is positively correlated with hatchability ($r = 0.67$, $p = 0.002$) and therefore adaptive control is a positive factor for hatchability; however, other factors such as the ventilation, CO_2 concentration and egg turning frequency have a high significance. It gives a new path to develop the theory of multi-parameter adaptive control systems that optimizes multiple parameters of the environment based on their integrated developmental models.

5.1.2 Bridging the Literature Gap on LPG-Fuelled Incubation Systems

Systematic review showed some research about the development of adaptive control systems for incubators using LPG fuel, however, no adaptive control architecture was found which is specifically designed for LPG fuelled incubation systems. Most previous studies on LPG based incubation (Musa et al., 2022; Babajide et al., 2025) have been done on back-up power usage or simple control strategies which have omitted the special thermal feature of combustion based heating. An adaptive control system for LPG combustion is presented and successfully developed for LPG combustion, while also being validated in an empirical test, to fill the gap and provide a methodology for future study of fuel-flexible incubation systems.

The combination of thermal energy storage and LPG heating involves a new approach to the methodological aspects of dealing with intermittency problems associated with combustion-based systems. The method used resulted in a thermal COP of 0.88 for the thermal system versus an electric COP of 0.71 for the conventional system, and shows that the use of thermal buffering can be effective in stabilizing the delivery of heat from intermittent combustion sources. The outcome is not only relevant to poultry incubation, but could be used in other agriculture applications where a sTable temperature or temperature profile is desired in an off-grid or unreliable grid environment.

5.1.3 Methodological Contributions to Incubation Research

A controlled experimental design was used in this study, with three replications and 840 eggs allocated equally among treatment and control, providing a sound methodological reference for future studies on incubation. Systematically collected 2,016 data points for each parameter per cycle make for a wealth of data for understanding the incubation dynamics and for validating the performance of the control system. As outlined in the Literature Review, the method of creating effect sizes, testing assumptions and extensive statistical analysis provides a level of rigor that mitigates concerns that the benchmarking protocols were not consistent. The combination of quantitative and qualitative performance information from the users' acceptance offers a methodological novelty that points to the importance of taking into account human factors in the adoption of technology. This mixed methods approach can demonstrate effectiveness beyond the technical performance of the technology by using self-efficacy theory (Bandura, 1997). The operator feedback thematic analysis has shown that, besides the technical performance, user confidence and the reduction of the operational stress are of utmost importance, when assessing the actual impact of smart incubation technologies.

5.2 Practical and Economic Implications

5.2.1 Transformative Potential for Smallholder Poultry Production

The direct and obvious implication of this research is the adaptTable LPG powered smart incubator for the small scale poultry production scenario in the developing countries. This 8.9 percentage point rise in hatchability (from 86.9% to 95.8%) was equivalent to a gain of 39 chicks per 420 egg batch. This means 390 extra chicks per year for a small-scale hatchery with an annual production of 10 batches; a significant boost in productivity which, in a small-scale hatchery, can be an effective contribution to livelihoods.

The economic impact is as well-suggested. The 47.8% of reduction in operating cost per cycle (₦7,440 vs ₦14,260) and 53.2% of reduction in cost per chick (₦19.3 vs ₦41.2) makes precision incubation technology economically feasible for smallholder farmers who would otherwise not be able to afford proprietary solutions. This cost saving is especially important in the context of Nigeria where the poultry sector is crucial for providing protein and livelihoods for millions of smallholder households. Lower cost per chick benefits the hatchery operator in terms of profitability and also the poultry farmer with lower input cost that may lead to better affordability of poultry products for the consumers.

In many developing countries, one of the challenges is the lack of reliable electricity supply, the LPG based heating subsystem with thermal energy storage addresses this critical constraint. The system allows for sTable incubation conditions even during power cuts, which can be devastating for electrically powered incubators, especially during times of critical incubation. The reliability improvement means that the economic investment of a hatchery operator and the stability of poultry supply chains is enhanced, thereby increasing the stability of the consumer, and the economy.

5.2.2 Implications for Hatchery Management Practices

The effectiveness of the adaptive system can have implications for hatchery management practices other than the hatchery technology developed in this study. The mobile monitoring interface will shift the way hatchery operators monitor incubation conditions from reactive to proactive, allowing the operator to remotely monitor the hatchery conditions and get an alert on site when it is needed. Reported high level of confidence and low operational stress of the operators imply that the system achieves not only better technical results but also better promotes the human operating experience of the hatchery.

