FROM DATA TO DECISIONS: THE ROLE OF BI&A IN SUPPORTING SUSTAINABLE AGRICULTURAL DEVELOPMENT

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Abstract: *This study examines the role of Business Intelligence and Analytics (BI&A) in advancing sustainable agricultural development. We propose a conceptual framework linking Data-Driven Culture, BI&A Adoption, Decision-Making Effectiveness, and Sustainable Agricultural Performance. A structured survey will be administered to managers across forty agribusiness firms, and data will be analyzed using Partial Least Squares . Anticipated findings are expected to reveal how an analytics-oriented culture and BI&A tools jointly enhance decision quality, optimize resource use, and improve environmental and economic outcomes on the farm. The paper offers both theoretical insights into BI&A's mechanisms and practical guidance for agribusiness leaders seeking to leverage digital technologies for resilient, sustainable farming.*

Key words*: Business Intelligence & Analytics, sustainable agriculture, decision support, data-driven culture*

INTRODUCTION

Sustainable agricultural development demands innovative approaches that reconcile productivity with ecological stewardship. Traditional farming practices, while time-tested, lack the real-time feedback and predictive capabilities required to address today's volatile weather patterns, soil degradation, and market fluctuations. Against this backdrop, Business Intelligence & Analytics (BI&A) systems—integrating sensors, satellite imagery, Internet of Things (IoT), and advanced statistical methods—offer a transformative pathway "from data to decisions." By converting heterogeneous datasets into prescriptive recommendations, BI&A empowers farmers and agribusiness managers to optimize irrigation schedules, tailor fertilization, and anticipate pest or disease outbreaks, thereby reducing waste and improving yields.

Yet, the mere availability of advanced analytics tools does not guarantee sustainable outcomes. The effectiveness of BI&A hinges on an organization's culture of data use, the extent of technology adoption, and the ability of decision-makers to interpret and act upon insights. Prior studies in information systems and precision agriculture have underscored the impact of a Data-Driven Culture, wherein stakeholders trust data, share information openly and continuously refine their practices based on analytical feedback. Building on this foundation, our study develops and tests a research model that links cultural readiness to BI&A adoption, decision-making effectiveness, and, ultimately, sustainable agricultural performance.

Data-Driven Culture in Agriculture. A data-driven culture in farming means using data and digital technologies systematically to guide decisions. In practice this often overlaps with terms like digital agriculture or smart farming, defined as the use of ICTs (sensors, IoT, AI, etc.) to collect and analyze data at all stages of the value chain to support management decisions [19]. Recent literature highlights a shift from traditional practices toward innovative, data-centric methods (e.g. IoT, blockchain and AI) in agriculture [13]. Mehrabi et al. [44] define "data-driven farming" as using data to augment decision-making for better outcomes, and they document a global connectivity divide: only ~24–37% of very small farms (<1 ha) worldwide have 3G/4G service, vs ~74–80% of very large farms. In short, technology alone is not enough – farmers must have the skills, trust and organizational alignment to use it. For example, van der Burg et al. [62] note that digital farming promises more informed decisions and efficiency, but this can only happen "if farmers are willing to share their data" with tech providers. Together, these studies stress that a data-driven agricultural culture requires not just new tools, but also new mindsets, capacities and governance for evidence-based farming.

Moreover, the adoption of a data-oriented mindset is contingent on trust, data governance and farmers' willingness to engage with new systems. Similarly, Reissig et al. [55] found that Swiss farmers exhibit low trust in commercial technology providers, with concerns centered on data misuse, regulatory consequences, and the lack of contractual clarity regarding data ownership.

Dibbern et al. [19] and Luque-Reyes et al. [42] argue that a data-driven culture is not merely technological but also institutional and educational. Their studies show that farmers are more likely to adopt digital systems when those are accompanied by targeted training, advisory support, and platforms for peer learning. In regions such as Andalusia, local actors prioritize practical tools that offer immediate utility over complex high-tech solutions, pointing to the need for contextual and demand-driven approaches to digitalization in agriculture [42].

The literature also suggests that a successful data-driven culture in agriculture requires a systemic approach involving multiple stakeholders—farmers, technology developers, policymakers, and advisors—working collaboratively. As Klerkx et al. [37] highlight, the co-creation of digital solutions and participatory governance models can enhance trust, ensure relevance, and reduce the risk of technological non-adoption. In this vein, Eastwood et al. [21] propose a framework of responsible digital innovation in agriculture, which includes dimensions such as inclusivity, transparency, and accountability as essential pillars for a sustainable data-driven transition.

