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EVALUATING AN AI-ENABLED INTERACTIVE ANALYTICS AND CONVERSATIONAL DECISION-SUPPORT SYSTEM FOR LIVESTOCK PHARMACEUTICAL SUPPLY CHAIN MANAGEMENT IN PAKISTAN

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Abstract

Livestock pharmaceutical supply chains depend on reliable information about inventory, purchasing, sales, supplier activity, and product demand. However, when operational records are maintained in separate spreadsheets, managers may face difficulties consolidating information, identifying stock imbalances, evaluating product profitability, and anticipating replenishment needs. This study presents the development of a self-service interactive analytics dashboard with a conversational assistant for livestock pharmaceutical supply chain management in Pakistan. The system was developed using spreadsheet-based records obtained from veterinary pharmaceutical wholesalers with consent. The project documentation describes three Excel files covering approximately 12 months of activity and more than 45 suppliers. Data were processed using Python-based tools, while the application combined a Flask backend with a React.js interface. Reported functions included inventory monitoring, low-stock identification, product-level sales and profit summaries, supplier analysis, and demand forecasting using an autoregressive integrated moving average (ARIMA) approach. A conversational interface was also incorporated to facilitate access to analytical information. The thesis reports illustrative outputs from the dashboard, including product stock quantities, sales volumes, and supplier-level purchasing summaries. However, the available documentation does not establish forecast accuracy, controlled usability outcomes, or measurable improvements in business performance. One exceptionally large reported profit value also requires verification before publication. The study contributes an applied system-development example for spreadsheet-dependent livestock pharmaceutical businesses and proposes an evaluation framework covering data integrity, forecast performance, usability, and operational impact. The findings should be interpreted as reported system functionality rather than proof of improved supply-chain outcomes.

1. Introduction

Livestock pharmaceutical supply chains connect medicine manufacturers and importers with distributors, wholesalers, veterinary practitioners, retailers, and livestock producers. Their effectiveness depends on product availability, dependable purchasing and sales records, inventory visibility, and timely replenishment. In Pakistan, veterinary pharmaceutical distribution also intersects with

animal health governance and the responsible use of antimicrobial medicines. A study of antimicrobial usage supply chains in Pakistan identified coordination and monitoring challenges across livestock and poultry stakeholders, emphasizing the importance of improving information and surveillance arrangements (Tahir et al., 2025).

At the operational level, pharmaceutical wholesalers must balance product availability against the financial cost of holding inventory. Overstocking may tie up working capital and increase exposure to expiry or obsolescence, while understocking can interrupt sales and product availability. These decisions become harder when sales, purchases, supplier records, and stock balances are maintained in separate spreadsheets. Although spreadsheets are inexpensive and familiar, inconsistent product names, different date formats, duplicated entries, missing values, and disconnected reporting can weaken the reliability of management information.

