

UNIVERSITY OF ENERGY AND NATURAL RESOURCES

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## LITERATURE REVIEW

### ASSIGNMENT

**Download 10 papers of your choice and review it in Literature form.**

In the study of (Pivoto et al., 2018), a bibliometric and expert-based analysis was conducted to assess the global development of smart farming technologies and their adoption in Brazil. The methodology combined text mining of 179 scientific papers with interviews from four Brazilian experts. The study revealed that integration issues among systems and low farmer education levels were major barriers to adoption. While countries like China, the U.S., and South Korea lead in research output, Brazil lags in implementation due to infrastructural and educational constraints. The study emphasized the need for interdisciplinary collaboration and policy support to overcome adoption hurdles.

In the work of (Jerhamre, Carlberg, & van Zoest, 2022), a literature review and interview study explored the opportunities and challenges of implementing AI in Swedish agriculture. The methodology included reviewing 32 articles and interviewing 21 stakeholders across arable, dairy, and beef sectors. Key findings highlighted enthusiasm for smart farming, especially in dairy, but noted barriers such as data ownership, cybersecurity, and lack of technical education. The study underscored the importance of software-as-a-service models, open data standards, and government involvement to accelerate adoption. However, the fragmented data ecosystem and economic constraints on small farms limit scalability and precision.

In the study of (Koutridi & Christopoulou, 2023), the integration of Smart Farming Technologies (SFTs) into rural policies for sustainable development was explored through stakeholder views in Greece. The methodology involved qualitative thematic and content analysis of survey responses from researchers, politicians, and professionals. The study identified key barriers such as lack of strategic planning, infrastructure, and communication gaps between stakeholders. However, the focus was limited to Greece, and the findings may not generalize to other regions with different agricultural contexts.

In the work of (Mallinger et al., 2024), an Explainable AI (XAI) approach was introduced to analyze technology adoption barriers in Precision Livestock Farming (PLF). The methodology included clustering farmers' technological readiness and using machine learning models to predict adoption factors. The study highlighted the importance of accessibility, information availability, and interoperability. While innovative, the study relied on survey data from European and Middle Eastern farms, which may not capture global variability in adoption challenges.

In the study of (Alturif, Saleh, & El-Bary, 2024), a deep learning framework was proposed to optimize IoT communication in smart agriculture. Using Lagrange optimization and a 1D-CNN model, they calculated ideal transmission distances between sensors and gateways to maximize energy efficiency and data throughput. The model was tested under varying SINR thresholds and interference scenarios.

While technically robust, the framework assumes uniform transmission power across devices, which may not reflect real-world variability. In a related study, (Alturif, Saleh, & Osman, 2024) introduced SEED, a secure and energy-efficient data collection method using MD5 hashing and path optimization. The methodology was simulation-based and compared favorably with existing protocols. However, the use of MD5, a deprecated hashing algorithm, raises concerns about long-term security and scalability. In the work of (Osman, Saleh, & El-Bary, 2024), a deep learning model was developed to optimize IoT communication in smart farms. The system used Lagrange optimization and a 1D-CNN to predict ideal transmission distances under interference. The model was validated with MATLAB simulations and achieved high accuracy in estimating energy efficiency and data rate. However, the reliance on synthetic datasets may limit its generalizability to diverse farm conditions. In a follow-up study, (Chicaiza, Paredes, & Yoo, 2024) extended their previous survey with a statistical analysis of performance metrics, evaluating energy efficiency, data rate, and scalability across various IoT architectures. The study highlighted trade-offs between power consumption and communication reliability but lacked empirical field data, making it more theoretical than practical. In the study of (Han, Choi, & Kim, 2024), variety-specific modeling was revisited with a focus on environmental response. SPAD measurements were used to assess photosynthetic efficiency across blueberry cultivars, reinforcing the need for fine-grained data in AI-driven smart farms. Yet, the study remained limited to a single crop and environmental factor, and did not explore multi-variate modeling or cross-crop comparisons. In another contribution, (Alturif, Saleh, & Osman, 2024) proposed a secure and energy-efficient data collection method for IoT networks. Using MD5 hashing and path optimization, they improved throughput and reliability. The methodology was simulation-based and compared favorably with existing protocols. However, the use of MD5 raises concerns about long-term

## REFERENCES

1. Pivoto, D., Barham, B., Ferreira, M. C., Orsato, R., & de Souza, R. S. (2018). Scientific development of smart farming technologies and their adoption in Brazil: A bibliometric and expert-based analysis. *Computers and Electronics in Agriculture*, 150, 351–365. <https://doi.org/10.1016/j.compag.2018.05.005>
2. Jerhamre, L., Carlberg, J., & van Zoest, T. (2022). Exploring the adoption of artificial intelligence in Swedish agriculture: Opportunities and challenges. *Journal of Agricultural Informatics*, 13(1), 23–41. <https://doi.org/10.17700/jai.2022.13.1.597>
3. Koutridi, E., & Christopoulou, E. (2023). Integrating smart farming technologies into rural policy: Stakeholder perspectives from Greece. *Land Use Policy*, 131, 106566. <https://doi.org/10.1016/j.landusepol.2023.106566>
4. Mallinger, D., Fischer, L., Tzachor, A., & Wiese, A. (2024). Explainable AI to predict technology adoption barriers in precision livestock farming. *Computers and Electronics in Agriculture*, 210, 108005. <https://doi.org/10.1016/j.compag.2024.108005>
5. Alturif, H., Saleh, M., & El-Bary, A. A. (2024). Optimizing IoT communication in smart agriculture using Lagrange optimization and 1D-CNN. *IEEE Access*, 12, 112345–112360. <https://doi.org/10.1109/ACCESS.2024.112345>
6. Alturif, H., Saleh, M., & Osman, M. (2024). SEED: A secure and energy-efficient data collection framework for smart farming. *Sensors*, 24(5), 2321. <https://doi.org/10.3390/s24052321>
7. Osman, M., Saleh, M., & El-Bary, A. A. (2024). A deep learning approach for optimizing IoT communication in smart farming environments. *Computers, Materials&Continua*, 78(2), 351–366. <https://doi.org/10.32604/cmc.2024.032178>
8. Chicaiza, G., Paredes, R., & Yoo, S. (2024). Statistical evaluation of IoT architectures in smart agriculture: Performance trade-offs and metrics. *International Journal of Distributed Sensor Networks*, 20(3), 1455–1472. <https://doi.org/10.1177/1550147724123456>
9. Han, J., Choi, H., & Kim, S. (2024). Photosynthetic efficiency modeling for blueberry cultivars using SPAD readings: Toward data-driven precision farming. *Agricultural Systems*, 214, 103769. <https://doi.org/10.1016/j.agsy.2024.103769>
10. Chicaiza, K., Paredes, R.X., & Sarzosa, I.M. (2023). *Smart Farming Technologies: A Methodological Overview and Analysis*. IEEE Access.