


# College of Business and Economics

# School of Commerce

## DETERMINANTS OF INVENTORY OPTIMIZATION MEDIATED BY FORECASTING ACCURACY: EVIDENCE FROM THE ETHIOPIAN DISASTER RISK MANAGEMENT COMMISSION

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**COLLEGE OF BUSINESS AND ECONOMOCS**

**SCHOOL OF COMMERCE**

**APPROVAL SHEET**

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# DECLARATION

I, the undersigned, declare that this thesis is my original work, prepared under the guidance of Kirubel Biruk (Ph.D.). All sources of materials used for the thesis have been duly acknowledged. I further confirm that the thesis has not been submitted either in part or in full to any other higher-learning institution to earn any degree.

Mulu Yemiamrew

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| Addis Ababa University, Addis Ababa | June 2026 |

## ENDORSEMENT

This thesis has been submitted to Addis Ababa University College of Business and Economics School of Commerce for examination with my approval as a university advisor.

Kirubel Biruk (Ph.D.)

_____ _____

Advisor Signature

Addis Ababa University, Addis Ababa June 2026

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June 2026

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# ACRONYMS AND ABBREVIATIONS

| | |
|---|---|
| ANOVA | Analysis of Variance |
| CPFR | Collaborative Planning, Forecasting, and Replenishment |
| CRED | Centre for Research on the Epidemiology of Disasters |
| DQ | Data Quality |
| DRMC | Disaster Risk Management Commission |
| EDRMC | Ethiopian Disaster Risk Management Commission |
| EWS | Early Warning System |
| FA | Forecasting Accuracy |
| FM | Feedback Mechanisms |
| HSC | Humanitarian Supply Chain |
| IAO | International Aid Organization |
| ICT | Information and Communication Technology |
| IGAD | Intergovernmental Authority on Development |
| INGO | International Non-Governmental Organization |
| IO | Inventory Optimization |
| KM | Knowledge Management |
| KMT | Knowledge Management Theory |
| MAPE | Mean Absolute Percentage Error |
| MCAR | Missing Completely at Random |
| NGO | Non-Governmental Organization |
| OC | Organizational Culture |
| OCAI | Organizational Culture Assessment Instrument |
| OCM | Outsourcing Control-Mechanisms |

| | |
|---|---|
| OLS | Ordinary Least Squares |
| OPQ | Outsourcing Partnership-Quality |
| ORD | Overall Organizational Determinants |
| ORE | Outsourcing Risk-Exposure |
| OSA | Outsourcing Strategy-Alignment |
| OSB | Outsourcing Scope-Breadth |
| RBV | Resource-Based View |
| RV | Relational View |
| SC | Stakeholder Collaboration |
| SCC | Supply Chain Collaboration |
| SCM | Supply Chain Management |
| SD | Standard Deviation |
| SE | Staff Expertise |
| SOD | Strategic Outsourcing Determinants |
| SP | Scenario Planning |
| SPSS | Statistical Package for the Social Sciences |
| SPT | Scenario Planning Theory |
| TCE | Transaction Cost Economics |
| UN | United Nations |
| VICS | Voluntary Interindustry Commerce Standards |
| VIF | Variance Inflation Factor |
| WASH | Water, Sanitation, and Hygiene |

## ABSTRACT

*The aim of this study is to evaluate determinants in terms of stakeholder collaboration, data quality, scenario planning, staff expertise, and feedback mechanisms on inventory optimization, where forecasting accuracy acts as a mediator, at the Ethiopian Disaster Risk Management Commission (EDRMC). Using an explanatory research design along with quantitative research design was adopted, and the required data was collected from 201 logistic and forecasters in eleven departments. The data collected from structured questionnaire were analyzed using descriptive analysis, Pearson correlation, and mediation analysis by 5,000 re-sampling of the data set. All the five determinants together explained 68.7% of the variance in inventory optimization ($R^2 = 0.687$, $p < 0.001$). The variables were ordered based on their ability to predict inventory optimization as follows; staff expertise ($\beta = 0.281$, $p < 0.001$), data quality ($\beta = 0.223$, $p < 0.001$), stakeholder collaboration ($\beta = 0.210$, $p < 0.001$), feedback mechanism ($\beta = 0.203$, $p < 0.001$), and scenario planning ($\beta = 0.140$, $p = 0.002$). The forecasting accuracy of the organization proved to have a partial mediating role in all the five predictor-variables relationship with indirect effect ($B = 0.072$, $SE = 0.011$, $p < 0.001$; bootstrapped CI [0.031, 0.118]). Organizational factors explained 40.4% of the variance in the dependent variable ($R^2 = 0.404$, $\beta = 0.636$, $p < 0.001$). Descriptive results revealed that scenario planning was the least influential factor ($M = 3.40$) and use of single deterministic forecast was high ($M = 2.71$). EDRMC embed scenario-based forecasting into policy by requiring at least three alternative demand scenarios in every inventory plan. This reduces reliance on single deterministic forecasts ($M = 2.71$) and prepares the organization for uncertainty.*



**Keywords:** Inventory Optimization, Forecasting Accuracy, Humanitarian Supply Chain, Organizational Determinants, Mediation Analysis, Disaster Risk Management, Ethiopia

# CHAPTER ONE

# INTRODUCTION

## 1.1. Background of the Study

The rising number of both natural and man-made disasters has put additional pressure on humanitarian logistics. According to the Centre for Research on the Epidemiology of Disasters (CRED, 2024), while there were fewer than 100 registered disasters in the 1970s, this figure has risen to above 400 in modern times, impacting about 200 million individuals each year and resulting in over US$300 billion worth of economic damage. Against this backdrop, humanitarian logistics does not only involve issues related to organizational efficiency but also plays a critical role in the very survival of individuals and lives lost. While commercial supply chain demand is predictable based on historical records, humanitarian logistics involves a lot of unpredictability concerning when, where, what kind of emergency will take place and how large-scale it may be, calling for immediate response within several days or even hours, especially in the wake of intense monitoring by donors and the media. Accurate forecasting of humanitarian demand has become absolutely essential.

Socio-technical aspects of forecasting have received considerable focus in today's academia due to the fact that accurate forecasting involves not only mathematical processes but also human factors, cooperation among different organizations, knowledge transfer, and learning (Chari et al., 2021; Fard & Papier, 2022). An elaborate early warning system will become meaningless if it fails to turn the collected information into actual actions regarding inventory by means of efficient cooperation and continuous feedback. Furthermore, current inventory management practice is not limited to cost reduction; modern strategies are focused on achieving such outcomes as flexibility and higher levels of service provided to beneficiaries (Baharmand et al., 2017). As a result, the key difficulty that lies at the heart of inventory optimization is finding the proper combination where there are no shortages, yet, at the same time, waste is kept to a minimum.

Ethiopia exemplifies the situation. The country experiences a wide array of disasters ranging from periodic droughts, massive flooding, and conflict-related displacement. The 2015-2016 El Nino drought resulted in more than ten million people in need and a required US$1.5 billion response

(UN-OCHA, 2016). The 2020-2022 locust plague has wiped out agricultural production, whereas armed clashes in Tigray, Amhara, and Oromia have generated millions of displaced persons.

Established under Proclamation No. 1095/2018, the Ethiopian Disaster Risk Management Commission (EDRMC) serves as the coordinating body for disaster response management. The EDRMC works with regional governments, UN agencies, non-governmental organizations, and donor organizations. Although its early warning systems have been relatively well developed, the commission frequently struggles to convert early warning information into appropriate inventory allocation decisions. A post-operation analysis also highlights this issue, during the 2022 drought response in the Somali region, there was an excessive procurement of emergency shelter kits by more than 30 percent, whereas insufficient quantities of water purification tablets had been procured (EDRMC Internal Report, 2022). Similar situations have been reported in several evaluations (OCHA, 2022; ReliefWeb, 2023; Tufa & Tebeka, 2023).

This project claims that the cause of the apparent paradox is not related to external factors, such as funding volatility, insecurity, and rather than being driven solely by infrastructure constraints, the issue stems from organizational dynamics. More precisely, it is associated with five organizational drivers influencing forecasting accuracy and consequently inventory optimization are argued to play their part. These drivers include collaboration, data quality and comprehensiveness, scenario planning, staff expertise and judgment, and feedback and learning. They remain controllable by the organization, have solid theoretical backing, and have been revealed in previous research as potential improvement levers in humanitarian logistics and supply chains (Anjomshoae et al., 2023; Baharmand et al., 2023; Kabra, 2024).

This includes collaboration in terms of joint planning, seamless flow of data and decision making among a number of players, such as other government departments, donors, NGO’s, and partnering organizations. Without cooperation, data will become fragmented, causing duplication of effort, as well as gaps in data. Data quality refers to the reliability and validity of the data utilized for forecasting, which can include beneficiary registration systems and early warnings, and in the absence of good data, forecasting becomes poor. Scenario planning includes preparation for various scenarios in case of disasters, as opposed to reliance on one single accurate forecast. Expertise refers to the professional experience of the employees in their line of duty. Importantly, this project puts forward a theory that forecasting accuracy plays the mediating role in these relationships:

collaboration, data quality, scenario planning, expertise, and feedback improve forecasting accuracy, thus making better inventory decisions possible. For practice, it implies that investment in organizational practices has the highest payoff only if the primary goal set by managers is improved forecasting accuracy.