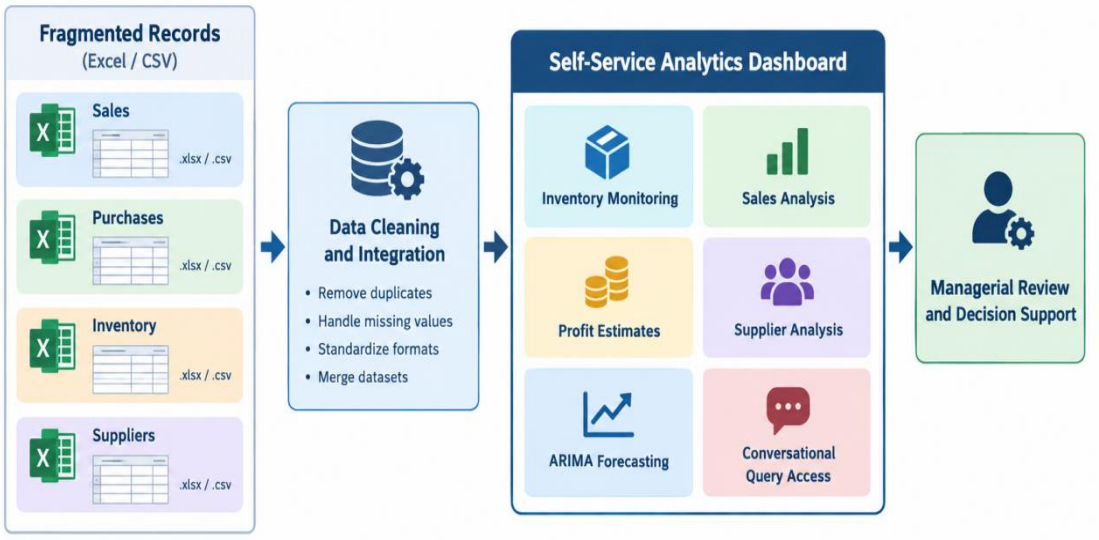
Data analytics offers a way to convert transaction records into information for operational decisions. Research on pharmaceutical supply-chain analytics identifies opportunities to use data for improving visibility and decision support while also highlighting implementation challenges (Nguyen et al., 2022). More broadly, supply-chain research has examined how data analytics and connected technologies can support monitoring and forecasting, while systematic reviews of artificial intelligence in supply-chain management describe applications across planning and operations (Koot et al., 2021; Toorajipour et al., 2021). However, the sophistication of a technology does not necessarily determine its suitability for smaller businesses with limited technical resources.

Interactive dashboards can consolidate key indicators and display exceptions in a common interface. Conversational assistants may further simplify information retrieval by allowing users to enter questions or choose familiar queries. Yet successful implementation requires more than building a functional interface. The definitions behind indicators, the quality of the underlying data, the reliability of forecasts, and the needs of intended users must all be considered. A scoping review of dashboard development and evaluation in health care likewise highlights the importance of implementation and evaluation, rather than treating dashboard deployment alone as evidence of effectiveness (Helminski et al., 2024).

The research gap is the limited context-specific documentation, within the literature considered here, of a single lightweight system integrating spreadsheet consolidation, inventory analytics, profitability summaries, supplier analysis, demand forecasting, and conversational access for livestock pharmaceutical wholesalers in Pakistan. A further unresolved question is whether the resulting indicators and forecasts are sufficiently accurate and interpretable to support operational decisions.

This study documents the development of a self-service analytics dashboard designed to address this gap. Its objectives are to: (1) consolidate heterogeneous operational spreadsheets; (2) provide interactive inventory, sales, profitability, and supplier summaries; (3) incorporate ARIMA-based demand forecasting; and (4) provide conversational access to analytical information. The contribution is an applied system-development account and an evaluation agenda, not a claim of proven financial or operational improvement.

FIGURE 1: Research problem and proposed system contribution



2. Literature Review

2.1. Pharmaceutical supply-chain analytics

Pharmaceutical supply chains require information that supports coordination between purchasing, storage, distribution, and financial management. Analytics can help transform transaction records into operational indicators, but the value of these indicators depends on data quality and the decisions they are intended to support. Nguyen et al. (2022) review the opportunities and challenges associated with analytics in pharmaceutical supply chains, providing a direct foundation for considering how fragmented records can be converted into more usable information.

Supply-chain analytics is commonly discussed in terms of descriptive, predictive, and prescriptive functions. Descriptive analytics summarizes recorded activity; predictive analytics estimates future conditions; and prescriptive analytics supports the selection of actions. These functions should be distinguished in a pharmaceutical dashboard. A current-stock report is descriptive, an estimate of future demand is predictive, and a replenishment recommendation that incorporates demand, lead time, safety stock, expiry, and purchasing constraints is prescriptive.