A long-standing drawback of the conventional incubator is its inadequate humidity for the hatching phase (Days 19-21); the adaptive system is able to automatically adjust the set point during this period. The practical implications of this feature include the ability of hatchery operators to make an automatic adjustment of humidity during the critical hatching period, which is a very skilled and demanding operation. The system automates this adjustment, further alleviating the skill load on operators and ensuring greater consistency of hatch results.

Some operators have expressed worry about the mobile app's learning curve, which emphasizes the need for user-centred design and training support when implementing smart technologies. This study indicates that user experience, training and support are key elements to successful technology adoption, in addition to technical capabilities. Overall training programmes with the focus on self-efficacy and confidence in the use of smart incubation technologies should be offered in hatcheries.

5.2.3 The Challenge of Energy Access and Sustainability

The adoption of LPG as the main energy source for incubation has implications on energy access and sustainability in off-grid contexts. LPG is used broadly in many developing countries, and is a cleaner and more efficient fuel than the traditional biomass fuels of firewood or charcoal. Enhancing the efficiency of the thermal energy storage subsystem developed in this study further helps to stabilize heat delivery and reduce fuel consumption.

The results of the energy consumption analysis shows that the adaptive LPG system consumes 12.4 kg of LPG and 8.2 kWh of electric per incubation cycle while the conventional electric system consumes 142.6 kWh of electric per incubation cycle. In areas in which electricity generation is carbon intensive, using LPG in this application may improve the situation when compared to the use of grid electricity. Additionally, the lower electricity use reduces strain on often overloaded electricity networks which may help to make electricity more available to other productive uses.

The hatchability and chick quality benefits of the adaptive system also help to reduce resource use in poultry production in terms of sustainability. A high hatch rate results in fewer eggs being lost, and stronger chicks have improved survival and performance rates, minimizing the use of resources in poultry production. This is an efficient measure that correlates with the other measures for the agricultural intensification which works towards minimizing environmental impact and improving food production.

5.3 Social and Policy Implications

5.3.1 Food Security and Nutrition

The results of this study have broader application for food security and nutrition in the developing world. Poultry production is an important source of animal protein for millions of people, and the production of animal protein is essential for child development and maternal health. The benefits of the adaptive incubation system in terms of improved hatchability and chick quality can help increase poultry production, which may enhance the availability and affordability of poultry to low-income groups.

The results of the study have important implications in the backdrop of the forecasted 70% rise in global demand for animal protein by 2050. In order to address this demand in a sustainable way, systems of agriculture need to be more efficient and productive. The adaptive LPG-fuelled smart incubator is a step towards this, by allowing precision hatchery management to yield the optimum production of the hatchery inputs. The economic efficiency gains can be crucial for smallholder farmers who work on thin margins and may be the difference between viable and non-viable poultry businesses.

The emphasis on an open, reproducible system design is socially relevant because it is a technology that is accessible to everyone. The system described in this paper is adaptive and it is hoped will be replicated and adapted by researchers and practitioners in low-resource areas, rather than proprietary commercial systems which may be expensive and impractical for smallholder farmers.

5.3.2 Implications for Technology Adoption and Rural Development

The implications for technology adoption and rural development are that levels of self-efficacy and operator confidence are important factors influencing technology adoption, which has policy and practice implications for agricultural development. Analysis of user feedback was themed to identify some of the benefits of using the adaptive system, with operators feeling more confident in their use of the system being more likely to report productivity benefits.

This implies that the adoption of technology relies not just as much on its performance but also on human factors like training, support, and user experience.

When developing a program to encourage the uptake of smart incubation technologies, these human considerations can be taken into account by policy makers and development practitioners. Training and support initiatives which increase operator self-efficacy and confidence can be as significant an investment as the development of technology. The strong appreciation for the user-centred feature and its ease of use, indicate that user-centred design is important when designing technology.

The job creation and income-generating aspects of the implications of the rural development are also relevant. Poultry production is one of the major employment activities in the rural community and efficient use of incubation can help in the sustainability and development of poultry business. The adaptive system can yield cost savings that can enhance the profitability of hatchery operations, thus allowing business growth and job creation. Power outages are unlikely to cause catastrophic losses to smallholder businesses due to the system's reliability throughout periods of outages.

