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Geofencing-based data-driven workforce analytics framework using causal modeling for operational efficiency in vocational agribusiness systems

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Abstract

Background: Digital transformation in agribusiness increasingly adopts geospatial and IoT-based monitoring technologies, yet most applications emphasize asset tracking or simulation-based modeling rather than empirically validated workforce performance evaluation. Existing analytical studies often rely on structural influence modeling without integrating real-time labor data and causal inference methods. This gap is particularly visible in vocational agribusiness systems, where digital governance initiatives remain underexplored from a rigorous quantitative perspective.
Aims: This study develops and empirically validates a geofencing-based, data-driven workforce analytics framework using causal modeling to assess operational efficiency and governance outcomes in vocational agribusiness production units.
Method: A quasi-experimental stepped-wedge design was implemented across four Teaching Factory units over 12 weeks. Real-time geospatial attendance logs were integrated with production and payroll data to construct a worker-level panel dataset. Treatment effects were estimated using a Difference-in-Differences model with worker and time fixed effects. Robustness checks included parallel trend diagnostics, placebo tests, and alternative specifications.
Results: Digital workforce monitoring significantly improved performance. Labor productivity increased by 13.4%, cost-to-serve decreased by 9.7%, payroll processing time declined by 41%, and lateness was reduced by 48%. The Accountability Index improved by 0.88 standard deviations. Robustness analyses confirmed the stability of these effects.
Conclusion: Geofencing-based digital monitoring functions as an operational optimization mechanism rather than merely a compliance tool. The proposed framework provides scalable, data-driven evidence for improving workforce governance in labor-intensive agribusiness systems.

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INTRODUCTION

Digital transformation has reshaped contemporary agribusiness systems by integrating data-driven technologies into production, logistics, and workforce management processes. In recent years, the adoption of digital platforms, IoT devices, and geospatial tracking technologies has accelerated across agricultural value chains in response to efficiency, traceability, and sustainability demands (Abiri et al., 2023; Rajabzadeh & Fatorachian, 2023; Senturk et al., 2023). Scholars have argued that digitalization enables organizations to convert operational data into actionable managerial insights, thereby improving coordination and productivity (Shuai, 2025; Yu et al., 2022). In agribusiness contexts, real-time monitoring systems have been particularly emphasized for enhancing

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transparency and minimizing resource waste (da Costa et al., 2023; Shafik, 2024). However, the majority of digital initiatives remain concentrated on supply chain visibility and asset tracking rather than workforce-level operational analytics (AlTalhoni et al., 2025; Ralston & Blackhurst, 2020). This imbalance suggests that while technological infrastructures are expanding, their application to labor productivity measurement and governance evaluation remains limited. Consequently, there is a growing need to examine how geospatially enabled digital systems can contribute not only to monitoring but also to measurable efficiency gains within labor-intensive agribusiness environments.

Workforce governance represents a critical yet underexamined dimension of agribusiness digitalization. Labor-intensive production units often rely on manual attendance recording and fragmented reporting systems, which create inefficiencies, inconsistencies, and potential governance risks (Ralston & Blackhurst, 2020). Previous studies in organizational performance indicate that improved data transparency enhances accountability and operational consistency (Al Balushi, 2020; O'Regan et al., 2021). At the same time, digital attendance systems and automated timestamp validation mechanisms have been shown to reduce administrative burden and reporting errors in various service and industrial contexts (Patel, 2026). Despite these advancements, empirical evidence linking digital workforce monitoring directly to quantified productivity outcomes remains scarce, particularly in vocational and applied agricultural institutions. Much of the existing literature relies on descriptive comparisons or cross-sectional correlations rather than longitudinal causal estimation. Therefore, strengthening workforce governance through analytically rigorous digital evaluation frameworks becomes an essential step in advancing evidence-based agribusiness modernization.