Koot et al. (2021) reviewed supply-chain decision support involving the Internet of Things and big-data analytics, illustrating how data collection and analysis can support monitoring and prediction. However, solutions relying on connected sensors or integrated infrastructures may not transfer directly to smaller wholesalers that depend on manually updated spreadsheets. For these businesses, standardizing existing records and providing reliable summaries may be a more feasible starting point than implementing a comprehensive real-time system.

2.2. Interactive dashboards and decision support

Dashboards consolidate selected indicators into visual summaries that help users monitor operations and investigate exceptions. Their usefulness depends on relevance, readability, accuracy, and integration into users' work. Helminski et al. (2024) reviewed dashboard development, implementation, and evaluation methods in health care. Although that review is not specific to livestock pharmaceutical wholesalers, it provides a methodological lesson: the existence of a dashboard does not by itself demonstrate that users understand it or make better decisions.

In the present context, useful dashboard modules include inventory monitoring, product-level sales analysis, estimated profitability, and supplier purchasing summaries. However, an indicator may be misleading if its calculation is not clearly

defined. For example, multiplying available stock by purchase price gives a simplified stock valuation, but its accuracy depends on the price field and inventory-costing method used. Similarly, multiplying the difference between sale and purchase prices by quantity sold estimates a transaction-level margin before other costs; it should not automatically be interpreted as net profit.

Dashboard design should therefore make units, time periods, calculation rules, and data limitations visible. Where information is incomplete, the interface should show uncertainty or missingness rather than implying that a calculated value is definitive.

2.3. Demand forecasting for inventory planning

Forecasting can help organizations estimate future demand from historical observations. ARIMA models represent temporal dependence through autoregressive, differencing, and moving-average components. They remain a useful statistical option when a sufficiently consistent time series is available, but model selection must reflect the characteristics of the data (Hyndman & Athanasopoulos, 2021).

Supply-chain forecasting research covers statistical methods, machine learning, and deep learning. Douaioui et al. (2024) review these approaches and emphasize the breadth of available forecasting methods. Nevertheless, greater model complexity does not automatically guarantee better performance for every product or setting. A simple statistical model may be an appropriate baseline, while irregular or intermittent demand may require different treatment.

Veterinary pharmaceutical demand can be influenced by seasonality, disease outbreaks, veterinary prescribing, supplier interruptions, product substitution, and purchasing cycles. If such factors are not represented in the data, a univariate ARIMA model may fail to anticipate sudden changes. Model evaluation should therefore use chronological holdout data and compare forecasts with a baseline, such as a naïve forecast. Metrics such as mean absolute error (MAE) and root mean squared error (RMSE) should be reported for the relevant products and forecast horizons (Hyndman & Athanasopoulos, 2021).

2.4. Conversational assistants and analytics access

Conversational agents can provide a natural-language route to information that might otherwise require navigating multiple charts or menus. Ling et al. (2021) review factors influencing adoption and use of conversational agents, highlighting the importance of user characteristics, perceived benefits, and context. In business analytics, an assistant may be useful when it reduces the effort required to retrieve clearly defined information.

However, rule-based and generative assistants have different risk profiles. A rule-based assistant maps supported keywords or predefined queries to known analytical operations. It may be predictable within its limited scope but less robust to unfamiliar phrasing. A generative assistant can interpret a broader range of language but may produce incorrect or unsupported answers unless connected to validated data and controlled functions. Research on artificial intelligence in supply-chain management also emphasizes the range of potential applications and the need to address practical implementation challenges (Toorajipour et al., 2021).

The project thesis refers both to GPT-based API integration and keyword-based predefined queries. The available description does not establish whether these were alternative versions, separate functions, or a combined implementation. Accordingly, this article treats the conversational assistant as a reported feature and identifies confirmation of its actual architecture as a publication requirement.

