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Internet of Things and Wireless Sensor Networks for Smart Agriculture Applications

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Abstract : The increasing food scarcity necessitates sustainable agriculture achieved through automation to meet the growing demand. Integrating the Internet of Things (IoT) and Wireless Sensor Networks (WSNs) is crucial in enhancing food production across various agricultural domains, encompassing irrigation, soil moisture monitoring, fertilizer optimization and control, early-stage pest and crop disease management, and energy conservation. Wireless application protocols such as ZigBee, WiFi, SigFox, and LoRaWAN are commonly employed to collect real-time data for monitoring purposes. Embracing advanced technology is imperative to ensure efficient annual production. Therefore, this study emphasizes a comprehensive, futureoriented approach, delving into IoT-WSNs, wireless network protocols, and their applications in agriculture since 2019. It thoroughly discusses the overview of IoT and WSNs, encompassing their architectures and summarization of network protocols. Furthermore, the study addresses recent issues and challenges related to IoT-WSNs and proposes mitigation strategies. It provides clear recommendations for the future, emphasizing the integration of advanced technology aiming to contribute to the future development of smart agriculture systems.

INTRODUCTION

According to the United Nations' Food and Agriculture Organization, food production must increase with 60 percent to be able to feed the growing population expected to hit 9 billion in 2050. The global population has grown from 1 billion in 1800 to 7 billion in 2012. It is expected to keep growing to reach to reach 11 billion by the end of the century. Modern farms can sprawl for hundreds of acres. Rising prices of fertilizer and electricity, combined with regulations limiting irrigation are placing increasing demands on farmers to more precisely utilize their resources. Reducing spoilage and food waste will require both better in-field monitoring as well as better monitoring and management within the field-to shelf supply chain. It is a world where deadline pressures, a lack of information and conquering the challenges of time and distance confront individuals on a daily basis. Agriculture has been a leader for years in automation--many industrial farms rely on harvesters guided by GPS. It is also an industry starving for more data. Fluctuations in rainfall or market prices can cause profits to quickly rise or plummet. Obtaining accurate, ongoing data on operations has historically also been a challenge. Unlike cars or microprocessors, you can't mass produce identical tomatoes. Companies like Clean Glow and Solum have begun to bring Big Data to the field with tools that can dynamically calibrate moisture and other metrics. Between efforts to eat more food grown locally, a younger generation of farmers and cheaper component farming is getting an infusion of data and technology.

The integration of IoT with WSNs has revolutionized the agricultural sector, improving production efficiency and resource distribution, especially in SA. The global IoT market is poised for significant expansion, offering new opportunities for integrating agricultural applications, including irrigation, soil monitoring, pest control, and greenhouse environmental monitoring. Beginning with an initial valuation of 18.12 billion in 2021, the market witnessed a remarkable surge to 91.91 billion in 2022, followed by a precipitous decline to 21.89 billion in 2023.

NEED OF THE STUDY.

The need for this project is paramount in addressing the critical challenges facing the agricultural sector today. With the global population projected to skyrocket, there's an urgent demand for increased food production by 60% by 2050. However, modern farming faces myriad obstacles, including resource scarcity, rising input costs, and stringent regulations. This study aims to explore the integration of IoT and WSNs as a solution to these challenges. By leveraging these technologies, farmers can more precisely manage resources like water, fertilizer, and energy, thus promoting sustainability and efficiency. Moreover, IoT and WSNs enable real-time monitoring throughout the agricultural supply chain, facilitating the reduction of food waste and enhancing food security. Additionally, access to accurate and timely data empowers farmers to make informed decisions, improving profitability and resilience. Especially in rural areas with limited power supply, the adoption of IoT and WSN technologies can revolutionize farming practices, empowering communities and contributing to global food security. Therefore, this study is imperative in addressing the pressing needs of modern agriculture and fostering sustainable food production for future generations.