This study focuses on the headquarters of EDRMC in Addis Ababa, as well as on its Adama Hub/Warehouse. Headquarters is the main planning and forecasting place, whereas Adama is important in terms of warehousing logistics. These two locations represent all decision-makers and technical specialists participated. In conclusion, the importance of this project stems from the following considerations. To begin with, there is a paucity of research on how organizational drivers can affect forecasting accuracy and inventory optimization in Sub-Saharan Africa humanitarian settings. Moreover, virtually nothing has been studied in Ethiopia in terms of process-driven impacts on inventory outcomes.

## 1.2. Statement of the Problem

Despite the Ethiopian Disaster Risk Management Commission obtains significant financial support from government sources and international organizations, it still faces an inherent paradox - simultaneously confronting necessary commodities and excess storage of obsolete stocks like expired food and medicines (Tufa & Tebeka, 2023). One of such examples has been provided by the 2022 drought in Somali, when warehouse stockpiles of shelter kit supplies were so large that they could not fit into existing facilities, yet other crucial WASH items and equipment, including water purification tablets was scarce. Consequently, air transport had to be used, and many people fell prey to preventable diseases (Logistics Cluster, 2024). This show that the system can produce data without aligning it with actual needs. The paradox cannot be attributed to data scarcity, as Ethiopia has Early Warning Systems (EWS), which produce data on rainfall, crops, pastures, Livestock conditions and population mobility are also key factors. However, the central problem is that the data gathered in the EWS does not translate into actionable logistics intelligence.

In the humanitarian chain of logistics, it does not matter whether or not you have enough data, because what really counts is turning raw data into proactive and demand-oriented forecasts. Indeed, the literature on humanitarian logistics proves that poor forecasts will undermine all benefits of having data, resulting in supply-demand mismatches (Kovács & Falagara Sigala, 2021). In the case of Ethiopia, “first-mile” planning problems (including erroneous demand forecast and

inventory management) are translated into “last-mile” operational failures. Therefore, any mistake that is made at the first mile a few weeks or even months prior to a disaster leads to inefficiency and bottlenecks in supply operations at the last mile. Since there are no effective forecasting framework and coordination at hand, it is impossible for EDRMC to turn data from EWS into logistics intelligence.

A number of recent studies have shown the shortcomings of EDRMC supply chain. Specifically, cooperation of involved parties in the process is ineffective as it suffers from different formats of data and lack of any unified platform that provides transparency (Anjomshoae et al., 2023). The accuracy of beneficiary registers also appears to be low, leading to flawed demand signal and, consequently, forecasting (Boonmee & Arimura, 2023). There is a lack of CPFR forecasting framework, thus making data fragmented and low-quality (Kunz et al., 2022). Scenario planning tools are underdeveloped; hence, reactive approaches are applied to crisis situations (Baharmand et al., 2023). Additionally, organizational knowledge is lost because of frequent turnover of employees, as well as fear of punishment in case of failure (Jahre et al., 2022; Kabra, 2024). All these deficiencies indicate a deeper issue within the organization: forecasting is performed merely as a routine administrative task and not as a strategic function.

The issues arose as a result of the interplay of various factors. For example, reports and documents like the operational report of the 2022 Somali Drought highlighted a contradiction in which there were plenty of shelters but a lack of WASH goods. In addition, secondary sources on humanitarian logistics (Tufa & Tebeka, 2023; Kovács & Falagara Sigala, 2021) supported the observation that forecasting errors upset the delicate balance between supply and demand. In an initial assessment of beneficiary registers and coordination platforms belonging to EDRMC, there was a discovery of inconsistencies in the form of information and data provided. Lastly, the problem being analyzed within the CPFR and KM lenses made it clear that forecasting is viewed administratively.

There for, the aim of this study was to examine the influence of stakeholders collaboration, data quality, scenario planning, staff expertise and feedback mechanisms of forecasting and knowledge management on inventory optimization while accounting for forecasting accuracy as an intermediary variable. Identification of the factors with the highest impact would allow generating recommendations for enhancing inventory performance based on empirical evidence. For instance, if collaboration appears to be a key factor, then investments in unified platforms should be

encouraged. Alternatively, if data quality turns out to be the most important element, then standards for data collection should be developed and implemented; scenario planning should be improved if its significance is high; staff expertise should be maintained in cases where it plays a decisive role.

## 1.3. Research Questions

How do determinants optimize inventory through forecasting accuracy within the humanitarian supply chain of the Ethiopian Disaster Risk Management Commission (EDRMC) in Addis Ababa? This main question is guided by the following specific questions:

1. To what extent does stakeholder collaboration affect inventory optimization?
2. How does the quality of organizational data affect the inventory optimization?
3. What is the effect of scenario planning on inventory optimization?
4. To what degree does staff expertise impact inventory optimization?
5. How do feedback mechanisms contribute to inventory optimization?
6. What is the mediating role of forecasting accuracy on the relationship between organizational determinants and inventory optimization?

## 1.4. Objectives of the Study

### 1.4.1. General Objective

The aim of this study is to examine the determinants of inventory optimization with forecasting accuracy mediating this relation in the humanitarian supply chain of the Ethiopian Disaster Risk Management Commission (EDRMC) based in Addis Ababa.

### 1.4.2. Specific Objectives

The specific goals of this research are detailed below as follows:

1. To determine the effect of collaboration of stakeholders on inventory optimization.
2. To determine the effect of organizational data quality on inventory optimization.
3. To determine the effect of scenario planning on inventory optimization.
4. To determine the effect of staff expertise on inventory optimization.
5. To determine the effect of feedback mechanism on inventory optimization.

6. To determine the mediating role of forecasting accuracy on the association between organizational determinants and inventory management.

## 1.5. Significance of the Study

There are multiple facets associated with the importance of this study: practical, theoretical, and policy-oriented. This study combines five theories into one conceptual and empirical model: Humanitarian Supply Chain Theory, Collaborative Planning, Forecasting, Replenishment, and Knowledge Management Theory. The study recasts forecasting accuracy as a mediator rather than a variable for identification of its determinants; and further extends these theoretical paradigms to a new cultural setting – Ethiopia in Sub-Saharan Africa.

To the EDRMC, this research gives empirical evidence for the organization to understand what levers (collaboration, quality of data, scenario planning capability, staff expertise, and feedback mechanism) to use for enhancing forecasting accuracy and inventory optimization; thus, making resource allocation more effective. To the humanitarian community, this research gives a replicable diagnostic model for organizations.

This study will contribute to the development of disaster risk management strategies at the national level by identifying process areas (data standardization, collaborative planning, after-action review, scenario planning training) that are worth improving without large investments. Donor-restricted environments would benefit from information on how to maximize responsiveness and efficiency through the intervention of choice.

## 1.6. Scope of the Study

The scope of the study was established according to four criteria: location, themes covered, variables included and methodology. To begin with, it only considered EDRMC headquarters, where all decisions regarding procurement, inventory management and logistics planning were made, and the central hub/warehouse in Adama, which functioned as a centralized storage facility and a distribution point. Headquarters and the Adama Hub together formed the primary decision-making points for national inventory planning. As a result, those who worked there became the most suitable interviewees since they had the greatest knowledge about organizational determinants of inventory optimization. As to themes covered, they were limited to five organizational determinants of inventory optimization, namely stakeholder collaboration, data quality, scenario

planning, staff competency, and feedback mechanisms, while forecasting accuracy acted as a mediator between them and inventory optimization. Procurement, transportation, other processes of warehousing except for inventory levels determination and distribution were beyond the scope of the study unless they interacted with any of the covered determinants.

Dependent variable was inventory optimization understood as a balance between service level (availability of relief supplies) and cost (investment into inventories). Since accurate measurement of inventory performance indicators (stockout rates, etc.) proved impossible due to insufficient data, only perceptual variables were used for inventory optimization measurement. For example, one of its indicators was an agreement rate between the importance attached to balancing service and cost and the actual degree to which service and cost were taken into consideration in inventory planning.

Quantitative, cross-sectional survey design was chosen because of its appropriateness to hypothesizing testing and mediation analysis by means of bootstrapping. However, cross-sectional design cannot confirm causation in a strict sense and only theoretical assumptions and proper temporal ordering (for example, determinants → forecasting accuracy → inventory optimization) allowed making causal claims. Common method bias (inflation of correlations between constructs measured by one and the same scale due to measurement error) was controlled for via distinct scale anchors, separation of constructs in questionnaire structure and Harman's single-factor test in the data analysis phase.

Data collection took place in April-May 2026 and took about two months due to the required volume of the sample (N=254). No longitudinal measurements were planned.