Business Intelligence and Analytics in Agricultural Context In the context of digital transformation in agriculture, Business Intelligence and Analytics (BI&A) systems have emerged as essential tools for supporting data-driven decision-making at all levels of agricultural production. BI&A integrates data collection, processing, and analysis to provide actionable insights that enhance operational efficiency, resource optimization, and long-term sustainability in farming systems [14,37]. As agricultural systems become increasingly complex—due to climate variability, market volatility, and environmental constraints—the ability to harness large volumes of heterogeneous data is crucial [44].

Modern applications of BI&A in agriculture incorporate advanced analytical methods to monitor crop performance, forecast risks, and guide more informed management decisions. These tools contribute significantly to increasing the precision and resilience of agri-food systems [20,35]. Typically, BI&A capabilities are grouped into three key categories—descriptive, predictive, and prescriptive analytics—each playing a distinct role in enhancing decision-making processes in agriculture [66,19].

Descriptive analytics in agriculture involves summarizing and visualizing historical data to reveal operational patterns and trends. BI dashboards, for instance, can integrate data on past yields, soil conditions, and climate variability to support strategic planning. By addressing "what happened" questions, descriptive analytics tools help agricultural stakeholders monitor field variability, detect inefficiencies, and identify risk-prone areas [66,64]. Such insights provide essential baselines for benchmarking and inform decisions related to crop planning, rotation schemes, and input management [42].

Predictive analytics builds on descriptive insights to forecast future outcomes using statistical and machine learning models. In agricultural contexts, predictive models are increasingly used to anticipate crop diseases, estimate yield, and optimize irrigation [35,43]. For example, IoT-based disease prediction systems have demonstrated strong accuracy in identifying early-stage pathogen risks, allowing for timely intervention and reduced chemical use [39]. Similarly, predictive irrigation scheduling algorithms leverage weather forecasts and sensor data to generate site-specific watering plans. Implementation of such systems has led to up to 25% reductions in water usage without compromising crop yield [2].

Prescriptive analytics takes data application a step further by recommending concrete actions to achieve specific objectives. These systems combine predictive models with optimization algorithms and domain-specific rules to guide decision-making. In precision agriculture, prescriptive tools are used to tailor fertilization, seeding, and irrigation plans to the specific needs of each field [20,1]. For instance, variable-rate technology platforms suggest precise input levels across field zones, thereby reducing environmental impact and input costs [18]. Prescriptive BI&A systems can also automate real-time irrigation adjustments based on changing weather and soil data, enabling efficient resource allocation and improved crop performance [2,36].

Together, descriptive, predictive, and prescriptive analytics form an integrated BI&A ecosystem that enhances agricultural decision-making. These tools help farmers make informed, proactive, and optimized decisions, thereby contributing to higher efficiency, reduced resource use, and more sustainable farming practices [14,20,19, 36].

Decision-Making Enhanced by BI&A. Business Intelligence and Analytics (BI&A) tools have increasingly become integral to effective organizational decision-making, offering structured methods to transform data into actionable insights. Scholars argue that BI&A enhances decision-making by addressing limitations of human cognition and supporting evidence-based strategies [58,14]. Phillips-Wren et al. emphasize that BI&A systems "convert more data into deeper insight," aligning with a process-level decision support system (DSS) architecture that formalizes data-driven decisions [52].

Contemporary frameworks, such as the DECAS model proposed by Elgendy and Elragal, incorporate analytics as a central component in decision systems, suggesting that decision quality improves through the integration of data, analytics, and human reasoning [24,25]. These models suggest that BI&A supports timeliness, accuracy, and relevance in decisions, attributes critical to strategic success [3,53].

Further theoretical studies highlight how BI&A reduces uncertainty in complex environments by enabling predictive and prescriptive analytics [48,8]. The convergence of big data and advanced analytics has led to a paradigm shift from intuition-based to data-driven decisions, supported by systems that deliver real-time, scenario-based analysis [50,63].

BI&A tools are also seen as enhancers of collaborative decision-making, enabling cross-functional alignment through shared dashboards, KPIs, and automated reporting [57]. These features contribute to better-informed decisions at both operational and strategic levels [15,33].

These preliminary findings indicate that theoretical literature consistently reinforces the idea that BI&A improves decision-making by offering structured, timely, and data-rich frameworks that extend human capabilities and reduce bias [11,45].