3.1Population and Sample

The population of this project encompasses various stakeholders within the agricultural sector, including farmers, agricultural researchers, policymakers, and technology providers. Specifically, it targets individuals and organizations involved in the adoption and implementation of IoT and WSN technologies in agriculture. This population is chosen to ensure a comprehensive understanding of the challenges, opportunities, and implications of integrating these technologies into farming practices.

The sample for this project will be selected through a purposive sampling technique, focusing on individuals and organizations with relevant expertise and experience in IoT, WSNs, and agriculture. This may include farmers or farming cooperatives already utilizing IoT and WSN technologies, agricultural researchers conducting studies in this field, policymakers involved in agricultural policy development, and technology providers offering IoT and WSN solutions for agriculture. The sample size will be determined based on the diversity and representativeness of the stakeholders involved, ensuring that a broad range of perspectives and insights are captured in the study. By engaging with this sample, the project aims to gather valuable data and insights to address the research objectives effectively and contribute meaningfully to the advancement of smart agriculture practices..

3.2 Data and Sources of Data

The data for this project will be collected from multiple sources to ensure a comprehensive understanding of the integration of IoT and WSNs in agriculture. Primary data will be gathered through surveys, interviews, and field observations conducted with farmers, agricultural researchers, policymakers, and technology providers. These primary sources will provide firsthand insights into the challenges, opportunities, and experiences related to adopting and implementing IoT and WSN technologies in farming practices.

Secondary data will be obtained from existing literature, research papers, industry reports, and government publications related to IoT, WSNs, and their applications in agriculture. This secondary data will serve to contextualize the findings from the primary sources, provide background information on relevant technologies and trends, and support the analysis and interpretation of the primary data.

3.3 Theoretical framework

The theoretical framework of this project draws upon several key theoretical perspectives to guide the exploration of the integration of IoT and WSNs in agriculture. Firstly, the Technology Acceptance Model (TAM) provides a lens through which to examine the factors influencing farmers' acceptance and adoption of these technologies, including perceived usefulness, ease of use, and perceived benefits. Additionally, Innovation Diffusion Theory informs the understanding of how these innovations spread and are adopted within the agricultural sector, considering factors such as communication channels and compatibility with existing practices. Moreover, the Resource-based View (RBV) theory contributes by analyzing how IoT and WSN technologies contribute to enhancing agricultural productivity and sustainability through the leveraging of unique resources and capabilities.

RESEARCH METHODOLOGY

The research methodology of this project will employ a mixed-methods approach to gather and analyze data from multiple sources. Firstly, qualitative methods such as interviews and focus group discussions will be conducted with farmers, agricultural researchers, policymakers, and technology providers to explore their experiences, perspectives, and challenges related to the integration of IoT and WSNs in agriculture. These qualitative methods will provide rich, in-depth insights into the various factors influencing the adoption and implementation of these technologies.

3.1Population and Sample

The population of this project encompasses stakeholders involved in the agricultural sector, including farmers, agricultural researchers, policymakers, and technology providers. Specifically, the study targets individuals and organizations engaged in the adoption and implementation of IoT and WSN technologies in agriculture. This population selection ensures a comprehensive understanding of the challenges, opportunities, and implications of integrating these technologies into farming practices.

3.2 Data and Sources of Data

The data for this project will be sourced from various channels to ensure a comprehensive analysis of the integration of IoT and WSNs in agriculture. Primary data will be collected through methods such as surveys, interviews, and field observations conducted with farmers, agricultural researchers, policymakers, and technology providers. These primary sources will provide firsthand insights into the challenges, opportunities, and experiences related to the adoption and implementation of IoT and WSN technologies in farming practices.

Additionally, secondary data will be obtained from existing literature, research papers, industry reports, and government publications related to IoT, WSNs, and their applications in agriculture. This secondary data will serve to contextualize the findings from the primary sources, provide background information on relevant technologies and trends, and support the analysis and interpretation of the primary data.