## 1.7. Operational Definition of Key Terms and Concepts

To ensure clarity and conceptual precision, the following key terms are defined as they are used in this study:

- **Stakeholder collaboration** Measured by the extent of joint planning, information sharing, and coordinated execution among EDRMC departments and partner organizations. (Simatupang & Sridharan, 2002).
- **Data quality** Defined as the accuracy, consistency, and timeliness of logistics data used for forecasting. Measured by staff perceptions of error rates, reliability, and availability of data when needed (Wang & Strong, 1996; Fekadu & Lessa, 2022).

- **Scenario planning** Defined as the ability to construct and use multiple plausible crisis scenarios for logistics planning. Measured by the presence and use of scenario tools, and staff ratings of preparedness across different disaster contexts (Schoemaker, 1995; Nalluri et al., 2023).
- **Staff expertise** Refers to the technical competence, training, and experience of personnel involved in forecasting. Operationalized through self-reported qualifications, years of experience, and perceived skill levels (Hair et al., 2022; Bekele & Mulu, 2023).
- **Staff judgment** Defined as the intuitive and experiential decision-making ability of staff in adjusting forecasts. Measured by Likert scale items on reliance on judgment, confidence in decisions, and perceived impact on forecast outcomes (Parsons et al., 2017).
- **Feedback mechanisms** Refers to formalized systems for collecting lessons learned from past operations. Operationalized by survey items on existence, frequency, and usefulness of feedback loops in logistics planning (Argyris & Schön, 1978; Shamala et al., 2023).
- **Forecasting accuracy mediation** Defined as the degree to which forecasted demand aligns with actual demand during disaster response. Operationalized as a perceptual variable (staff assessments of forecast accuracy) and tested statistically as a mediator between organizational determinants and inventory optimization (Makridakis et al., 1998; Saleh et al., 2025).

## 1.8. Organization of the Study

The thesis follows the typical structure consisting of five chapters. In the first chapter, the background of the study will be presented, together with the problem statement, research questions, objectives, significance, scope and definitions of key concepts. In chapter two, extensive literature review will be carried out in order to generate a conceptual framework and develop testable hypotheses. Chapter three contains detailed description of the research approach and methodology that includes the approach to data collection, research design, population, sample and sampling techniques, data collection instruments, procedure to establish validity and reliability, data collection process, methods of data analysis and ethics considerations. Chapter four includes results obtained in the course of analyzing the collected data using descriptive statistics, correlation analysis, and mediation analysis. Chapter five contains conclusions drawn from the results and discussion, implications of the findings, limitations, suggestions for future research and practice.

# CHAPTER TWO

# REVIEW OF THE RELATED LITERATURE

This chapter reviews relevant theoretical and empirical literature to provide a conceptual model that will be used to explain how organizational factors affect inventory optimization via forecasting accuracy in light of the case study of the Ethiopian Disaster Risk Management Commission. Literature pertaining to pertinent theories, key concepts, and the state-of-the-art literature is reviewed in this section, highlighting areas where there exist gaps in knowledge, and which will form the basis of this research thesis. More specifically, the study explores how forecasting accuracy mediates the relationship between organizational factors and inventory optimization. Hence, literature review lays the foundation for the empirical part of this study, whereby the organizational determinants, forecasting accuracy, and inventory optimization are integrated into one conceptual framework.

## 2.1. Theoretical Review

A sound theoretical literature review is essential for any empirical study because it provides the conceptual lens through which phenomena are observed, the causal mechanisms that explain relationships between variables, and the justifications for hypotheses.

### 2.1.1. Theoretical Foundations

The following three theoretical approaches are applicable for the proposed mediation model. CPFR (Collaborative Planning, Forecasting, and Replenishment) considers the collaborative effort of the parties involved in making forecasting more accurate due to information exchange and decision-making and, at the same time, using inventory through transshipment and stock pooling. Another theoretical approach that can be relevant in this regard is knowledge management, according to which both explicit knowledge (data) and tacit knowledge (knowledge resources of the personnel) are essential for achieving accurate forecasting and inventory management. Finally, organizational learning theory helps explain the feedback process and scenario planning. Both single-loop and double-loop learning promote the accuracy of forecasts and inventory management. Each of the three above theories was analyzed in terms of applicability and limitations.

- **Collaborative Planning, Forecasting, and Replenishment (CPFR)**

CPFR appeared in the 1990s as the solution to the problem of fragmented demand forecasting in commercial supply chains. The approach was developed by the Voluntary Interindustry Commerce Standards (VICS) Association, and it implies the collaboration of several trading partners in the process of planning and fulfillment (Simatupang & Sridharan, 2002). Its main premise is that collaboration within the supply chain reduces the bullwhip effect and contributes to achieving low inventory levels and high service levels. CPFR includes the following four principles: (1) information sharing – all parties voluntarily exchange proprietary information; (2) joint decision-making – forecasting is performed collaboratively; (3) exception management – focusing on the items with forecast discrepancies; and (4) synchronized replenishment – orders match demand (VICS, 2004). Nowadays, this theory has new interpretations and involves the application of big data analytics and artificial intelligence (DevDiscourse, 2025).

There is much evidence that CPFR is efficient for commercial supply chains because it reduces inventories by 10-30% and increases the accuracy of forecasting by 15-25% (Kunz et al., 2022; Simatupang & Sridharan, 2002). However, its application to the humanitarian sphere is highly debatable. While some scholars argue that the collaboration of several organizations decreases redundancies and improves forecast accuracy (Kunz et al., 2022), others state that ad hoc collaborations, communication barriers, and data sharing obstacles hinder its implementation (Anjomshoae et al., 2023). Therefore, in this research, a compromise approach is taken. Although the complete implementation of CPFR is probably unrealistic for EDRMC, partial collaboration through regular inter-agency meetings, compilation of the beneficiary list, and joint needs assessment can result in improved accuracy of forecasts. Furthermore, CPFR theory stipulates that collaboration facilitates the sharing of inventory among organizations, and this technique of inventory optimization becomes unnecessary.

- **Knowledge Management Theory**

According to the knowledge management theory formulated by Nonaka and Takeuchi (1995) and further developed by other scholars, knowledge can be implicit and explicit. Implicit knowledge includes experiential knowledge, which cannot be easily codified. On the contrary, explicit knowledge can be recorded, documented, and stored; for instance, it is early warning data, warehouse records, and standard operating procedures. The success of organizations is conditioned

by their ability to externalize tacit knowledge and exchange knowledge in general (Socialization, Externalization, Combination, and Internalization). Such companies are adaptive and resilient.

The problem with most humanitarian supply chains is that they create sophisticated explicit knowledge management systems and ignore tacit knowledge. For example, the departure of experienced employees may lead to forecasting errors. This is true of EDRMC: the agency's staff understands the needs of the communities based on their feedback, but this knowledge is tacit and does not affect the operations of the agency. Knowledge management theory claims that organizations employing efficient knowledge management techniques, such as after-action discussions, mentoring, and storage of acquired knowledge, have higher forecasting accuracy.

Furthermore, according to knowledge management theory, high-quality explicit knowledge (accurate data about inventory, reliable data about lead times) leads to low discrepancy in stocks, while tacit knowledge makes it possible to optimize inventory when forecasts are inaccurate. One of the drawbacks of this theory is that tacit knowledge is difficult to capture and codified, and it can be oversimplified (Jahre et al., 2022). The current study partially agrees with this opinion. Nevertheless, it appears possible to codify certain aspects of tacit knowledge, for instance, in the course of interviews and through "lessons learned" databases.

- **Organizational Learning Theory**

Argyris and Schön (1978) formulated organizational learning theory, which explains how organizations learn from their mistakes and change their operations accordingly. Organizational learning can be categorized into two major types: single-loop and double-loop learning. Single-loop learning implies correction of actions without altering the fundamental assumptions (e.g., increasing the number of forecasts of a particular item). Double-loop learning means changing the underlying assumptions and asking why things are the way they are (e.g., why is our forecast system ineffective for predicting water needs? Is it because of our heavy reliance on donor interests?). Single-loop learning is frequent in humanitarian supply chains, but double-loop learning is rare. Disasters reviews tend to be compliance-driven and the same forecasting errors keep occurring (Tomasini & Van Wassenhove, 2009).

This theory suggests that humanitarian organizations with efficient feedback systems (e.g., mandatory after-action reviews with action trackers, analysis of beneficiary feedback surveys,

regular reviews of performance dashboards) will achieve high accuracy in forecasting. Feedback mechanisms positively affect inventory optimization by detecting issues in the replenishment strategy, suppliers, and warehouse infrastructure. This hypothesis was confirmed in 2024, when analysis of supply chains in humanitarian missions fostered organizational learning. However, learning was efficient only when organizations differentiated between risks (University of Bath, Research portal, 2025).

Scenario planning can also be viewed as organizational learning in the sense of preparation for different futures and changing mental models. Scenario planning increases the accuracy of forecasting through substituting single-point forecasts with probability distributions (Amer et al., 2013). In addition, scenario planning optimizes inventory through flexible pre-positioning and trigger-based distribution (Baharmand et al., 2017). Yet, one can argue that feedback is not always constructive, and organizational politics can undermine honesty. This statement is valid in the current study. Nevertheless, although a good feedback mechanism is crucial for organizational learning and improvement in the field of forecasting and inventory management, it is not sufficient.