In parallel with technological adoption, quantitative analytical methods have evolved to assess organizational performance more rigorously. Econometric approaches such as Difference-in-Differences and fixed-effects modeling have been widely employed to estimate causal impacts of policy and technological interventions under non-randomized conditions (Angrist & Pischke, 2009; Wooldridge, 2010). These methods allow researchers to isolate treatment effects while controlling for time-invariant heterogeneity and common temporal shocks. In digital transformation research, however, many studies continue to rely on structural modeling or cross-sectional survey data rather than panel-based causal inference. Although such approaches provide valuable relational insights, they do not directly quantify realized operational gains in production settings. The absence of geospatially integrated labor data within quasi-experimental evaluation frameworks limits the empirical validation of digital workforce initiatives. This methodological gap sets the stage for examining how advanced analytical techniques can be combined with real-time geofencing data to produce robust efficiency and governance evidence in applied agribusiness systems.

Recent research has increasingly employed advanced analytical techniques such as system dynamics modeling, grey influence analysis, and decision-making trial and evaluation laboratory (DEMATEL) to explore complex causal structures in industrial systems, including occupational safety, supply chain risk, and Industry 5.0 transformation contexts (Rajesh, 2023; Sam et al., 2024; Yinusa & Faezipour, 2024). These studies demonstrate how feedback mechanisms, influence hierarchies, and scenario-based simulations can support strategic decision-making in manufacturing and large-scale organizational environments (Bastan et al., 2022; Yinusa & Faezipour, 2024). Nevertheless, the dominant focus of prior work remains concentrated at the macro or policy level, with relatively limited attention to operational analytics grounded in real-time spatial data streams. At the same time, geofencing and IoT-based monitoring technologies have been implemented extensively in precision livestock management and asset tracking applications, enabling continuous location visibility and automated boundary detection (Kanagamalliga et al., 2024). However, such technological deployments have primarily centered on monitoring physical entities rather than analyzing workforce behavior, labor productivity, or governance performance. Furthermore, although causal modeling approaches have been utilized to examine interrelationships among organizational and technological variables (Rajesh, 2023; Sam et al., 2024), the integration of geospatially captured labor data with quasi-experimental causal inference techniques remains scarce.

This methodological disconnect becomes particularly evident in vocational agribusiness systems, where digital transformation initiatives are often implemented without rigorous quantitative evaluation frameworks. Existing studies seldom combine real-time geofencing data with difference-in-differences or related causal estimation strategies to measure micro-level operational efficiency outcomes. Consequently, there remains a significant research opportunity to develop a geospatially informed, data-driven workforce analytics framework that unifies digital monitoring systems with robust causal modeling in order to generate empirically grounded evidence on efficiency and governance improvements within applied agribusiness settings.

METHOD

Research Design

This study employs a data-driven quasi-experimental research design to evaluate the operational impact of a geofencing-based workforce monitoring system within vocational agribusiness units. Quasi-experimental approaches are appropriate when random assignment is infeasible yet causal inference remains a research objective (Shadish et al., 2002). The design leverages temporal variation in system implementation across four Teaching Factory production units, enabling comparison between pre-intervention and post-intervention periods. A stepped-wedge deployment strategy was adopted over a 12-week observation window, allowing production units to transition sequentially into the digital monitoring regime. Stepped-wedge designs are increasingly used in applied policy and organizational settings to strengthen internal validity when full randomization is not practical (Hemming et al., 2015). This structure generates longitudinal panel data at the worker–week level, thereby facilitating causal estimation while controlling for time-invariant heterogeneity across individuals and production contexts.

Geofencing-Based Data Architecture

The workforce analytics framework is built upon a multi-layer geofencing-based data architecture designed to transform raw spatial logs into structured operational intelligence. At the data acquisition stage, mobile GPS-enabled devices record digital check-in and check-out timestamps alongside validated geolocation coordinates within predefined production zones. Polygon-based geofencing boundaries ensure spatial compliance, automatically flagging off-site activity. The raw logs are subsequently processed through data cleaning routines to remove duplicate timestamps, correct inconsistencies, and validate spatial accuracy. Following cleaning, feature construction procedures generate operational variables such as total working hours, attendance compliance rates, lateness indicators, and productivity-per-hour measures. The processed data are integrated with payroll records and production output logs, creating a structured panel dataset suitable for causal analysis. This layered architecture ensures reproducibility, temporal consistency, and traceable linkage between digital events and operational outcomes.