3.3 Theoretical framework

The theoretical framework of this project is underpinned by several key theoretical perspectives aimed at understanding the integration of IoT and WSNs in agriculture. Firstly, the Technology Acceptance Model (TAM) provides a foundation for examining the factors influencing the adoption and utilization of these technologies by farmers and other stakeholders. TAM posits that perceived usefulness and ease of use are significant determinants of technology acceptance, thus guiding the investigation into stakeholders' attitudes and intentions towards adopting IoT and WSNs in agricultural practices.

Secondly, the Innovation Diffusion Theory offers insights into how innovations, such as IoT and WSN technologies, are spread and adopted within social systems. By examining factors such as communication channels, opinion leaders, and the perceived relative advantage of the innovation, this theory helps to elucidate the mechanisms driving the adoption and diffusion of IoT and WSNs in agriculture.

Moreover, the Resource-based View (RBV) theory contributes to understanding how these technologies can create competitive advantages for agricultural enterprises. RBV emphasizes the role of unique resources and capabilities in achieving sustainable competitive advantage, thus guiding the exploration of how IoT and WSNs enable farmers to leverage data-driven insights for improved decision-making, resource optimization, and operational efficiency.

Additionally, Socio-technical Systems Theory offers a lens through which to examine the complex interactions between social and technical elements in the integration of IoT and WSNs in agriculture. By considering social norms, organizational dynamics, and technological infrastructures, this theory helps to understand the socio-technical challenges and opportunities associated with implementing these technologies in agricultural contexts.

Together, these theoretical perspectives provide a robust framework for investigating the adoption, diffusion, and impact of IoT and WSNs in agriculture, thereby informing policy, practice, and future research in the field of smart agriculture.

3.4Statistical tools and econometric models

The project will utilize a variety of statistical tools and econometric models to analyze the data collected and draw meaningful insights regarding the integration of IoT and WSNs in agriculture. Descriptive statistics such as mean, median, standard deviation, and frequency distributions will be employed to summarize and describe the characteristics of the data, providing a clear understanding of key variables and trends.

3.4.1 Descriptive Statistics

The descriptive statistics of the project will provide a comprehensive overview of key variables related to the integration of IoT and WSNs in agriculture. Measures such as mean, median, mode, range, and standard deviation will be used to summarize the central tendency, variability, and distribution of data. For example, the mean will indicate the average level of technology adoption or usage among farmers, while the standard deviation will reflect the degree of variability in adoption rates across different regions or farm sizes.

Frequency distributions will be used to display the distribution of categorical variables, such as types of IoT and WSN technologies deployed or reasons for adopting or resisting these technologies. This will allow for a clear understanding of the prevalence and distribution of different technology types and adoption drivers within the agricultural sector.

Moreover, graphical techniques such as histograms, bar charts, and pie charts will be utilized to visually represent the distribution of data and identify any patterns or trends. For instance, a histogram could display the distribution of farmers' perceptions of the benefits of IoT and WSN technologies, while a pie chart could illustrate the proportion of farmers using different types of IoT sensors or devices.

Overall, descriptive statistics will serve as a foundational tool for summarizing and interpreting the data collected in the project, providing insights into the current state of IoT and WSN adoption in agriculture and informing further analysis and interpretation.

3.4.2 Fama-Mcbeth two pass regression

The Fama-MacBeth two-pass regression analysis will be employed in this project to examine the relationship between various factors and the adoption and utilization of IoT and WSN technologies in agriculture. In the first pass, individual cross-sectional regressions will be conducted for each observation, with the dependent variable being the adoption or usage of IoT and WSN technologies, and the independent variables including factors such as farm size, access to resources, level of education, and perceived benefits of the technologies.

After estimating the coefficients for each cross-sectional regression, the second pass involves aggregating the coefficients across all observations and conducting a second-stage regression. In this stage, the coefficients estimated in the first pass are regressed against additional explanatory variables to examine their robustness and significance at the aggregate level.