2.5. Synthesis and research gap

Prior literature supports the relevance of analytics in pharmaceutical supply chains, the importance of dashboard evaluation, the use of forecasting for planning, and the potential role of conversational agents. The specific unresolved issue addressed here is the integration of these functions in a lightweight system for spreadsheet-dependent livestock pharmaceutical wholesalers, alongside explicit attention to data and forecast validation.

The study's contribution is therefore not the invention of a new forecasting algorithm or dashboard method. It is the documentation of an applied integration and the identification of the validation steps needed to establish whether its outputs are reliable and useful in the intended business setting.

Table 1. Literature synthesis and relevance to the present study

Research area	Contribution of existing literature	Remaining limitation for this application	Relevance to the project
Pharmaceutical analytics	Identifies opportunities and challenges for analytics in pharmaceutical supply chains (Nguyen et al., 2022).	Does not establish performance for this particular wholesaler dashboard.	Justifies consolidating operational data.
Supply-chain data analytics	Reviews connected data and analytics for monitoring and decision support (Koot et al., 2021).	Many settings differ from manually maintained spreadsheet environments.	Supports a lightweight data-integration approach.
Dashboard evaluation	Reviews dashboard development and evaluation methods (Helminski et al., 2024).	Evidence comes from health care rather than livestock pharmaceutical wholesaling.	Motivates usability and implementation evaluation.
Demand forecasting	Reviews supply-chain forecasting methods and their applications (Douaioui et al., 2024).	Model performance varies by data structure and demand pattern.	Supports product-specific forecast validation.
Conversational agents	Synthesizes factors associated with agent adoption and use (Ling et al., 2021).	Does not validate the accuracy of this specific assistant.	Motivates testing answer accuracy and usability.
Pakistan livestock pharmaceutical context	Describes antimicrobial supply-chain monitoring and coordination challenges (Tahir et al., 2025).	Does not evaluate this dashboard or establish its effects on antimicrobial use.	Establishes local relevance without overstating impact.

3. Theoretical Framework

This study uses a socio-technical decision-support framework. The framework treats the dashboard as an interaction among operational data, data-processing procedures, analytical methods, user interfaces, and managerial interpretation. Technical functionality is necessary, but its practical value depends on the reliability of the data and the way users understand and act on the outputs.

The framework has five stages:

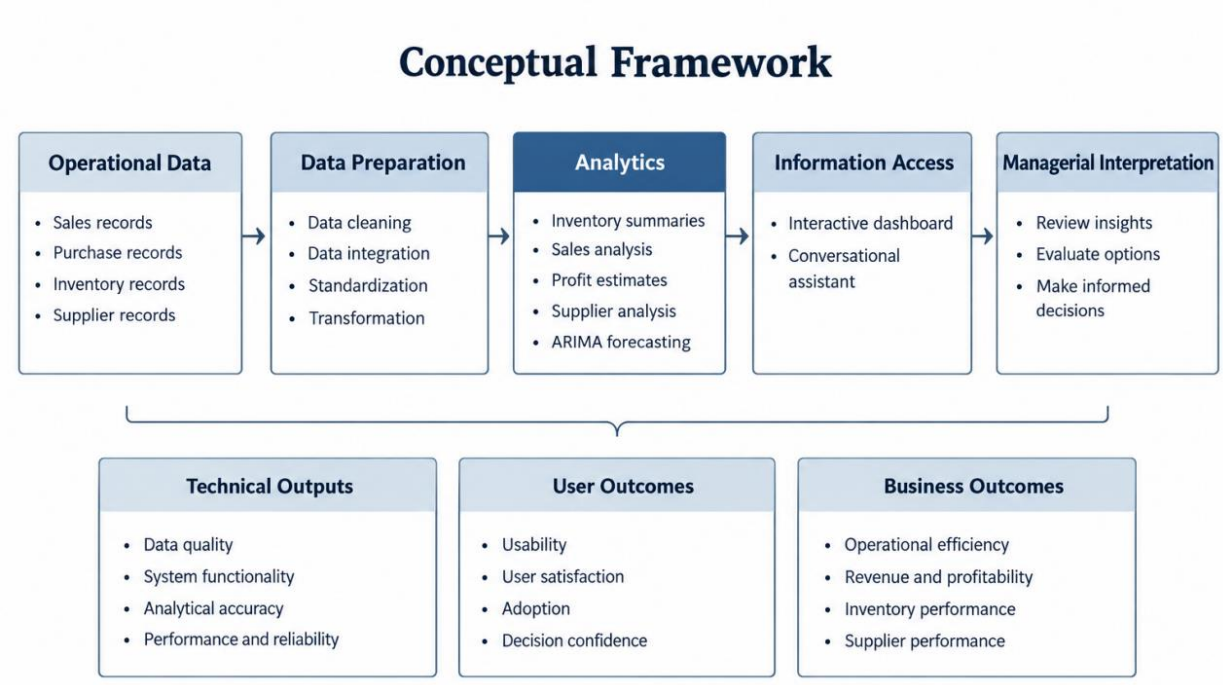
Operational data: sales, purchases, stock quantities, medicine identifiers, dates, and supplier records.