The policy and institutional implications of this study are summarized:

- The adaptive LPG-fuelled smart incubator was successfully demonstrated and has the potential to influence agriculture and energy policy. Governments and development institutions could consider policies to encourage the use of smart incubation technology, including discounted smart incubators for smallholder farmers or financial assistance to cover the initial price of smart incubators, Investment in LPG infrastructure to guarantee fuel supply, Sponsorship of training programmes to develop confidence and skills of operators, Funding for Research and Development of additional innovations in adaptive incubation technologies and Standards and certification programmes to assure quality and safety of smart incubation systems.
- The potential of using LPG as a clean burning fuel has implications for energy policy especially in a developing country where it is necessary to reduce the use of traditional biomass fuels. LPG is emerging as a transition fuel that can supply clean cooking and productive energy to rural households. LPG could be used for agricultural applications, like incubation, which can help to build a diversified rural energy economy.

5.3.3 Implications for future research

The project will examine opportunities for system enhancement.

The results from this study point to some areas for future research and system improvement. The correlation between setpoint adjustment accuracy and hatchability was moderately good ($r = 0.67$), meaning that other factors such as the ventilation rate, the level of CO_2 and the egg turning consistency also have an impact on the hatchability. Studies are recommended to explore combining more sensors and control parameters to optimize these factors at the same time.

Machine learning integration holds great promise, especially in the field of precision hatchery management. Today this system applies a predictive developmental model to determine the setpoint, however machine learning algorithms can be trained to improve the prediction of the setpoint based on real-time incubation results. Such a system would help to reduce its sensitivity to interbatch variations and would allow for better optimization of incubation conditions for various genetic lines or egg characteristics.

Another research opportunity is the development of adaptive egg turning algorithms. The existing system automatically turns the eggs at a specified time but it is known that the most convenient egg turning schedule can vary according to the developmental stage of the embryo. Hatchability and chick quality could be further improved by an adaptive turning algorithm which changes the frequency and angle of turning according to the needs of the embryo.

5.4 Replication and Scaling Studies

In order to validate the results of this study, there is need to conduct replication and scaling studies in various geographical and operational environments. The findings of this study are strong, but further testing will need to be conducted to evaluate the performance of the system under other ambient conditions, egg types and hatchery conditions.

Future studies to scale up the system should examine the system's performance when using larger egg capacities, since the current system only tested approximately 420 eggs per batch. To implement the adaptive control architecture at a commercial scale, it is important to understand how it works.The economic practicability of the system at various scales should also be examined, such as the cost and benefit analysis of the capital investment and operating costs.

5.5 Comparative Effectiveness Research

Comparative effectiveness research is needed to evaluate the performance of the adaptive LPG system with other smart incubation technologies, such as commercial systems and various energy configurations.This kind of research might be helpful in identifying good practice in some locations, and could be the foundation for the development of a tool for benchmarking incubation systems.

The results on hatchability rate of the adaptive system (95.8%) are comparable with or better than the best results of commercial systems, suggesting that open and low cost systems have a competitive edge with proprietary ones. This finding needs to be corroborated by independent research that will directly compare the performance of various systems under uniform conditions.

5.6 Limitations and Cautions

The results of this study are compelling and warrant attention, but some limitations should be noted in interpreting the results. The study was conducted on a particular type of egg (Gallus gallus domesticus) and at one location, so the results may not be generalizable to other species and locations. A sufficient number of samples were used to find the differences observed, but this was limited by the incubator space and availability of fertile eggs.

The energy cost analysis used the current Nigerian tariff rates which might not apply in other circumstances. The cost savings of the LPG system rely on the relative prices of the fuels, which can vary between different regions

and over time. The economic results should be explored further in future research to determine how sensitive they are to fluctuations in the fuel price.
The qualitative results showed user acceptance (n = 8 operators), but there may be other operators that have different views. The results of these studies should be confirmed by larger-scale user acceptance studies and other factors to discover which contributes to technology adoption.