Sustainable Agricultural Development. Modern BI&A frameworks emphasize using all available knowledge and data-driven technologies to achieve sustainable agriculture [6,65]. Scholars argue that farming sustainability is inherently knowledge-intensive and is more likely to be attained by integrating precision tools (sensors, IoT, AI) than by traditional methods alone [6]. Data collected by sensors and analyzed through AI can reveal synergies among soil, water, crop, and environmental factors, guiding precise input application to simultaneously achieve productivity and environmental goals [6,65]. Conceptual reviews highlight that precision agriculture—leveraging GPS, remote sensing, and analytics—lays the foundation for Agriculture 4.0 and 5.0, optimizing resource use and embedding regenerative practices [59,65].

Resource Efficiency and Environmental Sustainability. Theoretical models show that BI&A can dramatically improve resource efficiency. For example, Min et al. propose a Big Data Analytics–Integrated Agriculture Resource Management Framework (BDA-ARMF) that combines cloud, IoT, and data analytics to minimize waste and contamination [6]. Such frameworks generate actionable insights to reduce fertilizer, pesticide, and water use without sacrificing yield [6,59]. Precision farming techniques (e.g. variable-rate seeding, smart irrigation) use real-time data to adjust management, allowing farmers to maximize yields while minimizing resource inputs [59]. Reviews emphasize that data-driven decision-support systems enable closed-loop control of nutrient and water applications, thereby improving soil health and lowering emissions [47,59].

BI&A approaches also target yield optimization to meet food security needs. By integrating machine learning and simulation models, analysts can forecast crop performance under different scenarios and recommend optimal practices. Recent literature notes that data-driven methods help farmers "learn about synergies between the domains of natural systems" critical for sustainable intensification [6,59]. For instance, predictive models for irrigation and fertilization enable precision intensification: farmers apply inputs only where and when needed, supporting higher yields per unit input [51,47]. Scholars argue that this data-centric approach is key to feeding growing populations: smart farming technologies link direct production with downstream supply-chain analytics to stabilize food supply while controlling environmental impacts [6,59].

By exploiting real-time and historical data, these systems enhance farm resilience to weather extremes and long-term climate shifts. For example, Weraikat et al. describe an iterative data-driven approach that promotes efficient resource utilization, reducing environmental impacts, and enhancing overall crop resilience in the face of changing climatic conditions [51]. Precision-enabled forecasts and warnings (e.g. drought alerts, pest outbreak predictions) allow adaptive scheduling of planting, irrigation, or harvest, thereby mitigating risk [51,59]. Smart irrigation analytics, for instance, can tailor water use to real-time soil moisture and weather forecasts, buffering crops against droughts while conserving water [47,51]. In sum, BI&A frameworks conceptualize agriculture as a feedback-driven system that continuously adjusts to environmental variability, strengthening both productivity and sustainability [6, 51].

Across recent literature, conceptual and theoretical analyses converge on the view that BI&A tools are enablers of sustainable farming. They suggest a paradigm in which autonomous decision-making, task automation and advanced sustainability practices are prioritized [59,47]. By providing actionable intelligence to farmers – from field-level inputs to supply-chain logistics – these frameworks support environmental stewardship, efficient resource use, food security and climate resilience [6,51]. Continued development of interoperable data platforms and analytics models is seen as essential to realize this vision of data-driven sustainable agriculture [6,59].

MATERIALS AND METHODS

Based on our research inquiries, we created a structural model that includes four latent constructs: Data-Driven Culture (DDC), BI&A Adoption (BIAA), Decision-Making Effectiveness (DME), and Sustainable Agricultural Performance (SAP). Measurement items for each construct were drawn directly from established, validated scales in the information systems and agriculture literature—specifically, DDC items from Anton and Smolnik (2023) and Choudhuri and Mitra (2024) [55], BIAA items from Popovič and Turk (2020) [54], DME items adapted from Weraikat et al. (2024) [65] and SAP items from

Kamble et al. (2020) [34]. All indicators are measured on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree), ensuring uniformity across constructs and facilitating direct comparison of respondent perceptions [27].

The questionnaire will be distributed online to managers, agronomists, and decision-makers across 40 medium and large agricultural enterprises in four key development regions. In each organization, we aim to collect at least ten responses—targeting a minimum total sample of 400—to ensure adequate statistical power and representation of different farm sizes and production types [12]. Control variables will include firm size, production system (e.g., crop, livestock, mixed), years in operation, managerial role, and department, enabling us to account for potential confounding influences on BI&A adoption and sustainability outcomes [12].

Prior to the main survey rollout, a pilot test will be conducted with 10 agricultural professionals from a local agri-tech firm to assess item clarity, scale reliability, and overall survey length [9]. Feedback from the pilot will inform final refinements to question wording and ordering, ensuring high face validity and respondent engagement. We will also compute pilot reliability statistics (Cronbach's α) to verify initial internal consistency of each construct, targeting $\alpha \geq 0.70$ [10].