Data preparation: standardization, record integration, and checks for missing or duplicate values.

Analytics: inventory summaries, sales analysis, simplified profit calculations, supplier comparisons, and demand forecasts.

Information access: interactive charts and a conversational interface.
Managerial interpretation: stock verification, replenishment review, sales monitoring, and supplier assessment.
The expected pathway is that better-standardized records enable more consistent calculations, while consolidated presentation may make information easier to inspect. Forecasting may add a forward-looking view, but a forecast is not itself a replenishment recommendation. Actionable replenishment requires consideration of lead time, safety stock, expiry, minimum order quantities, and budget constraints.
The framework separates three outcome levels. Technical outputs concern whether the system produces the intended indicators and forecasts. User outcomes concern usability, comprehension, task completion, and trust. Business outcomes concern changes in stockouts, inventory turnover, expiry losses, or replenishment performance. These outcomes require separate evaluation; evidence of technical operation cannot substitute for evidence of user benefit or business impact.

FIGURE 2 : Socio-technical conceptual framework



4. Methodology

4.1. Research design and data source

The project used an applied system-development approach. According to the thesis, three Excel files were obtained from veterinary pharmaceutical wholesalers with consent. The records covered approximately 12 months of activity and included more than 45 suppliers. The exact number of observations, precise coverage dates, number of participating wholesalers, and completeness of individual fields are not specified in the material available for this manuscript.