5.7 Conclusion of Implications

This study's findings have implications in the theoretical, practical, economic, social and policy areas. This successful development and empirical validation of the adaptive LPG-fuelled smart poultry incubator is a valuable contribution to the precision hatchery management, filling important gaps in the literature. The adaptive control strategies proved to be a transformative approach for biological incubation systems, as evidenced by their superior performance on all the key metrics: temperature and humidity stability, hatchability and chick quality, energy consumption, responsiveness of the system, and user acceptance.
The economic considerations are especially noteworthy as the adaptive system had a 47.8% reduction in operating cost and a 53.2% reduction in cost per chick. Such cost savings allow precision incubation technology to be economically viable for smallholder farmers and hatchery agents in developing nations, thus enhancing livelihoods, food security and development in rural communities.
The social and policy implications emphasize the need for user-centred design, training support, and enabling policy environments when adopting a technology. This open and reproducible system design is inclusive innovation and sustainable development, where precision incubation technology is available to everyone.
Implications for future research include opportunities for system enhancement, replication studies, and comparative effectiveness studies. This study lays the groundwork for further exploration and development of smart incubation technologies that could enhance their efficiency and usability.
Finally, this paper demonstrates the potential of adaptive control strategies, LPG heating, and TES, and monitoring systems through IoT technology as viable ways towards precision hatchery management in resource-limited situations. This study contributes to the largely researched literature on incubation systems to address the two major gaps identified in the literature without achieving them namely: consistent hatchability; and an adaptive control architecture is not available on LPG-fuelled incubation systems; thereby contributing towards sustainable intensification of poultry production to meet up the ever increasing demand for animal protein and improve the smallholder farmer's livelihood.

6. Conclusion and Limitations

The aim of this study was to fill two important technology gaps in smart poultry incubation: the large variability of reported hatchability results for the different existing IoT-enabled incubators and the lack of adaptive control architectures that can adapt to the changing physiological needs of an evolving embryo. The proposed integrated solution that incorporates predictive developmental modelling, adaptive control strategies, LPG heating with thermal energy storage and multi-sensor IoT networks for continuous monitoring of the incubator has been developed and validated with real-time mobile monitoring for smart poultry incubator, proving the capability of overcoming these limitations. The system had a hatchability rate of 95.8%, which was 8.9 percentage points higher than the conventional fixed set point electric incubator (86.9%) (an extra 39 chicks per 420-egg batch). Stability of temperature was maintained at ±0.25°C in comparison to the conventional system at ±0.65°C while the humidity stability was ±2.1%RH compared to the conventional system at ±5.3%RH, and the conventional system was not able to make a critical increase of moisture from 55-60%RH to 65-70%RH during the hatching phase, which the adaptive system could successfully perform. The system showed higher energy efficiency, which decreased operating cost per cycle by 47.8% and cost per chick by 53.2% than the conventional system, with a thermal COP of 0.88 vs. 0.71, and with a three times faster response to correct temperature and humidity deviations. This high degree of setpoint adjustment accuracy (94.2 % for 21 days of incubation) and the strong positive correlation with hatchability ($r = 0.67$, $p = 0.002$), proves the theoretical assumption of embryonic development following predicTable patterns, which can be modelled and used for proactive control of the environment. The mixed-methods evaluation with feedback from the users showed that operators expressed high levels of confidence, less stress in their work, and felt they gained in terms of productivity, providing evidence for the role of self-efficacy and user-centered design in technology incorporation.
There are however a number of key caveats to the above results. Eggs were selected by non-probability convenience sampling, which is suiTable for controlled experimental studies in which eggs are not available for sampling from a large population, but may compromise the generalizability of results to other populations of eggs that have different quality characteristics, genetic lines or fertility profiles. The study was carried out in one geographical and operational setting (a peri-urban farming environment in Kano, Nigeria), under specific ambient conditions, patterns of electricity service delivery and user demographics that may impact the transferability of the findings to other contexts with varying climatic conditions, electricity provisioning realities and socioeconomic contexts. Moreover, the qualitative user acceptance segment, which is a rich source of information on the operator experiences and perceptions, did not have a large number of operators (n = 8) and the findings of the thematic analysis might not fully capture the range of user perceptions in other hatchery settings and operator profiles. In spite of all these limitations the experimental design (3 replications), the systematic data sampling on time schedule of 15 min (2016 data points per parameter per cycle) and the high level of statistical testing of data (large effect sizes, Cohen's $d > 2.0$) provides very convincing experimental evidence that adaptive control methods are

superior in biological incubators and establishes a demanding methodologically standard for future research in this area.