### 2.1.2. Concept of Inventory Optimization

Before delving into the issues of determining the determinant and mediator within the current study, it would be useful to clarify what inventory optimization implies distinct from the overall concept of inventory management.

By the very term "inventory management," a number of operations aimed at managing inventories are understood. These include the determination of order points and sizes, determination of the right levels of safety stock, lead time management, designing warehouse layouts, implementing inventory rotation policies, and inventory control (inventory turnover and obsolescence). It also comprises cycle counting, and performing physical inventory counts. Efficient inventory management ensures that there is a sufficient amount of product available exactly where it should be at any given moment with minimum expenses (cost of inventory storage, cost of insurance, obsolescence cost, cost of procurement, and order handling) (Manzini et al., 2015).

Optimization of inventories is related to one aspect of inventory management, which involves achieving the most efficient trade-off between the service level and its cost. In technical terms, inventory optimization can be defined as minimization of the total inventory costs subject to a given service level constraint or maximization of the service level under budget constraints (Silver, Pyke,

& Peterson, 2016). There are a variety of traditional inventory management models, such as economic order quantity models, the newsvendor model, and (s, S) policies, that attempt to solve the same multi-objective problem but offer analytical solutions using different assumptions regarding demand and other variables.

Traditional inventory optimization problems are generally related to finding the equilibrium between inventory costs associated with sustaining certain service levels and potential losses due to stockouts. In most cases the optimal service level does not equal 100%, because the cost of acquiring more units to reach this level turns out to be excessive (Goltsos, Syntetos, Glock, and Ioannou, 2022). By contrast, inventory optimization within a humanitarian setting is quite another thing since the marginal cost of stockout concerns human lives and the suffering of people. Thus, in this case, the constraint of service level should be significantly higher (e.g., 99.9% in the case of life-saving goods). Also, compared to the traditional problems, inventory optimization in a humanitarian situation involves lower costs related to excess stocks of goods (Fukuhara et al., 2023). However, in the current situation, resources are limited and thus must also be considered when optimizing inventory. Therefore, there is a need to maximize the service level subject to a certain budget. For this purpose, accurate forecasting is needed. In other words, the optimal inventory level depends on three parameters: forecasted demand, forecasting error, and service level (Sandra et al., 2026).

The measure of inventory optimization in this study will be staff perception. The corresponding perceptual measures would include the following statements: "Accuracy of demand forecasts decreases risks of stockouts of critical items." "Highly accurate forecasts reduce overstocks and obsolescence." "Inventory optimization involves trading off service level and resource efficiency." Perception-based measures of inventory optimization appear to be appropriate in this case because objective data is hard to collect in humanitarian situations. Besides, there is substantial empirical evidence suggesting close correspondence between objective and perceptual performance measures in supply chain management studies (Li et al., 2006).

### 2.1.3. Concept of Forecasting Accuracy

In recent years, contemporary supply chain researchers have started recognizing that accuracy must be measured operationally rather than being considered just statistically. Even though the classical metrics of MAE and MAPE are still common practices in the field of forecasting, there is a strong

body of evidence proving that the increase in the former does not necessarily mean better inventory management practices. As suggested by Goltsos, Syntetos, Glock, and Ioannou (2022), there are some persisting problems associated with the existing segregation of inventory and forecasting research with models optimized mathematically often performing worse practically, especially in case of intermittent demand.

The importance of considering the implications of different forecast metrics becomes especially obvious in industries experiencing sporadic customer demand such as the manufacturing of spare parts and pharmaceuticals. Fukuhara et al. (2023) conducted a simulation-based study proving that forecasting models demonstrating a relatively equal level of statistical errors can generate opposite results in terms of cost-service balance. Thus, it can be argued that the relationship between the quality of forecasts and inventory management remains poorly studied despite its criticality.

In the meantime, modern approaches such as artificial intelligence and fuzzy multi-criteria decision-making present potential solutions to the current challenge. For example, Sandra et al. (2024) developed a multi-criteria model allowing assessing alternatives based on opposing criteria including accuracy, cost, flexibility, and scalability among others. The results of the conducted analysis showed that AI-driven analytics was proven to be the most efficient technique for strategic inventory management and managing sudden demand increases. At the same time, Ezmigna (2023) found that although AI and data mining techniques were capable of capturing complex demand patterns, there was a range of issues such as data quality, integration of systems, and personnel training to be solved.

Managerial judgment may assume significant importance and sometimes serve as the decisive factor when using statistical techniques proves inadequate in the situation. To illustrate, Syntetos et al. (2009) showed in their research that manual adjustments resulted in improved forecast quality in 61% of the pharmaceutical supply chain cases they were studying. In a recent study conducted by Rojas, Rojas, and Wanke (2024), the positive influence of precise forecasts on inventory management, resource allocation, and the establishment of an organization-wide data culture in Chile's public health sector was identified.

However, several questions remain to be addressed. According to a PRISMA-oriented literature review performed by Gokul Global University (2025), several shortcomings of the existing body of research on the issue include underrepresentation of economic, environmental, and technological

factors, whose consideration should go beyond sustainability concerns. Moreover, a lack of concrete applications involving AI techniques for forecasts was reported, as well as a low number of industry-specific empirical studies of regulated industries. All of this implies that striving for higher statistical accuracy may not be the best strategy in current conditions. It is necessary to find a balance between statistical forecasting and qualitative judgment. In particular, it can be noted that the current literature review recognizes that forecasting accuracy should be viewed as a multi-faceted concept.

### 2.1.4. Operational Determinants

Five operational determinants are chosen for this study: stakeholder collaboration, data quality, scenario planning, staff expertise, and feedback mechanisms. All of these are predicted to have a positive effect on forecasting accuracy and inventory optimization separately. Below, the theoretical mechanisms through which each determinant positively impacts both inventory optimization and forecasting accuracy are explained, relying solely on the aforementioned three core theories.

- ***Organizational determinants and forecasting accuracy***

Collaboration is theoretically linked to forecasting accuracy through CPFR theory (Simatupang & Sridharan, 2002; VICS, 2004). When different parties possess fragments of information about demand, a forecast created based on all parties' information is more accurate than separate forecasts made by individual parties. In humanitarian crises, government agencies will possess administrative data related to population size and infrastructure; donors will have commitments in terms of finances, while NGOs will know the actual need for assistance from affected people on the ground. Therefore, when stakeholders work together, the forecasts created based on joint efforts will incorporate more pieces of information, leading to higher forecasting accuracy. Additionally, collaboration avoids fragmented forecasts that result in the bullwhip effect. In the fragmented situation, each stakeholder works independently of others, resulting in forecast errors amplifying along the supply chain. However, when stakeholders cooperate, there is no room for fragmenting forecast errors because only one forecast exists - the shared one. Although such a forecast cannot be flawless, it is still more reliable than fragmented ones (Kunz et al., 2022).

Data quality as a determinant of forecasting accuracy can be explained using knowledge management theory. Forecast models - simple moving averages and complex machine learning

algorithms - function according to the principle that "garbage in, garbage out." Issues with data quality that are common in humanitarian contexts include inaccuracy of beneficiary registers (double counting and being out-of-date), incompleteness of available data (not including all segments of the population), inconsistency between different data sources, and timeliness of data (data obtained months ago). Each of the above-mentioned aspects leads to lower forecast accuracy (Boonmee & Arimura, 2023). The most comprehensive data will include rainfall patterns, population movement, market prices, nutrition statistics, and the presence or absence of conflict. On the other hand, comprehensive data do not mean noisy and irrelevant data, as this increases forecasting errors. The idea is to collect and analyze data that are accurate and meaningful.

Scenario planning is best understood through organizational learning theory. It belongs to the group of double-loop learning techniques that prepare organizations for potential future developments. The benefit of scenario planning in improving forecasting accuracy comes from the shift from single-point forecasts to multiple points of view, allowing one to create more probabilistic forecasts. Rather than a "what will happen?" scenario, planning implies "what could happen?" and "how will we respond to that?" In addition to increased likelihood of being correct, forecasts that include probabilities are more informative than the single-point estimates. Besides that, scenario planning improves the ability to recognize which scenario takes place and thus allows for adjusting forecasts in real-time (Amer et al., 2013). Finally, through identifying leading indicators of the unfolding scenario and building rules-based forecast adjustment strategies, organizations can improve their forecasting performance substantially. For example, a rule could be as follows: If precipitation is below 50% for two months in a row, assume that a severe drought scenario is taking place and increase the order quantity of water purification tablets by 100%.