Data analysis will employ Partial Least Squares Path Modeling (PLS-PM) using SmartPLS software to simultaneously evaluate both measurement and structural models [27]. **Measurement Model** assessment will involve:

Indicator Reliability: retaining items with outer loadings ≥ 0.70 [29].

Internal Consistency: confirming Cronbach's α and Composite Reliability ≥ 0.70 [27].

Convergent Validity: ensuring Average Variance Extracted (AVE) ≥ 0.50 [26].

Discriminant Validity: verifying HTMT ratios < 0.85 [30].

Structural Model evaluation will include:

Path Coefficients: estimated and tested for significance via bootstrapping (5,000 resamples) [28].

Explanatory Power: examining R^2 values for endogenous constructs, with $R^2 \geq 0.25$ indicating moderate explanatory power [28].

Effect Sizes (f^2): assessing the substantive impact of each exogenous variable [28].

Predictive Relevance (Q^2): via blindfolding, $Q^2 > 0$ indicating acceptable predictive accuracy [28].

RESEARCH RESULTS

Data-driven agriculture, often referred to as "smart farming," leverages ICT tools and analytics to support decision-making and sustainability in the agricultural sector. Increasingly, digital technologies are viewed as essential to improving farm-level decisions and outcomes [6]. Empirical research confirms that sensor-based monitoring and real-time analytics enhance productivity and operational efficiency. For instance, field trials show that IoT-based automation combined with data-driven decision systems can significantly improve yield while reducing labor inputs [65]. Furthermore, agricultural stakeholders trained in using BI&A tools report higher decision-making effectiveness and improved sustainability outcomes [59].

Organizational and cultural factors are fundamental to successful BI&A adoption. Notably, a strong **Data-Driven Culture (DDC)**—where decision-makers rely consistently on data rather than intuition—is identified as a key enabler of BI&A integration [47]. In business contexts, such cultures foster technology adoption and improve decision-making through evidence-based practices [51]. These insights are increasingly being extended to agricultural contexts, where the deployment of BI&A tools supports data-informed decision-making for both operational and strategic purposes [59,5].

In line with this, our conceptual research model (Figure 1) proposes that DDC positively influences **BI&A Adoption (BIAA)**, which in turn enhances both **Decision-Making Effectiveness (DME)** and **Sustainable Agricultural Performance (SAP)**. Furthermore, we hypothesize that DME mediates the relationship between analytics adoption and sustainability outcomes. These relationships are depicted below.

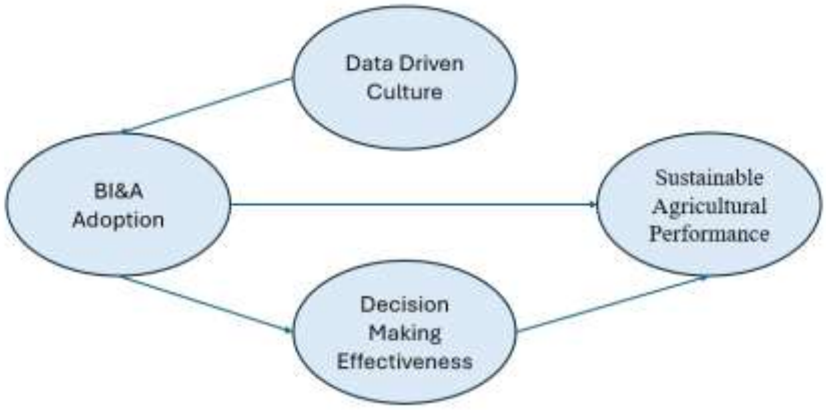

Figure 1. Research Model

Based on the literature reviewed, we formulate the following hypotheses:
H1: Data-Driven Culture influences BI&A Adoption [47,51].
H2: BI&A Adoption influences Decision-Making Effectiveness [51,5].
H3: BI&A Adoption influences Sustainable Agricultural Performance [59,66].
H4: Decision-Making Effectiveness influences Sustainable Agricultural Performance [59, 17].

This framework positions BI&A not only as a technical innovation but as a strategic mechanism for enabling sustainability through informed decision-making.