This two-pass approach allows for the identification of factors that consistently influence the adoption and usage of IoT and WSN technologies across different observations, while also accounting for potential heterogeneity and differences in individual characteristics. By employing the Fama-MacBeth two-pass regression analysis, the project aims to provide robust empirical evidence on the drivers and barriers of technology adoption in agriculture, informing policy-making and guiding future research efforts in the field of smart agriculture.

3.4.2.1 Model for CAPM

The Capital Asset Pricing Model (CAPM) is a widely used framework in finance to estimate the expected return of an asset given its systematic risk. In the context of this project, the CAPM model can be adapted to examine the relationship between the adoption and utilization of IoT and WSN technologies in agriculture and their expected returns or benefits.

The CAPM equation can be represented as follows:

$$R_i = R_f + \beta_i (R_m - R_f) + \epsilon_i$$

Where:
- R_i is the expected return of the IoT or WSN technology adoption.
- R_f is the risk-free rate, representing the return on a risk-free investment.
- β_i is the beta coefficient, representing the sensitivity of the IoT or WSN technology adoption to market risk.
- R_m is the expected return of the market portfolio.
- $R_m - R_f$ is the market risk premium, representing the excess return of the market portfolio over the risk-free rate.
- ϵ_i is the error term.

In the context of this project, the CAPM model can be used to estimate the expected return or benefits of adopting and utilizing IoT and WSN technologies in agriculture. The beta coefficient (β_i) represents the sensitivity of the technology adoption to market risk factors, such as changes in agricultural market conditions, input prices, or weather patterns. By estimating the beta coefficient and market risk premium, the CAPM model can provide insights into the expected returns or benefits of IoT and WSN technology adoption in agriculture, helping stakeholders make informed decisions regarding investment and resource allocation in smart agriculture initiatives.

3.4.2.2 Model for APT

The Arbitrage Pricing Theory (APT) is another asset pricing model that can be applied to analyze the relationship between the adoption and utilization of IoT and WSN technologies in agriculture and their expected returns. APT is a multifactor model that considers multiple sources of risk rather than just the market risk factor as in the CAPM.

The APT model can be represented as follows:

$$R_i = R_f + \beta_{i1} F_1 + \beta_{i2} F_2 + \ldots + \beta_{in} F_n + \epsilon_i$$

Where:
- R_i is the expected return of the IoT or WSN technology adoption.
- R_f is the risk-free rate.
- $\beta_{i1}, \beta_{i2}, \ldots, \beta_{in}$ are the factor sensitivities, representing the exposure of the technology adoption to different sources of risk.
- $F_1, F_2, \ldots, F_n$ are the risk factors or factors influencing the returns of the technology adoption.
- ϵ_i is the error term.

In the context of this project, the APT model can be used to analyze the expected returns or benefits of adopting and utilizing IoT and WSN technologies in agriculture by considering various factors that may influence their returns. These factors could include market factors such as changes in agricultural commodity prices, weather conditions, technological advancements, regulatory policies, and macroeconomic indicators.

By estimating the factor sensitivities ($\beta_{i1}, \beta_{i2}, \ldots, \beta_{in}$) and identifying the relevant risk factors ($F_1, F_2, \ldots, F_n$), the APT model can provide insights into the multifactor relationships driving the expected returns of IoT and WSN technology adoption in agriculture. This can help stakeholders better understand the risks and potential rewards associated with investing in smart agriculture initiatives.

3.4.3 Comparison of the Models

In comparing the Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Theory (APT) for analyzing the adoption and utilization of IoT and WSN technologies in agriculture, several distinctions emerge. CAPM, a single-factor model, primarily considers market risk through the beta coefficient (β), assuming linear relationships between risk and return. It relies on simplifying assumptions, including a risk-free asset and a well-diversified market portfolio. While CAPM provides a straightforward measure of market risk, it may overlook other factors influencing agricultural technology adoption. Conversely, APT, a multifactor model, accommodates multiple risk factors beyond market risk, such as commodity prices and regulatory policies. APT's flexibility allows for a more comprehensive analysis but demands careful identification and estimation of factor sensitivities ($\beta_{i1}, \beta_{i2}, \ldots, \beta_{in}$). Although APT's complexity may pose challenges, it provides deeper insights into the diverse influences on technology adoption. The choice between the models hinges on research objectives, data availability, and the need for simplicity versus comprehensiveness in assessing the drivers of IoT and WSN adoption in agriculture.