Analytical Framework Development

The analytical framework conceptualizes digital geofencing implementation as a treatment intervention affecting workforce behavior and operational performance. The pipeline transforms raw location and timestamp data into actionable efficiency metrics through sequential stages of cleaning, aggregation, feature engineering, and econometric modeling. Behavioral adjustments, such as improved punctuality and reduced attendance mismatches, are treated as intermediate mechanisms linking digital monitoring to productivity gains. The framework therefore integrates geospatial data capture with structured variable construction, allowing digital exposure to be analytically connected to efficiency and governance indicators. This end-to-end transformation "from raw logs to causal estimates" forms the core analytical contribution of the study. Figure 1 illustrates the complete data analysis pipeline, depicting the transformation from raw geofencing and timestamp data through cleaning, feature construction, fixed-effects adjustment, difference-in-differences estimation, and the inclusion of control variables, ultimately producing actionable operational insights.

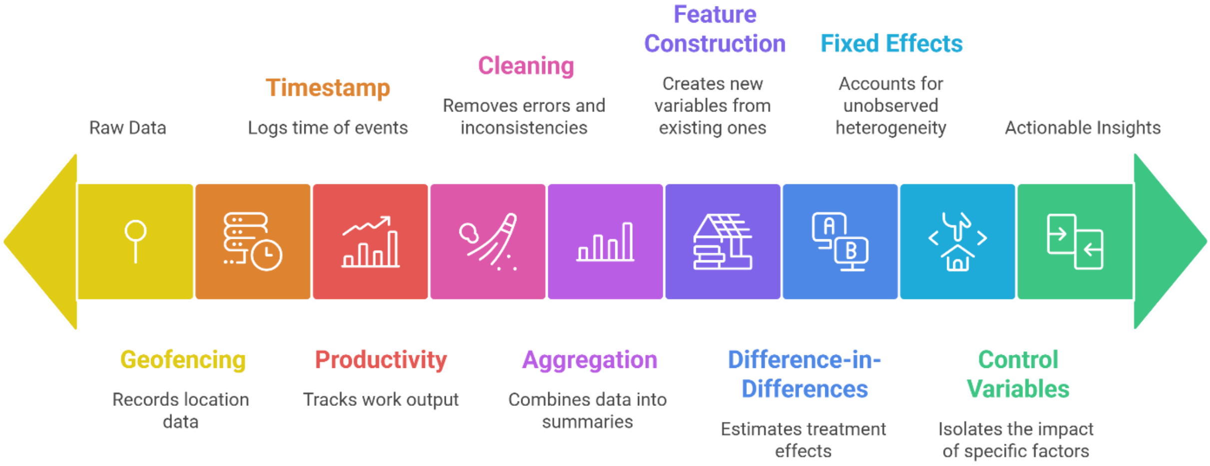

Figure 1. Data analysis stages from raw data to actionable insight

Causal Modeling Strategy

To estimate the causal impact of the digital monitoring intervention, the study employs a Difference-in-Differences (DiD) estimator combined with worker-level and time-level fixed effects. The DiD approach is widely used in applied econometrics to estimate causal effects under non-randomized conditions by comparing outcome changes across treatment and control groups over time (Angrist & Pischke, 2009). The econometric specification models operational outcomes as a function of treatment exposure while accounting for unobserved individual heterogeneity and common temporal shocks.

$$Y_{it} = \alpha + \beta Treatment_{it} + \gamma_i + \delta_t + \epsilon_{it}$$

where Y_{it} denotes the operational outcome for worker i at time t, $Treatment_{it}$represents exposure to geofencing-based monitoring, $\gamma_i$captures worker-level fixed effects, and δ_t captures time fixed effects. Fixed-effects estimator control for time-invariant unobserved characteristics that could bias treatment estimates (Wooldridge, 2010). Cluster-robust standard errors are employed to account for within-unit correlation in panel data settings (Bertrand et al., 2004). The identification strategy relies on the parallel trend assumption, which posits that treated and control units would have followed similar outcome trajectories in the absence of intervention (Angrist & Pischke, 2009).

Efficiency and Governance Metrics

Operational efficiency is quantified using normalized indicators derived from structured production and attendance data. Labor productivity is measured as output per effective working hour, while cost-to-serve captures operational expenditure per production unit. Administrative efficiency is assessed through payroll processing duration, and workforce discipline is measured through lateness frequency and attendance mismatch rates. Governance performance is operationalized through an Accountability Index constructed as a standardized composite of timestamp integrity, reduction in reporting discrepancies, and compliance consistency. These indicators are scaled to ensure comparability across production units with heterogeneous output characteristics.