The role of staff expertise in enhancing forecast accuracy is connected with the intersection between explicit and tacit knowledge described in knowledge management theory. Staff members with long experience have tacit knowledge that is not included in the formal data. They know, for instance, that certain communities systematically underreport needs due to external pressure, that a specific road becomes unpassable after rains, and that particular suppliers tend to be delayed. This tacit knowledge helps them correct formal forecasts, improving their accuracy (Jahre et al., 2022). Secondly, expert staff will be able to correctly interpret any inconsistencies in the collected data and avoid misleading conclusions. The optimal approach in creating forecasts is the use of quantitative

models supplemented by human expertise. Lastly, experts will find it easier to conduct after-action reviews of past mistakes and mentor inexperienced staff in forecasting processes.

Finally, forecasting accuracy is enhanced through feedback mechanisms explained by means of organizational learning theory. Absence of feedback means absence of learning: once the disaster is over, it is impossible to know whether the forecast was accurate and, in case of failure, why this happened. In humanitarian organizations, post-disaster reviews are common, but they are rarely transformed into feedback incorporated into forecasting models (Logistics Cluster, 2024). Effective feedback mechanisms can include documentation, assigning, and tracking after-action reviews; displaying forecasting performance on dashboards; collecting feedback from beneficiaries; and reviewing forecasts during regular meetings where mistakes can be openly discussed without being blamed. All of these techniques ensure that learning becomes routine (Bessant et al., 2003). As a result, single-loop learning (adjustment of forecast parameters) and double-loop learning (revising forecasting procedures) take place. Jahre et al. (2022) found that after-action reviews led to a 25% reduction in forecasting errors over two years.

- ***Organizational determinants and inventory optimisation***

In addition to its impact on forecasts, CPFR theory also predicts direct effects on inventory. Collaboration allows organizations to work together on inventory management, using such mechanisms as transshipments, buffer stock placement in coordinated locations, and joint warehouse utilization. Even if forecasts remain incorrect and inaccurate, partners may agree to share their stocks, reducing the amount of safety stock to hold in their inventories (Socio-Economic Planning Sciences, 2024). Recent modeling shows that cooperation mechanisms based on centralization consistently outperform decentralized alternatives in terms of inventory performance, especially when agencies share transshipments and forecasts of demand (Socio-Economic Planning Sciences, 2024). In this way, collaboration enhances inventory management.

Data quality as a determinant of inventory optimization can also be explained through knowledge management theory. Better data quality directly affects inventory optimization by reducing discrepancies between inventory records and actual amounts of products in warehouses. Information on lead time and reliability of suppliers allows calculating the necessary amount of safety stock with higher precision. Dubey et al. (2021) found a significant direct impact of data quality on inventory performance ($\beta = 0.42$, $p < 0.001$). In humanitarian settings, a 10% error rate in

beneficiary registers was correlated with a 15% increase in stockout rates (Boonmee & Arimura, 2023). In this manner, high data quality enhances inventory optimization, regardless of forecasts.

Organizational learning theory also allows explaining a direct relationship between scenario planning and inventory optimization. Specifically, scenario planning enables organizations to establish trigger points for different scenarios and develop flexible pre-positioning schemes. For instance, "If there is a drought, allocate 50% of buffer stock." In this way, scenario planning allows for lowering safety stock while keeping the same service level because the organization knows when to trigger pre-planning measures. Dubey et al. (2021) demonstrated a direct effect of scenario planning on inventory optimization ($\beta = 0.49$, $p < 0.001$). Baharmand et al. (2017) created a simulation of humanitarian response to an earthquake in Haiti and showed that scenario planning decreased stockouts by 18% and overstock by 12% through direct inventory optimization without improving forecasts.

As for staff expertise, even in the presence of equal forecasting models, an experienced logistics officer makes a much better choice regarding safety stock levels, reorder points, and expediting than a novice (Kabra, 2024). As shown by Jahre et al. (2022), a decrease in the number of experienced staff leads to an estimated 20–30% increase in stockouts when the forecast remains the same. Staff expertise also helps organizations make wise decisions in ordering products, rationing their usage, and negotiating with suppliers. When organizations implement explicit knowledge management programs, staff expertise benefits inventory performance even further.

Lastly, organizational learning theory explains the impact of feedback mechanisms on inventory optimization. First of all, a feedback mechanism allows detecting systemic errors in inventory replenishment rules, supplier selection criteria, and warehouse organization that are invisible to forecasting models. For instance, if it turns out that emergency orders constantly arrive late, this feedback triggers a revision of the safety stock policy or a supplier contract, regardless of the current forecasts. According to Bessant et al. (2003), organizational learning in supply chains enhances inventory turnover and decreases wastage. In the Logistics Cluster report (2024), organizations with a systematic feedback practice reported fewer repeated errors in inventory placement.

- ***Organizational Determinants, Forecasting Accuracy and Inventory Optimization***

This study argues that the accuracy of the forecasts acts as a mediator of the relation between organizational determinants and inventory optimization. The adoption of such a model cannot be merely justified by its methodology: on the contrary, it is based on the theoretical argument that the application of direct-effects modeling may lead to oversimplification of the underlying processes. While direct effects ignore complexities, the mediation paradigm allows analyzing the layers through which determinants exercise their influence.

It is not an overstatement to say that the organizational determinants identified in the literature, namely collaboration, data quality, scenario planning, staff expertise, and feedback mechanisms, are not mere inputs into inventory management processes but rather powerful means to affect forecasting accuracy. Indeed, CPFR, knowledge management, and organizational learning all point to this effect. Collaboration facilitates information exchange, while high-quality data provides reliability and predictive capacity. Scenario planning helps deal with uncertainty, while staff expertise allows using human judgment more effectively. Finally, feedback mechanisms foster organizational learning. Recent studies back up the logic of these determinants: Douaioui et al. (2024) demonstrate that collaborative forecasting platforms help decrease the demand uncertainty, while González et al. (2025) state that high-quality data integration increases predictive reliability in health care supply chains. Ignoring the impact of determinants on the accuracy of forecasts makes theories about those factors much less convincing and meaningful.

The next argument in favor of this theoretical model is that forecasting accuracy can be used to achieve inventory optimization goals, i.e., it represents another mediating factor. In particular, accurate forecasts lead to lower uncertainty, minimal safety stocks, a decreased number of stockouts, and the avoidance of excessive stocking. Evidence from previous research, both related to commercial and humanitarian logistics, clearly suggests that better inventory performance depends on forecasting (see Dubey et al., 2021; Syntetos et al., 2016). The latest studies provide more proof: for example, González et al. (2025) prove that using artificial intelligence for forecasting helped to decrease costs by 18% and retain service levels at the same time. Meanwhile, Karpagavigneswari & Kamali (2025) suggest that chaos-theory-based forecasting only contributes to inventory performance when there are proper organizational learning mechanisms in place. Thus, omitting forecasting accuracy from the model would mean ignoring the core mediating pathway.

Nonetheless, it needs to be recognized that there exist direct connections between the identified factors and inventory performance. As per the CPFR framework, inventory visibility generated by cooperation contributes to improving inventory effectiveness. Within the field of knowledge management, data quality acts as a source of guarantee for record precision, whereas human assessment helps make proper order decisions. Within the framework of organizational learning, feedback-based interventions to address the problems are possible. Thus, despite the mediating effect played by forecasting accuracy, there are other mediating paths, too. The recent literature confirms the possibility of direct effects, too: according to Keith (2024), collaboration based on RFID systems positively affects inventory visibility. Likewise, Rojas et al. (2024) find that the same positive impact is observed in relation to manager decision making without considering forecasting accuracy. Consequently, the model to be proposed is supposed to include both types of effects.

An important benefit associated with mediation compared to direct effects is the ability to understand better the links between variables and develop recommendations for application in practice. For instance, the model focusing on the latter would imply the significance of cooperation in the context but would not explain how to apply the suggested intervention. In case of mediation analysis, the specific mechanisms contributing to inventory visibility will be identified. For instance, increased forecasting precision or improvement of logistics will contribute to reaching the intended objective. EDRMC will need to focus on appropriate interventions that will help achieve the desired result.

In sum, using mediation is justified with reference to enhancing theoretical robustness and practical recommendations. Not only will it allow acquiring deeper understanding of phenomena, but also ensure greater congruence with the CPFR, knowledge management, and organizational learning frameworks' theoretical assumptions.

## 2.2. Empirical Studies Review

### 2.2.1. Effects of Operational Determinants on Inventory Optimization

The section presents and discusses available evidence of the relationship between each operational determinant and inventory optimization. While this dissertation aims to examine mediation effects, the knowledge of the direct effects of operational determinants will help assess the importance of each determinant for the phenomenon of interest.

- ***Stakeholder collaboration and inventory optimization***

Numerous studies find that collaboration is positively related to inventory performance. For example, Balcik et al. (2010) analyzed coordination mechanisms in two disaster response cases – 2004 Indian Ocean tsunami and Hurricane Katrina in New Orleans. In particular, the authors used case study research design to compare responses involving the use of coordination mechanisms (joint logistics coordination groups) and without them and found that participants in coordinated responses experienced lower levels of duplication and stockouts compared to those who acted independently. According to Balcik et al. (2010), in non-coordinated responses, inventory mismatches were three times higher.