4.2. Data preparation and integration

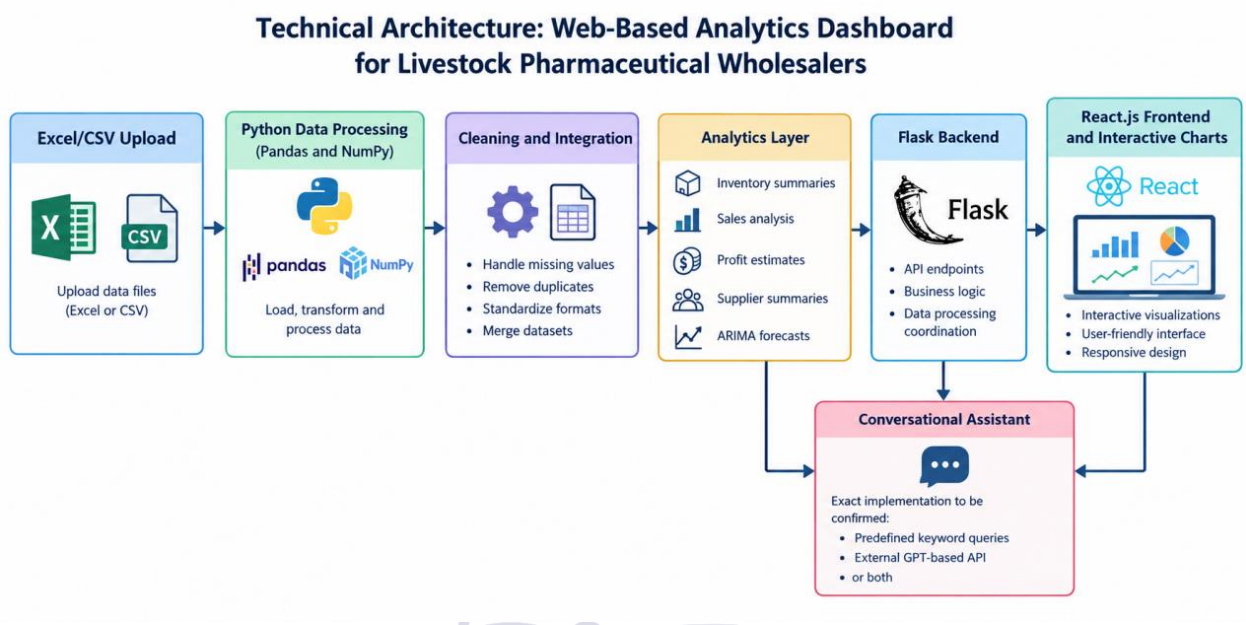
Python libraries, including Pandas and NumPy, were used to process the records. The reported preparation steps included standardizing column names and date formats, normalizing supplier names, handling missing values and duplicates, and joining records through medicine, supplier, and date fields where applicable.
These operations are consequential: inconsistent identifiers can split a single supplier across multiple categories, while incorrect joins can duplicate quantities or inflate financial totals. A reproducible implementation should preserve a raw-data

copy, document every transformation, and reconcile totals before and after cleaning.

4.3. Application architecture

The system used Python-based processing, a Flask backend, and a React.js frontend with interactive charting. The thesis describes Excel/CSV upload, inventory summaries, low-stock alerts, product-level sales and profitability visualizations, supplier summaries, and forecast outputs. The system was intended to enable self-service analysis without requiring direct integration with an enterprise resource planning system.

FIGURE 3 : System architecture and data flow



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4.5. Forecasting and evaluation

The thesis describes ARIMA forecasting and identifies ARIMA(1,1,1) in its limitations. Model selection reportedly considered autocorrelation patterns and the Akaike information criterion. However, the available material does not provide complete product-specific specifications, exact training and holdout dates, forecast horizons, or numerical error metrics.

A rigorous evaluation should fit the model on earlier observations and test it on later observations, compare it with at least one baseline, and report MAE or RMSE. Where product demand is intermittent, results should be reported separately rather than aggregated in a way that conceals poor performance for low-volume products.

4.6. Conversational functionality and ethics

The thesis describes a conversational interface but provides inconsistent descriptions of GPT-based API integration and predefined keyword queries. The deployed architecture should be confirmed and documented accurately. The available project material also does not establish a controlled usability evaluation.

The thesis states that data were supplied with consent and that privacy was considered. Before deployment, commercially sensitive supplier and transaction information should be protected. If external language-model services received uploaded data or queries, the information transmitted, applicable provider terms, and data-retention arrangements should be reviewed.

Table 2. System modules, reported outputs, and required validation

Module	Reported functionality	Validation required before operational reliance
Data preparation	Standardization, cleaning, and record integration	Audit join keys, duplicates, missing values, units, and reconciliation totals.
Inventory monitoring	Stock summaries and low-stock flags	Reconcile against physical stock and documented thresholds.
Sales analysis	Product-level sales quantities	Verify dates, returns, product units, and duplicate transactions.
Profit calculations	Sale-price/purchase-price difference multiplied by quantity	Audit prices, quantity multipliers, returns, discounts, taxes, and aggregation.
Supplier analysis	Supplier-level purchase summaries	Define the denominator and distinguish physical volume from monetary value.
ARIMA forecasting	Forecast outputs for selected products	Document forecast horizon, holdout period, MAE/RMSE, and baseline comparison.
Conversational assistant	Query-based access to analytical information	Confirm implementation and test answer accuracy, unsupported responses, and usability.