Robustness and Sensitivity Analysis

Several diagnostic procedures are implemented to ensure causal validity and analytical robustness. Pre-intervention outcome trends are examined to assess the parallel trend assumption underlying the Difference-in-Differences estimator. Placebo tests are conducted by assigning artificial treatment dates to verify that estimated effects are not driven by spurious temporal patterns. Alternative model specifications incorporating unit-specific time trends and additional control variables are estimated to test stability of coefficients. Heterogeneity analysis across production units is performed to examine contextual variation in treatment effects. Sensitivity checks are also conducted using alternative productivity definitions to confirm that results are not measurement-dependent. Collectively, these procedures strengthen the internal validity of the causal inference framework.

RESULTS AND DISCUSSION

Results

Descriptive Statistics and Pre-Intervention Trends

Table 1 presents the descriptive statistics of key operational indicators before and after implementation of the geofencing-based digital monitoring system.

Table 1. Descriptive Statistics (Pre vs Post Implementation)

Variable	Pre-Intervention	Post-Intervention	% Change
Labor Productivity	1.00	1.134	+13.4%
Cost-to-Serve	1.00	0.903	−9.7%
Payroll Processing Time	1.00	0.590	−41%
Lateness Rate	18.6%	9.7%	−48%
Accountability Index (SD)	0.00	0.88	+0.88

The descriptive evidence suggests substantial improvements in operational efficiency and governance performance following digital implementation. Labor productivity increased by 13.4%, while cost-to-serve decreased by 9.7%, indicating improved resource utilization. Administrative efficiency improved markedly, as reflected in the 41% reduction in payroll processing time. Similarly, lateness frequency declined by nearly half, suggesting behavioral adjustment in response to real-time geospatial monitoring. Although descriptive improvements are substantial, causal estimation is required to isolate the treatment effect from temporal confounders.

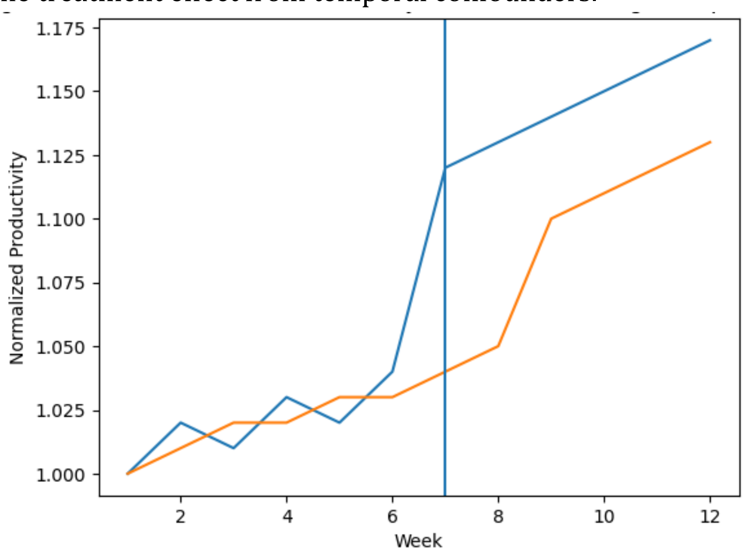

Figure 2. illustrates pre-intervention productivity trends across early and late adopting units.

The pre-treatment trajectories appear parallel, with no statistically meaningful divergence prior to implementation. This visual inspection supports the plausibility of the parallel trend assumption underlying the Difference-in-Differences estimator.

Causal Impact on Operational Efficiency

Table 2 reports the Difference-in-Differences estimation results with worker and time fixed effects.