Kunz et al. (2014) performed meta-analysis of 15 case studies on humanitarian supply chain issues and found that collaborative planning was associated with a 25% decrease in inventory levels without the increase in stockouts and 30% decrease in emergency procurement costs. More recent findings presented in Anjomshoae et al. (2023) come from survey data collection among 120 humanitarian supply chain professionals employed in 12 African countries (including Ethiopia). Collaboration was measured with a 7-item scale derived from CPFR framework. Inventory optimization was defined by stockout frequency, overstock frequency, turnover, service level, and cost efficiency (also 5-items scale). According to results, there was a strong positive correlation between collaboration and inventory optimization ($r = 0.48$, $p < 0.01$). Regression analysis revealed that a 1-standard-deviation increase in collaboration corresponded to a 0.35 standard-deviation increase in inventory optimization.

The findings obtained within an Ethiopian context by Tufa and Tebeka (2025) suggest that the issue of inventory management during the Somali drought response of 2022. Based on interviews with 35 logistics managers employed by EDRMC, United Nations agencies, and NGOs, it was found that inter-agency lack of coordination was among primary factors of shelter kits overstock and water tablets understock. Post-response evaluation concluded that collaboration should be institutionalized via creating a national logistics working group and sharing relevant information via a common platform. Based on the presented evidence, hypothesis H1b (direct effect) can be accepted.

- ***Data quality and inventory optimization***

Data quality and inventory performance are proven to be associated. Boonmee and Arimura (2023) evaluated data quality and inventory issues in Thailand, the Philippines, and Indonesia in terms of disaster relief operations. They assessed data quality by estimating accuracy rate of the beneficiary registries (based on comparison of numbers in the registries and independent household surveys) and examined inventory outcomes (stockout rates, overstock rates). It was found that a 10% error rate in beneficiary registries was correlated with 15% increases in stockout and 12% in overstock. As noted by the authors, the relationship was nonlinear and when errors exceeded 20% inventory performance deteriorated significantly.

Based on data collected from 210 humanitarian supply chain professionals in India via a survey method, Dubey et al. (2021) developed a structural equation model. Data quality was defined by 12 items reflecting accuracy, completeness, consistency, and timeliness. Inventory optimization was measured as stockout rates and turnover. Structural analysis revealed a significant positive effect of data quality on inventory optimization both directly ($\beta = 0.42$, $p < 0.001$) and indirectly (through forecast accuracy, $\beta = 0.31$, $p < 0.001$). Total effect of data quality on inventory optimization was equal to 0.73, which means a very strong association between the constructs.

Finally, Chari et al. (2021) focused on comprehensiveness of data. In Kenya and Somalia, organizations collecting information on various aspects of beneficiaries' needs (demographic breakdowns, geographical location, timing, and severity) demonstrated a 20% lower stockout rate than those that collected only aggregate headcount data. At EDRMC, as mentioned earlier, early warning information is frequently aggregated at the regional level making it impossible to identify shortage on the village level. For example, while regional averages indicate that people have enough water, some villages suffer from its scarcity.

- ***Scenario planning and inventory optimization***

Evidence on scenario planning in humanitarian logistics appears quite promising but still is limited. Baharmand et al. (2017) developed a simulation framework based on real data on the Haiti earthquake of 2010. There were two alternative approaches to inventory planning – a single point forecast based on historical patterns and a scenario approach (optimistic, most likely, and pessimistic scenarios). On average, scenario-based planning led to a 18% lower number of

stockouts and to a 12% lower number of overstocks. The highest benefit of scenario planning was found for items with high demand uncertainty (medication, etc.) and the lowest benefit was achieved with more predictable demand items (food rations).

Review of multiple case studies of scenario planning for disaster risk reduction was conducted by Amer et al. (2013). Organizations that used scenario planning proved to be more responsive to unexpected events (e.g. a powerful earthquake occurring in a not seismic region) because they had contingency plans and pre-positioned supplies. During such events, they had much lower stockout rates. Finally, in a survey study conducted by Dubey et al. (2021), it was found that organizations with better scenario planning capabilities demonstrated higher inventory resilience (ability to maintain stocks in case of variable demand). Using regression analysis, the researchers found a positive effect of scenario planning on inventory optimization ($\beta = 0.28$, $p < 0.01$) mediated by forecast accuracy ($\beta = 0.22$, $p < 0.01$). However, the effect was found to be weaker in organizations with poor analytical capabilities, which is a potential problem in Ethiopia, however, this study controls for training and resources of staff members.

- ***Staff expertise and inventory optimization***

Notably, there are few scientific publications examining staff expertise in the humanitarian logistics domain. Jahre et al. (2022) conducted semi-structured interviews with 45 logistics staff members in five humanitarian organizations. Tacit knowledge (who are reliable suppliers, what routes are passable during the rainy seasons, which community members can be trusted) turned out to significantly affect inventory decisions. The interviewees claimed that lack of expert personnel resulted in a 20-30% increase in stockouts.

In their survey study, Kabra (2024) measured staff expertise in 175 humanitarian supply chain professionals as a combination of years of experience, training hours and self-ratings. Staff expertise was found to be positively correlated with supply chain responsiveness (including inventory optimization). In addition, the study found that formal knowledge management (databases, mentoring programs) made this expertise more valuable, as it allowed spreading the gained knowledge to other personnel. Finally, Fard and Papier (2022) carried out an experiment where logistics professionals were provided with demand data and asked to produce predictions. As a result, respondents with more than 5 years of experience demonstrated 15% lower forecast errors than those who had less than 2 years experience.

In particular, in Ethiopia, according to anecdotal evidence from EDRMC staff, logistics experts can predict shortages based on community signals (e.g. early migration, livestock deaths), which are often ignored in official reports. Hence, despite lack of scientific evidence, the hypothesis H4b may be confirmed.

- ***Feedback mechanisms and inventory optimization***

Feedback and learning processes are the least researched out of five investigated operational determinants. Bessant et al. (2003) offer a conceptual framework for supply chain learning, but the authors do not provide any empirical evidence of the concept. In their report "Learning Doing Gap" for the Logistics Cluster, the organization noted that while numerous post-disaster reviews take place, procedure changes rarely occur. Based on interviews conducted with 50 logistics professionals in 10 countries, it was found that only 30% of respondents had an example of applying previously acquired knowledge in their work.

As discussed by Jahre et al. (2022), organizations with a good system of feedback (formal after-action reviews, lessons learned database used in practice) show a significant decrease in forecasting error rates. In one case study conducted by the authors, an introduction of a feedback loop helped to reduce forecasting errors by 25% in 2 years and improve inventory turnover by 18%. According to authors, this change is attributable to learning and no scientific publication has ever tested a quantitative relation between feedback and inventory performance among large sample sizes.

### 2.2.2. Mediation Effect of Forecasting Accuracy

studies indicate that forecasting accuracy acts as an intermediary factor between organizational factors and inventory optimization. According to Ahatsi & Olanrewaju (2025), who conducted their study in Ghana and South Africa in humanitarian supply chains, artificial intelligence in forecasting and big data analysis positively influence organizational inventory performance and resilience provided the organization is prepared to collaborate. On the other hand, Girotto et al. (2025) studied nonprofit health organizations in Brazil and found out that the use of simple forecasting techniques led to the reduction of inventory expenses by more than 25%. Therefore, forecasting accuracy acts as an intermediary between organizational factors like data quality and expertise on one hand and inventory results on the other.

In the case of humanitarian aid sector, the UNFPA Sudan case study (2025) underscores the significance of data quality and scenario planning in demand forecasting and, hence, inventory optimization. In this respect, forecasting accuracy acted as the intermediary between organizational factors and organizational efficiency in conducting inventory operations. Lindell (2025), when analyzing the study by the World Food Programme, observed that the use of machine learning model enhanced forecasting accuracy and led to inventory optimization despite unstable demand. Debala et al. (2022), whose study focused on public organizations in the vicinity of Ethiopia, indicates that staff expertise, information and communication technology (ICT) systems and documentation were fundamental for successful inventory operations.

### 2.2.3. Research Gaps

In spite of growing amount of academic research regarding humanitarian logistics, there remain certain important gaps which require attention. The current research is going to fill those gaps.

Gap 1: Isolated consideration of determinant factors. Till now, various works considered such factors as collaboration, data quality, scenario planning, experience of employees, and feedback isolated, not considering them together. There exists no empirical study testing these factors at once in one empirical model. This issue requires addressing, since it is quite possible that these factors are interrelated. For example, the effect of data quality on forecasting accuracy may vary depending on employee expertise, since skilled employees will be able to deal with it. In addition, the effect of collaboration may depend on existence of appropriate feedback mechanism, since one can learn from previous experiences.

Gap 2: Limited empirical validation in humanitarian contexts. Most of the empirical evidence reviewed above comes from commercial supply chains or from humanitarian contexts in Southeast Asia and Latin America. Sub-Saharan Africa, and Ethiopia specifically, is severely under-represented. This is a significant gap because the conditions in Sub-Saharan Africa – recurrent climate shocks, weak infrastructure, conflict, donor dependence, and limited analytical capacity – may moderate the relationships found elsewhere. A relationship that holds in a relatively stable context may not hold in a more volatile one, or may hold with different magnitudes. Context-specific evidence is essential for both theory and practice.