5. Results

The thesis reports that the dashboard brought together inventory, sales, profitability, supplier, and forecasting information within a single interface. The following examples are thesis-reported outputs; they should not be interpreted as independently audited results.

Inventory monitoring. PINK WOUND SPRAY was reported with a stock quantity of 1,409.4 units. TRICURE INJ 50ML was reported with 2 units against an illustrative threshold of 5 units. These examples show how stock visibility and low-stock flags were represented. The fractional quantity requires checking against the product's unit of measure, and the threshold should not be interpreted as a validated replenishment rule.

Sales and profitability. PENIVET 5 INJ was reported as a high-volume product, with 80,810 units sold. The thesis also reports PKR 74,347,149,261.6 as profit for OXYTOCIN INJ. This exceptionally large figure requires a transaction-level audit before it can be published as a reliable financial result. Potential issues to check include quantity multipliers, currency units, duplicate joins, price fields, and aggregation logic.

Supplier analysis. STAR LABORATORIES GENERAL was reported as accounting for 59% of purchase volume. The thesis does not clearly establish whether this percentage refers to monetary value or physical quantity. Its denominator and time period therefore need confirmation.

Forecasting. The thesis describes forecast-related attention to ENDECTIN INJ 50ML and BRICS INJ 1GM. However, no validated forecast-accuracy scores or comparison with existing purchasing practices are available in the supplied material. These examples illustrate the intended function rather than demonstrate reliable restocking recommendations.

FIGURE 4 : Dashboard analytical modules and reported outputs



Table 3. Examples of thesis-reported outputs and their interpretation

Reported output	What it may illustrate	Important qualification
PINK WOUND SPRAY: 1,409.4 units	Product-level stock visibility	Verify unit definition and source records.
TRICURE INJ 50ML: 2 units; example threshold 5	Low-stock flag functionality	Confirm threshold logic and physical stock.
PENIVET 5 INJ: 80,810 units sold	Identification of high-volume products	Verify period, units, returns, and aggregation.
OXYTOCIN INJ: PKR 74,347,149,261.6 reported profit	Example of a calculated profitability output	Unusually large; do not publish as validated until audited.
STAR LABORATORIES GENERAL: 59% reported purchase volume	Supplier-level concentration summary	Confirm denominator and whether measured by value or quantity.
Forecasts for selected products	Intended forward-looking decision support	No reported accuracy metrics establish forecast reliability.

6. Discussion

The project illustrates how a lightweight analytics architecture can combine operational information that might otherwise remain distributed across spreadsheets. Its main contribution is the integration of data preparation, descriptive reporting, simplified financial calculations, supplier summaries, forecasting, and conversational access. This aligns with the opportunities identified in pharmaceutical supply-chain analytics literature, where the usefulness of data depends on converting records into information relevant to operational decisions (Nguyen et al., 2022).

The inventory and sales modules could help managers identify products requiring review and understand recorded purchasing or sales patterns. However, visibility should not be confused with impact. A low-stock flag does not establish that a stockout was prevented, and a supplier summary does not demonstrate improved purchasing efficiency. These outcomes depend on data accuracy, user response, replenishment constraints, and the availability of resources to act on the information.

The forecasting component is a potential extension beyond retrospective reporting, but its performance remains unestablished. ARIMA can provide a transparent statistical baseline, yet its usefulness depends on demand characteristics and out-of-sample evaluation

(Hyndman & Athanasopoulos, 2021). Reviews of supply-chain forecasting identify a range of statistical and machine-learning approaches, reinforcing the need to select methods based on data and validation rather than technological novelty (Douaioui et al., 2024). In the present application, the absence of reported forecast errors prevents a defensible claim that the model produces reliable replenishment estimates.