The results of this study play an important part in theory, practice and policy implications, and suggest some lines of future research and system improvement. An open and easily reproducible, adaptive control architecture of LPG-fuelled incubation systems is developed, validated, and fills a gap in the literature, which can be adapted by researchers and practitioners in resource-constrained environments. The current activities are focused on expanding the system to other species of poultry and egg types, continued testing of the adaptive control strategy with more extended ambient conditions and under various operating conditions, and the development of a more accurate prediction model based on the collection of additional empirical data. The study offers strong evidence that for hatchery operators and poultry producers, precision incubation technology is economically feasible for smallholder farmers and that incorporation of adaptive control technology and mobile monitoring can lower the operational costs and enhance business sustainability and hatchability. From the developer's perspective, user-centred design principles and extensive training are a crucial component to create the operator's self-efficacy and confidence, which will enable successful technology adoption and continued use. The evidence has been used to support investment in LPG infrastructure, making LPGs more cost-effective through subsidies or financial mechanisms, and training programmes to build operator skills and confidence. Based on the results achieved from this study, some ideas are suggested for future work: Adaptation of machine learning algorithms to the real-time incubation data for better prediction of set point and reduce sensitivity to interbatch variation, Development of adaptive egg turning algorithms based on the stage of incubation to further improve hatchability and better chick quality and Comparative effectiveness research to compare the adaptive LPG system with the commercial proprietary systems under standard conditions and provide adequate cost benefit analysis.A viable and transformative approach to precision management under resource-constrained conditions has been demonstrated, offering a pathway towards sustainable intensification of animal protein production, as a solution to the need for increasing animal protein supply in the world, and improving the livelihoods of smallholder farmers for whom animal husbandry is essential, by combining adaptive control strategies, LPG heating with thermal energy storage, IoT-enabled multi-sensor networks, and mobile monitoring.

Declarations

Ethics Approval and Consent to Participate

Animal Ethics

a. **Ethical Approval:** The study was approved by the Institutional Animal Care and Use Committee (IACUC) of Maryam Abacha American University of Nigeria (MAAUN), with approval number MAAUN/IACUC/2025/027.
b. **Ethical Guidelines:** All experimental procedures involving animals were performed in accordance with the institutional guidelines of MAAUN and the Basel Declaration on animal research (https://animalresearchtomorrow.org/en).
c. **Source of Animals:** The fertile eggs used in this study were obtained from the poultry flock of the Poultry Research and Training Facility (PRTF) at MAAUN, Kano, Nigeria. The eggs were collected from hens owned by the institution. No animals were purchased from commercial sources. No informed consent was required from an external owner as the animals were owned by the institution where the research was conducted.
d. **Anesthesia and Euthanasia:** This study involved the incubation of fertile eggs and the hatching of chicks. No anesthesia or euthanasia methods were applied to the animals (embryos or chicks) during the experimental period. The study did not involve any invasive procedures on live animals.

Human Ethics

a. **Ethical Approval:** The qualitative data collection involving human hatchery operators was reviewed and approved by the Institutional Review Board (IRB) of MAAUN, with approval number MAAUN/IRB/2025/043.
b. **Accordance with Guidelines:** All procedures involving human participants were performed in accordance with the ethical standards of the institutional research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.
c. **Informed Consent:** Informed consent was obtained from all individual participants (hatchery operators) involved in the study. All participants were informed of the study's purpose, risks, and benefits, and they provided their informed consent prior to participation. No participants under the age of 16 were involved in this study.

Data Availability Statement

The datasets generated during and/or analysed during the current study are not publicly available due to institutional data sharing policies and confidentiality agreements but are available from the corresponding author on reasonable request.

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Conflict of Interest
The author declares no conflict of interest. The design, development, and evaluation of the adaptive LPG-fuelled smart poultry incubator was independent and free of influence from any organization or individual from a commercial or financial perspective.

Author Contributions

a. **Conceptualization:** The researcher conceptualized the research idea, identified the gaps, and stated the objectives and hypotheses.
b. Methodology: Designed the controlled experimental setup, the adaptive control architecture, selected the instruments and sensors, and set up the data collection procedures.
c. **Software and System Development:** Implemented the adaptive control algorithm, programmed the PIC12F683 microcontroller, designed the IoT sensor network, and wrote the mobile application interface.
d. **Investigation:** Conducted the experimental trials and carried out data collection for three incubation cycles, operating both the adaptive LPG-fuelled system and the conventional control system.
e. **Data Curation and Formal Analysis:** Performed all statistical analyses (normality tests, homogeneity of variance tests, independent sample t-tests, effect size calculations) using SPSS version 27 and conducted thematic analysis of qualitative feedback using NVivo 14.
f. **Writing – Original Draft Preparation:** Drafted the initial manuscript (Introduction, Literature Review, Methodology, Findings, Implications, and Conclusion).
g. **Writing – Review and Editing:** Reviewed, revised, and edited the paper for clarity, coherence, and journal standards.
h. **Visualization:** Prepared all Figures, Tables, and schematics in the manuscript.
i. **Project Administration:** Responsible for project management, resources, equipment acquisition, and collaboration with the Poultry Research and Training Facility.

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