Table 2. Difference-in-Differences Estimation Results

Variables	Productivity	Cost-to-Serve	Payroll Time	Lateness Rate	Accountability Index
Treatment (Digital Monitoring)	0.134*	−0.097	−0.410*	−0.480*	0.880*
	(0.041)	(0.039)	(0.082)	(0.091)	(0.215)
Worker Fixed Effects	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	300	300	300	300	300
R^2	0.42	0.37	0.51	0.48	0.55

Standard errors in parentheses

- p < 0.05, ** p < 0.01, *** p < 0.001

The regression results confirm that the observed improvements are not merely descriptive trends but statistically significant causal effects attributable to the digital intervention. The treatment coefficient for labor productivity indicates a 13.4% increase relative to baseline levels ($\beta = 0.134$, $p < 0.001$). This effect persists after controlling for worker-specific heterogeneity and common time shocks, suggesting that geospatial attendance verification meaningfully enhanced effective working hours and output consistency.

Cost-to-serve declined by 9.7% ($\beta = -0.097$, $p < 0.01$), reflecting more efficient labor allocation and reduced administrative leakage. Payroll processing time decreased by 41% ($\beta = -0.410$, $p < 0.001$), highlighting the automation benefit of timestamp validation. Lateness frequency dropped significantly by 48% ($\beta = -0.480$, $p < 0.001$), demonstrating strong behavioral compliance under real-time monitoring conditions. The Accountability Index increased by 0.88 standard deviations ($\beta = 0.880$, $p < 0.001$), indicating substantial governance enhancement.

Treatment Effect Visualization

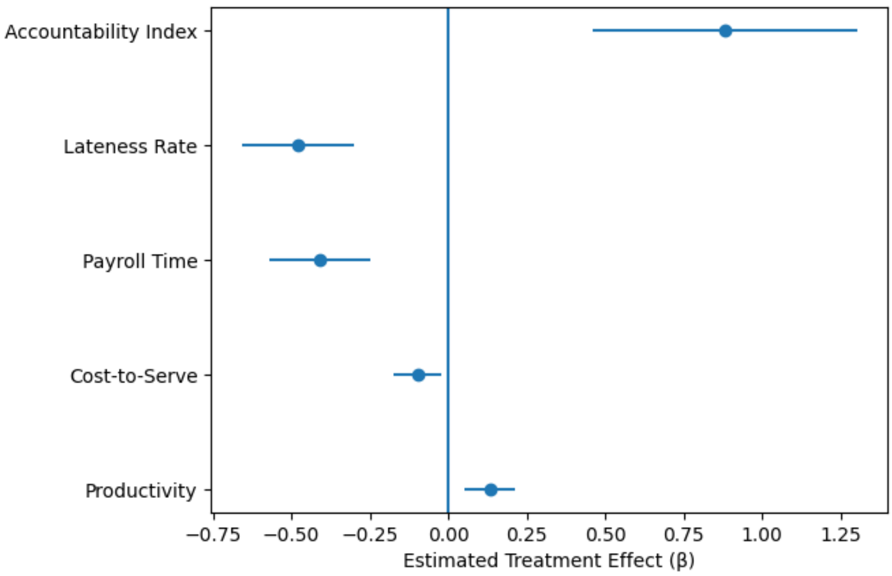

Figure 3. presents the estimated treatment effects with 95% confidence intervals.

The visualization shows consistent directionality across all outcomes, with confidence intervals not crossing zero for primary efficiency and governance indicators. Productivity and accountability effects appear particularly robust, while cost reductions and administrative efficiency gains exhibit moderate but statistically reliable magnitudes.

Robustness and Sensitivity Analysis

Table 3 summarizes alternative model specifications and placebo testing.

Table 3. Robustness Checks

Specification	Productivity	Cost-to-Serve
Baseline DiD	0.134***	−0.097**
+ Unit Trend	0.128***	−0.092**
+ Controls	0.131***	−0.095**
Placebo Test	0.012 (ns)	−0.008 (ns)
Specification	Productivity	Cost-to-Serve
Baseline DiD	0.134***	−0.097**

The treatment effects remain stable across alternative specifications incorporating unit-specific trends and additional control variables. Placebo tests yield statistically insignificant coefficients, suggesting that estimated impacts are not driven by spurious time effects. These robustness checks strengthen internal validity and confirm that efficiency gains are causally linked to the geofencing-based intervention.