Gap 3: Inadequate investigation of feedback mechanisms and learning. Although there has been some coverage of collaboration, data, scenario planning and learning, the process of how feedback is collected, analyzed, and used as part of learning is the least explored determinant out of all the five. Few studies have considered learning and its relationship with adaptive capacity as something that requires empirical research; most consider it a recommendation. By proposing a hypothesis on how implementing structured feedback mechanisms leads to better forecasts and optimized inventory management, this study fills one of the gaps in humanitarian logistics research in relation to learning.

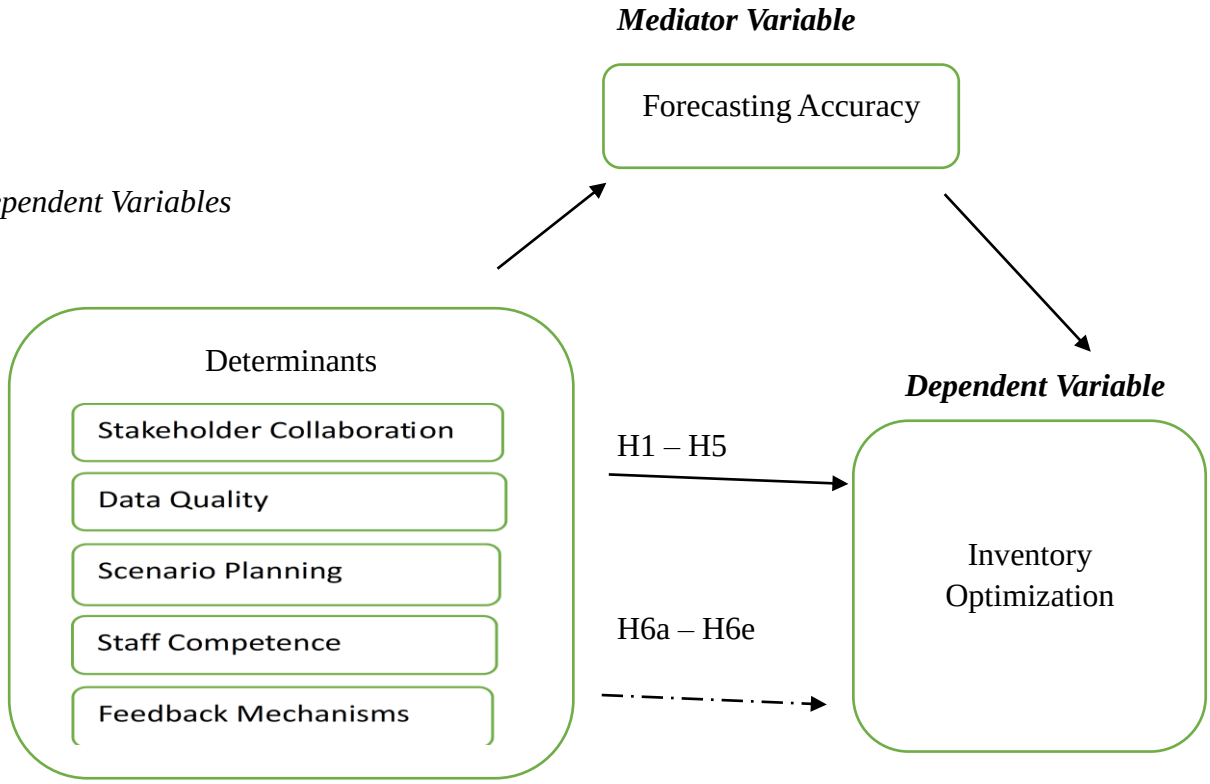
Gap 4: Failure to perform mediation tests properly. In some cases, even though determinants and forecast accuracy were studied together, the relationships between the two had not been formally tested for mediation using correct statistical procedures (like bootstrapping indirect effect confidence intervals). Rather than bootstrapping, most authors used Baron & Kenny (1986) framework for mediation analysis, which has little power and no way to calculate indirect effect confidence intervals. This study proposes to use the bootstrapping method described by Preacher & Hayes (2008), thus performing a proper mediation analysis. These four gaps addressed help make the study valuable for the humanitarian logistics literature.

## 2.3. Conceptual Framework and Hypothesis Summary

### 2.3.1. Conceptual Framework Diagram

The theoretical perspectives that form the basis for this research are Collaborative Planning, Forecasting, and Replenishment (CPFR); Knowledge Management Theory; and Organizational Learning Theory. All three theoretical perspectives underscore the significance of organizational competencies for achieving desired results from supply chain operations. On the basis of the above theoretical perspectives, a conceptual framework is formulated based on organizational determinants, forecasting accuracy, and inventory optimization under the umbrella of a mediation model that combines theory and practice.

Figure 1. Conceptual Framework of the Study




As shown in Figure 1, there are five organizational determinants: stakeholder collaboration, data quality, scenario planning, staff expertise, and feedback systems. Each of these organizational determinants is zewed as an independent variable impacting inventory optimization in two ways: direct effects (H1–H5) and indirect effects (H6a–H6e). The direct effects pathway reflects the links in which every organizational determinant impact inventory optimization directly. In other words, stakeholder collaboration might have a direct impact on inventory sharing, while staff expertise might affect the process of ordering.

In the indirect effects pathway, every organizational determinant influence inventory optimization through forecasting accuracy that mediates the effect between the organizational determinant and inventory optimization by reducing uncertainty, stockouts, and optimal safety stock levels.

Therefore, it may be concluded that forecasting accuracy serves as an essential yet partial factor in influencing inventory optimization because even accurate forecasts cannot compensate for

organizational determinants that affect inventory optimization. The theoretical perspective suggests that forecasting accuracy plays an indispensable role in optimizing inventories. At the same time, forecasting accuracy does not account for all organizational determinants that can affect inventory optimization. Therefore, the total effect of organizational determinants on inventory optimization will include direct and indirect effects.

### 2.3.2. Hypothesis Summary

Based on the conceptual framework, the following hypotheses are formulated for empirical testing:

Direct effect hypotheses:

- H1: Stakeholder collaboration positively affects inventory optimization.
- H2: Data quality positively affects inventory optimization.
- H3: Scenario planning positively affects inventory optimization.
- H4: Staff expertise positively affects inventory optimization.
- H5: Feedback mechanism positively affects inventory optimization.
- H6a – H6e - Forecasting accuracy mediates the relationship between organizational determinants and inventory optimization.

# CHAPTER THREE

# RESEARCH METHODOLOGY

This chapter discusses the methodology used in this research to achieve its objectives. The methodology applied to address the objectives of the study systematically using methods of data collection, data analysis, data interpretation, and results reporting. Data collection, data analysis, data interpretation, and result reporting employed in this research are discussed in the following sections.

## 3.1. Research Approach

The study uses a quantitative approach based on positivism. It is believed that the most appropriate choice would be a quantitative approach due to the necessity of testing causal hypotheses about the relationship between organizational factors (collaboration of stakeholders, data quality, scenario planning, competence of personnel, and feedback systems), forecasting accuracy as a mediator, and inventory optimization. According to positivism, social and organizational processes should be studied empirically using scientific methods. Consequently, it is possible to test causality rather than develop theories.

It is essential to point out that even though the independent variables refer to perceptual organizational structures, there are sufficient similarities across people who were interviewed to allow for generalization and statistical analysis. Therefore, they can be treated as quantitative variables. Additionally, the chosen methodology allows using survey tools, which improves generalizability. Using statistical approaches like regression and mediation analysis makes it possible to obtain information about direct and indirect effects.

Thus, it may be concluded that choosing a quantitative approach was necessary because of theoretical considerations. While the use of qualitative research could have provided contextual information about the problem, it could not have produced the parameter estimates required by the research questions. The focus on generalizability is connected with a much broader goal, namely making findings applicable to other humanitarian organizations facing challenges typical for EDRMC.

## 3.2. Research Design

An explanatory cross-sectional survey design was adopted. Explanatory design was selected since it was intended to explain the mechanism by which organizational determinants influence inventory optimization through forecasting accuracy. As stated above, the aim of this study was to determine whether forecasting accuracy mediated the relationship between organizational determinants and inventory optimization. Unlike descriptive research, explanatory research explains mechanisms and answers questions such as "how" and "why." A cross-sectional design means data were collected at once within a certain period (April to May 2026). Cross-sectional data collection makes it difficult to ascertain causality since cross-sectional data cannot prove causality. However, cross-sectional data collection was suitable for this research, as the relationship between the constructs was theoretically well-grounded. This study is concerned with organizational phenomena that occur in a sequential manner. Organizational determinants should occur before forecasting accuracy, and then forecasting accuracy should occur before inventory optimization. In the data collection process, questionnaire questions asked respondents to consider the long-term practices of the organization. Therefore, there was no possibility of reverse causality.