The conversational interface may reduce the effort needed to retrieve information, particularly for users who are unfamiliar with complex analytics software. However, the assistant's practical value depends on the accuracy of the answers and the consistency of the calculations it uses. Adoption research on conversational agents indicates that context and user-perceived benefits matter (Ling et al., 2021). A business assistant should retrieve results from validated analytical functions, identify the relevant date range and units, and acknowledge when a query cannot be answered.

The Pakistan livestock context provides a rationale for improving operational information, but claims about animal health or antimicrobial stewardship must remain limited. Tahir et al. (2025) discuss supply-chain monitoring and coordination issues in the livestock and poultry sector. A wholesaler dashboard could potentially improve visibility of recorded transactions, but it does not itself establish appropriate antimicrobial use, reduced resistance, or regulatory compliance. Those outcomes require additional data, governance, and evaluation.

Overall, the project is best understood as an applied decision-support prototype. Its potential contribution is practical integration, while its effectiveness must be established through validation of the data, forecasts, user experience, and operational outcomes.

7. Implications

7.1. Managerial implications

Wholesalers could use consolidated summaries to prioritize stock checks, investigate unusual sales patterns, and review supplier purchasing activity. Alerts should be treated as prompts for verification rather than automatic instructions to order. Profit estimates should be reconciled with accounting records before supporting financial decisions.

7.2. Technical implications

The system requires documented data transformations, reproducible calculations, clear units, and transparent error handling. Forecasts should be accompanied by the forecast horizon, model specification, and validation metrics. Conversational answers should be grounded in controlled analytical functions, not generated independently of the dashboard's verified calculations.

7.3. Sector and policy implications

Improved digital recordkeeping may support more consistent operational visibility in livestock pharmaceutical distribution. However, any future regulatory or antimicrobial-monitoring application would require suitable medicine classifications, reliable usage information, appropriate governance, and alignment with relevant requirements. This study does not establish such sector-level effects.

8. Limitations and Future Research

The available thesis documentation does not specify the exact observation count, detailed date coverage, or full dataset completeness. The financial outputs and supplier percentage have not been independently audited, and the reported OXYTOCIN INJ profit figure is particularly important to verify. The forecasting component lacks numerical MAE/RMSE results, a documented chronological holdout period, and comparison with baseline methods. The conversational assistant's implementation also requires clarification, and no controlled usability or longitudinal business-impact evaluation is documented.

Future work should first reconcile cleaned data with source records and audit the formulas used for stock valuation, profit, and supplier shares. Forecasting should be evaluated with chronological holdouts and baseline comparisons, including separate treatment of intermittent-demand products. User studies should assess answer accuracy, task completion, error rates, comprehension, and satisfaction. A prospective operational evaluation could examine stockouts, inventory turnover, expiry

losses, and replenishment time before and after implementation while accounting for other changes in business practices.

9. Conclusion

This study documents the development of a self-service interactive analytics dashboard with a conversational assistant for livestock pharmaceutical supply chain management in Pakistan. The system combined spreadsheet processing, inventory monitoring, sales and profit summaries, supplier analysis, and ARIMA-based demand forecasting within a common interface.

The reported outputs illustrate the types of information the dashboard was designed to provide, but they do not establish forecasting accuracy, usability, or measurable business improvements. Financial calculations, supplier percentages, dataset details, and the conversational architecture require additional verification. The dashboard should therefore be positioned as an applied system-development contribution rather than a validated supply-chain optimization solution.

The next research stage should prioritize data reconciliation, transparent forecasting evaluation, confirmation of conversational functionality, and testing with intended users. These steps would provide the evidence needed to determine whether self-service analytics can support more dependable inventory and procurement decisions for spreadsheet-dependent livestock pharmaceutical businesses.

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