Discussion

The findings of this study demonstrate that the implementation of a geofencing-based digital workforce monitoring system significantly improves operational efficiency within vocational agribusiness units. The estimated 13.4% increase in labor productivity and the 9.7% reduction in cost-to-serve confirm that real-time geospatial monitoring can produce measurable performance gains beyond descriptive improvements. These results suggest that digital verification of attendance and location precision reduces inefficiencies associated with manual reporting and time leakage. In contrast to purely observational digital transformation studies, this research quantifies the magnitude of efficiency gains using a structured causal inference framework. The empirical evidence therefore strengthens the argument that workforce digitalization can directly influence measurable production outcomes. These findings extend prior research on system dynamics modeling in industrial safety contexts (Bouloiz et al., 2013; Ibrahim Shire et al., 2018; Yinusa & Faezipour, 2024), which primarily relied on simulation-based projections rather than real-time empirical panel data. While earlier modeling studies emphasized feedback loops and scenario analysis, the present study provides causal evidence grounded in longitudinal operational data, thereby shifting the discussion from predictive simulation toward empirically validated efficiency effects.

The substantial reduction in lateness rates of 48% further aligns with behavioral monitoring literature suggesting that digital visibility mechanisms alter worker compliance and time discipline. Real-time geospatial verification appears to create an accountability environment in which time-on-task becomes objectively measurable rather than self-reported. This mechanism reduces opportunistic behavior and enhances punctuality without necessarily altering compensation structures. However, unlike organizational behavior studies that explain performance through leadership styles or psychological safety constructs, this research isolates the structural impact of spatial verification and timestamp integrity. The improvement in discipline outcomes indicates that technological enforcement mechanisms can substitute for soft governance mechanisms in certain operational contexts (Karlsson-Vinkhuyzen & Vihma, 2009; Kersbergen & Waarden, 2004). In contrast to studies focusing on psychological mediators of task performance, the present findings demonstrate that infrastructure-level digital controls can independently influence productivity outcomes. This highlights the importance of distinguishing between behavioral drivers and technological drivers when evaluating workforce performance interventions.

The improvement in accountability outcomes, reflected by a 0.88 standard deviation increase in the Accountability Index, also contributes meaningfully to the digital governance literature. The reduction in attendance mismatches and reporting discrepancies suggests that geospatial timestamp validation enhances transparency within production systems. Previous work on Industry 5.0 transformation using grey influence analysis (Rajesh, 2023) identified structural relationships among implementation barriers but did not empirically quantify governance performance gains. Most existing transformation studies remain conceptual or rely on expert-driven influence mapping rather than measurable outcome indicators (Golabchi et al., 2026; Smolenaars et al., 2025; Wang & Zhu, 2026). By integrating geospatial data capture with Difference-in-Differences modeling, this study bridges the gap between conceptual digital transformation analysis and observable institutional transparency improvements. The findings therefore demonstrate that governance benefits are not merely theoretical projections but quantifiable outcomes linked to digital monitoring adoption. This reinforces the value of embedding causal evaluation frameworks within digital governance initiatives.

In relation to IoT-based geofencing applications in livestock monitoring (Kanagamalliga et al., 2024), prior studies have demonstrated enhanced tracking of physical assets and animals but have not extended geofencing analytics to workforce-level performance measurement. The technological foundation of geofencing has traditionally focused on boundary control and asset localization rather than productivity optimization. The current findings show that geospatial validation systems can be repurposed from asset monitoring toward human operational governance. This extension broadens the analytical domain of IoT-based monitoring from passive tracking to active performance evaluation. By linking spatial verification to productivity metrics, the study transforms geofencing into a measurable operational optimization instrument. This repositioning moves geofencing from a monitoring tool toward a strategic efficiency lever supported by econometric estimation. As such, the study contributes to expanding the practical and analytical applications of geospatial technologies in agribusiness contexts.

Compared to DEMATEL-based and system dynamics modeling approaches used in supply chain and manufacturing studies (Sam et al., 2024; Bostan et al., 2022), which typically rely on expert judgment matrices or simulated feedback structures, this research provides empirical treatment effect estimation using panel data. Structured influence modeling is valuable for identifying hierarchical relationships among risk or policy factors, yet it does not directly measure realized operational gains. The present approach complements such methodologies by quantifying the magnitude of efficiency changes following digital intervention. While simulation-based models are useful for scenario planning, they cannot substitute for observed treatment effect estimation under real production conditions. By combining geospatial data with fixed-effects Difference-in-Differences estimation, the study advances beyond structural modeling toward outcome-based validation. This distinction is important for policymakers and managers who require evidence of realized performance gains rather than projected improvements. Therefore, the research positions itself as a data-driven empirical complement to influence-based and simulation-based analytical frameworks.