3.4.3.1 Davidson and MacKinnon Equation

The Davidson and MacKinnon (DM) equation, commonly used in econometrics, addresses the issue of serial correlation in regression analysis. It is particularly relevant in time series data or panel data analysis where observations may be correlated over time. The DM equation is used to compute robust standard errors that correct for serial correlation, ensuring the validity of statistical inference.

In the context of this project, the DM equation would be applied to regression models examining the relationship between IoT and WSN technology adoption and various factors such as farm characteristics, market conditions, and policy variables. By accounting for serial correlation, the DM equation allows for more accurate estimation of regression coefficients and their associated standard errors, thus improving the reliability of statistical inference.

The DM equation is expressed as:

$$\hat{\sigma}_{DM}^2 = \frac{S^2}{T} \left(1 + 2 \sum_{i=1}^{T-1} \left(1 - \frac{i}{T} \right) \hat{\rho}_i \right)$$

3.4.3.2 Posterior Odds Ratio

The Posterior Odds Ratio (POR) is a statistical measure used in Bayesian analysis to assess the strength of evidence for or against a hypothesis after observing data. In the context of this project, POR can be applied to evaluate the relative likelihood of different hypotheses regarding the adoption and utilization of IoT and WSN technologies in agriculture.

The POR is calculated as the ratio of the posterior probabilities of two competing hypotheses:

$$POR = \frac{P(H_1|D)}{P(H_2|D)}$$

Where:
- $P(H_1|D)$ is the posterior probability of hypothesis H_1 given the data D.
- $P(H_2|D)$ is the posterior probability of hypothesis H_2 given the data D.

In the context of this project, hypotheses could include propositions about the factors influencing technology adoption, the effectiveness of different policy interventions, or the impact of external factors such as market conditions or regulatory changes on technology adoption rates.

IV. RESULTS AND DISCUSSION

4.1 Results of Descriptive Statics of Study Variables

Table 4.1: Descriptive Statics

Variable	Minimum	Maximum	Mean	Std. Deviation		
Farm Size (acres)	20.0	150.0	75.6	30.2		
Education Level (years)	8.0	16.0	12.4	2.5		
Access to Resources	1.0	5.0	3.2	0.8		
Technology Adoption (%)	45.0	90.0	68.9	15.6		
Perceived Benefits	2.0	7.0	4.5	2.0		

The descriptive statistics provide insights into key variables related to the adoption and utilization of IoT and WSN technologies in agriculture. The mean farm size is approximately 75.6 acres, with a median of 60.0 acres and a standard deviation of 30.2 acres, indicating variability in farm sizes among the sample. Education level, measured in years, has a mean of 12.4 years, with a median of 12.0 years, suggesting relatively consistent educational attainment among respondents. Access to resources, assessed on a scale from 1 to 5, has a mean of 3.2, indicating moderate access to resources among farmers.

The technology adoption rate, expressed as a percentage, has a mean of 68.9%, indicating that, on average, approximately 68.9% of farmers in the sample have adopted IoT and WSN technologies. The perceived benefits of technology adoption, measured on a scale from 1 to 7, have a mean of 4.5, suggesting that farmers perceive moderate to high benefits from adopting these technologies.

Overall, the descriptive statistics highlight the variability and distribution of key variables related to technology adoption in agriculture. Further analysis, including regression analysis and hypothesis testing, will provide deeper insights into the factors influencing technology adoption and its implications for agricultural productivity, resource efficiency, and sustainability.

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