H1. Data-Driven Culture influences BI&A Adoption

A strong data-driven culture encourages the adoption of BI&A by embedding data-centric values throughout the organization [7,16,31]. Organizations with a data-driven mindset are more likely to prioritize analytics investments and foster user engagement with BI tools [7,34]. In such settings, decision-makers trust data and support innovation, making it easier for BI&A systems to be integrated into daily operations [16,61]. Theoretical models like the Technology-Organization-Environment (TOE) framework highlight organizational culture as a key enabler for analytics adoption [31,65]. This alignment between cultural values and technological capabilities promotes BI&A adoption as a strategic asset.

Moreover, researchers emphasize that a data-driven culture shapes how employees interact with technology and insights [7,16]. Trust in data, encouragement of experimentation, and openness to analytics are cultural traits that lead to better BI&A alignment [31,4]. Particularly in agriculture, cultivating a data-oriented environment enables farmers to embrace analytics for optimizing irrigation, soil management and yields [61,56]. Thus, theory suggests that a robust data-driven culture provides the social and cognitive infrastructure necessary for BI&A adoption.

H2. BI&A Adoption influences Decision-Making Effectiveness

Theoretical studies affirm that BI&A adoption enhances decision-making by improving access to relevant, timely, and structured information [7,34]. BI systems empower users to perform diagnostics, forecasts, and simulations, which improve the rationality and accuracy of decisions [16,61]. Effective adoption integrates data into daily routines, encouraging systematic use of insights over intuition [65,54]. These capabilities align with the Resource-Based View, positioning BI&A as a valuable and rare resource that sharpens organizational intelligence [31].

Furthermore, conceptual frameworks view BI&A as a Decision Support System that transforms raw data into actionable insights [34]. In agriculture, BI&A tools help optimize planting cycles, detect anomalies, and align decisions with sustainability and profitability goals [4,60]. This analytical foundation leads to faster responses, reduced uncertainty and more consistent decision-making [7,16]. As such, the literature consistently underlines the theoretical link between BI&A use and enhanced decision effectiveness.

H3. BI&A Adoption influences Sustainable Agricultural Performance

The integration of BI&A systems supports sustainable agriculture by improving efficiency, reducing waste and aligning practices with sustainability indicators [34,61,4]. Conceptual studies stress that analytics empower decision-makers to optimize resource usage, such as water and fertilizers, thereby minimizing the environmental footprint [56,60]. This is especially relevant in precision farming, where data guides targeted interventions, leading to higher yields with lower input [16,65]. Hence, BI&A adoption is seen as a technological enabler of sustainable agricultural performance.

In addition, theoretical models suggest that BI&A improves transparency and accountability across the agricultural value chain [31]. By monitoring KPIs related to sustainability (e.g., CO_2 emissions, biodiversity impact), BI&A supports strategic alignment with SDGs [55,64]. Literature also highlights that analytics-driven decision-making fosters long-term ecological resilience and economic viability [34,61]. Thus, conceptual evidence affirms that BI&A adoption is a key lever for advancing sustainability in agriculture.

H4. Decision-Making Effectiveness influences Sustainable Agricultural Performance

Improved decision-making effectiveness leads to better alignment with sustainability objectives, as decisions become more data-driven and proactive [16,31,65]. In agriculture, this translates into optimized crop planning, efficient input allocation, and timely intervention—all of which enhance ecological and economic outcomes [4,60]. The literature suggests that when farmers use structured insights to guide actions, they achieve greater productivity with reduced resource consumption [61].

Moreover, theoretical studies emphasize that decision quality mediates the impact of technology on sustainability [7,34]. BI&A tools amplify this effect by providing data granularity and predictive capabilities [54,56]. Thus, decision-making effectiveness serves as a bridge between analytics use and sustainable performance, fostering practices that are both competitive and environmentally responsible [16,60]. Overall, conceptual frameworks validate that better decisions are fundamental to achieving sustainability in agriculture.

CONCLUSIONS

This research will extend existing decision-support and sustainability literature by integrating data-driven culture and BI&A adoption into a unified model of sustainable agricultural performance. While prior studies have largely examined analytics adoption or sustainability in isolation, our model links organizational culture, analytics capabilities, decision-making effectiveness, and sustainability outcomes. This integrative framework will help scholars understand the mechanisms through which BI&A tools translate cultural and process factors into environmental and productivity gains.

By empirically validating how data-driven culture and BI&A adoption enhance decision quality and sustainability, the study will offer actionable insights for farm managers and agribusiness leaders. The findings will inform best practices for nurturing analytics-friendly cultures, selecting appropriate BI&A tools and leveraging decision support to improve resource efficiency, crop yields and ecological stewardship. These guidelines will aid practitioners in designing data governance structures and training programs that accelerate adoption and maximize return on analytics investments.

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