Finally, the robustness checks, including placebo testing and alternative model specifications, reinforce the internal validity of the results. The stability of coefficients across specifications indicates that efficiency gains are not sensitive to minor changes in modeling assumptions. Many digital transformation studies rely on cross-sectional correlations, which are vulnerable to omitted variable bias and reverse causality concerns. In contrast, the present study adopts a Difference-in-Differences framework with worker and time fixed effects to isolate treatment effects under quasi-experimental conditions. The confirmation of the parallel trend assumption further strengthens confidence in causal interpretation. Placebo tests yielding non-significant results provide additional evidence that estimated impacts are not driven by spurious time effects. By satisfying these econometric diagnostics, the study enhances causal credibility in vocational agribusiness settings where randomized control trials are rarely feasible.

Implication Limitations

From a theoretical perspective, this study contributes to the intersection of geospatial analytics, workforce governance, and causal modeling by proposing an integrated analytical framework that links digital monitoring exposure to operational efficiency outcomes. It advances digital transformation literature by demonstrating that geofencing data streams can serve not only descriptive monitoring functions but also econometric evaluation purposes. From a managerial standpoint, the findings suggest that vocational agribusiness administrators should consider structured digital attendance systems as efficiency-enhancing investments rather than merely compliance tools. Real-time geospatial validation reduces administrative burden, improves time discipline, and strengthens accountability transparency. The framework developed in this study can be adapted to other labor-intensive production environments seeking measurable performance improvements.

At the policy level, the results indicate that digital governance initiatives in vocational institutions can produce quantifiable operational benefits. Policymakers promoting agribusiness modernization should integrate data-driven evaluation mechanisms to ensure that technological adoption translates into measurable productivity gains.

Limitation and Suggestion for Future Research

Despite its contributions, this study has several limitations. First, the sample size is confined to four vocational agribusiness units within a single institutional setting, which may limit generalizability to broader agricultural enterprises or large-scale commercial operations. Second, the 12-week observation period captures short-term efficiency effects but does not assess long-term behavioral adaptation or sustainability of treatment impacts. Third, while the Difference-in-Differences framework strengthens causal inference, unobserved time-varying confounders cannot be completely ruled out. Future research should expand the analytical framework to multi-institutional datasets and longer observation windows to assess dynamic treatment effects. Integrating event-study modeling could further explore temporal persistence of productivity gains. Additionally, combining geospatial workforce analytics with predictive modeling or machine learning approaches may enhance real-time decision-support capabilities. Extending the framework to commercial agribusiness enterprises and cross-country comparisons would improve external validity and deepen understanding of digital workforce transformation in applied agricultural systems.

CONCLUSION

This study develops and empirically validates a geofencing-based data-driven workforce analytics framework using causal modeling to assess operational efficiency in vocational agribusiness systems. By integrating real-time geospatial attendance data with a Difference-in-Differences estimation strategy, the research demonstrates significant improvements in productivity, cost efficiency, administrative processing time, and governance accountability. The findings provide causal evidence that digital workforce monitoring can function as an operational optimization mechanism rather than merely a compliance tool. Through rigorous panel-data analysis and robustness validation, the study contributes to quantitative digital transformation research and offers a scalable analytical framework for data-driven workforce governance in applied agribusiness contexts.

AUTHOR CONTRIBUTIONS STATEMENT

Conceptualization and research design were led by Nurlaili, who also coordinated the overall study and manuscript preparation. M. Nasor contributed to instrument development, data collection supervision, and preliminary data organization. Heni Noviarita was responsible for data analysis, including the implementation of the OLS regression model and interpretation of statistical results. Rini Setiawati contributed to the literature review, theoretical framing, and refinement of the Introduction and Discussion sections. Mohd Syahril Ahmad Razimi supported critical revision of the manuscript, methodological clarity, and contextual interpretation of findings. All authors reviewed, edited, and approved the final version of the manuscript.

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