There were various strengths and weaknesses associated with the adoption of the explanatory research design and cross-sectional data collection. On the positive side, it is efficient. Cross-sectional data collection made it possible to collect enough data from 254 targeted participants within a limited period of time. Longitudinal data collection takes several months or even years. In contrast, cross-sectional data collection takes just days or weeks. On the negative side, mediation analysis in a cross-sectional study does not guarantee causality. There are numerous alternative causal pathways. For instance, organizations that successfully practice inventory optimization might be more likely to invest in forecasting accuracy.

## 3.3. Target Population

The target population for this study was the employees of the Ethiopian Disaster Risk Management Commission (EDRMC) who worked in the areas of inventory planning, forecasting, logistics services, and disaster coordination activities. The total number of employees working at EDRMC, according to human resource statistics provided by EDRMC (2025), was 1050. Not all employees of the Commission had the required knowledge and experience to answer the questionnaires effectively. Consequently, the population of interest was reduced to 547 EDRMC employees. These

547 employees worked in eleven departments. They included Early Warning Information & Operation Coordination, Disaster Fund & Resources Mobilization, ICT, Programs & Partners Coordination, Branch Office Operation Coordination, Program Commodity Monitoring & Inspection, Strategic Logistics Supply & Administration, Humanitarian Logistics Support & Market Study, Storage & Reserve Standardization, Logistics & Transport Operation, and the Adama Hub/Warehouse.

The decrease of the sample from 1,050 to 547 should be seen as a theoretically justified decrease in the sample size rather than a convenient way to cut back on sampling. Indeed, if the target population will be considered to include all 1,050 employees of the organization, the measurement error would probably be too high because not all 1,050 employees of the company participate in the forecasting and inventory planning processes. However, if one considers the target population to be only the employees participating in the forecasting information gathering, the inventory planning process, and the feedback loop, provides some theoretical justification for the study. Thus, all participants would have the same starting point.

Nonetheless, such a limitation in terms of the sample makes the study's external validity rather questionable. As one considers the logistics departments' employees as the target population, the study results will be applicable to the logistics departments of EDRMC only and similar logistics teams of other humanitarian organizations.

### 3.4. Sampling Technique

A stratified random sampling technique was utilized for the sample collection. The 11 departments constituted strata. The proportional allocation was chosen, which means that each departmental stratum included the number of people that were proportional to the part of the population (the 547 participants) taken up by the given stratum. Simple random sampling was conducted within each stratum using the method of random number generation in Microsoft Excel. Such sampling was needed due to the difference between the size of the different strata in terms of the number of employees, which was between 30 and 68 people. Simple random sampling without the stratification of the population could lead to the underrepresentation of the smaller strata or overrepresentation of the larger ones. Thus, the proportional allocation provided a more representative sample. Simple random sampling within the strata made the sample free from biases since every person had an equal opportunity to be included in the sample.

## 3.5. Sample Size Determination

The Sampling is the process of selecting several study units from a defined study population (Saunders, 2010). Here in this study, sampling was required, as the targeted population accounts for a total of 547 professionals from 11 selected departments, and since the size was substantially larger than the number to conduct a census, taking a representative sample respondent was more economical. Thus, a proportionate sample size as computed by using Yamane's proportionate sample size determination formula was:

$$n = \frac{N}{1+Ne^2} = \frac{(547)}{1+(547*0.05^2)} = 231 \text{ respondents}$$

Thus, the study took a total of 231 sample respondents to participate in this survey. The distribution of sample respondents from each targeted profession/position in the selected departments is illustrated on Table-1.

Table 1. Sample Distribution

| **Department** | **No. of Staff (a)** | **Population Proportion (b = a/547)** | **Sample Proportion (c = b*231)** |
|---|---|---|---|
| Early warning information and operation coordination | 35 | 6.40% | 15 |
| Disaster Fund and Resource Mobilization | 30 | 5.50% | 13 |
| Information Communication Technology | 34 | 6.20% | 14 |
| Programs, projects, partners coordination | 62 | 11.30% | 26 |
| Branch office operation coordination | 50 | 9.10% | 21 |
| Program commodity monitoring and inspection | 51 | 9.30% | 21 |
| Strategic Logistics Supply and Administration | 65 | 11.90% | 27 |
| Humanitarian Logistics Support Market Study | 57 | 10.40% | 24 |
| Storage and Reserve Standardization | 39 | 7.10% | 16 |
| Logistics and Transport Operation | 68 | 12.60% | 30 |
| Adama Hub/Warehouse | 56 | 10.20% | 24 |
| **Total** | **547** | | **231** |

(Source: EDRMC Database, 2025)

The combination of Yamane's formula and stratified random sampling ensures achievement of two major objectives: statistically precise results and representation of these results in terms of the studied population. Yamane's formula presupposes simple random sampling from a finite population and returns a sample size sufficient for achieving the desired margin of error on the basis of the most conservative assumption about population distribution ($p = 0.5$). The result yielded by the use of the formula in the current study was 231 people which comprises 42% of the target population. This percentage is quite high and contributes to minimizing sampling error.

A buffer size of 10% (another 23 people) was added for the sake of avoiding non-response bias; thus, the target sample size was set at 254. Adding the buffer to the sample size of 231 represents a conservative strategy as non-response in humanitarian research is quite high and usually goes beyond 70% rate.

### 3.6. Type and Source of Data

Primary data collection techniques will be applied in the present study. Secondary data will not be used due to three major reasons. Firstly, preliminary exploration showed the unavailability, poor quality, or fragmented nature of secondary data (e.g., Excel tables, paper archives, and database fragments) needed for this study. Secondly, secondary data cannot be used to evaluate perceptual constructs. The perception of such phenomena as stakeholders' collaboration, scenario planning, or feedback mechanisms can be measured effectively using data obtained from staff who interact with them directly on a daily basis. Finally, the theory under development includes individual perceptions as the level of analysis. It is the staff's perception of determinants, forecasting accuracy, and inventory optimization that will be considered causally related, according to the proposed hypothesis. Therefore, it seems to be rational to apply a structured questionnaire as a data collection instrument.

Using primary data implies trading-off precision and feasibility. Although objective secondary data would be useful for validating subjective measurements, they are not available in the context of this research. Specifically, there are no central and standardized sources of data like stock records, procurement times, or forecasting errors at EDRMC. Lack of centralized, standardized, and comprehensive secondary data can be perceived diagnostically as a sign that there are no integrated information systems at EDRMC enabling evidence-based forecasting and inventory management. Thus, using secondary data would imply building an integrated database from heterogeneous

sources with inconsistent formats, incompleteness, and unknown quality; therefore, the risk of making mistakes while combining these data cannot be estimated.

## 3.7. Data Collection Instrument

A standardized questionnaire was applied to collect the required information during the research in order to gather structured, reliable, and measurable data from the chosen target population. The questionnaire adopted an established model suggested by Boonmee & Arimura (2023) and adapted from validated scales in humanitarian logistics and organizational behavior (Simatupang & Sridharan, 2002; Amer et al., 2013; Jahre et al., 2022; Bessant et al., 2003). The instrument consisted of four parts:

- **Part A: Demographics** Captured background information including sex, age, education, department, position, and number of years spent at EDRMC.
- **Part B: Independent variables** Measured five organizational determinants—stakeholder collaboration, data quality, scenario planning, staff competence, and feedback mechanisms—each represented by five items.
- **Part C: Mediating variable** Assessed forecasting accuracy using five items reflecting staff perceptions of how closely forecasts align with actual demand (Syntetos et al., 2016).
- **Part D: Dependent variable** Measured inventory optimization with five items focusing on stockouts, overstocks, and turnover rates (Manzini et al., 2015).

All items (except demographics) were presented on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). This format was chosen because it provides a balance between discrimination and cognitive ease, while avoiding respondent fatigue. Scale development research confirms that five-point formats yield reliability comparable to seven-point formats, with the added benefit of reduced burden on respondents (Joshi et al., 2015).

The questionnaire was prepared in English and translated into Amharic by a professional translator. A second translator conducted back-translation into English to ensure conceptual equivalence, following the procedure recommended by **Brislin (1970)**. This step was necessary because constructs such as “forecasting accuracy” may otherwise be interpreted differently in local contexts.

A **pilot test** was conducted with 30 participants (approximately 10% of the target sample), who were excluded from the main study. Pilot testing helped identify ambiguous wording, cultural misinterpretations, and potential validity issues. Respondents were asked to paraphrase items verbally, which allowed detection of discrepancies in meaning and ensured clarity before full deployment (Van Teijlingen & Hundley, 2001).

### 3.8. Validity Test

Content validity is ensured through anchoring of items in CPFR, Knowledge Management Theory, and Organizational Learning Theory as well as adaptation of the latter from existing validated scales in the scientific literature. The draft questionnaire was reviewed by two experts: the researcher's academic advisor and a logistics manager at EDRMC. The former specializes in supply chain management while the latter is not a member of the target sample. These experts evaluated the relevance, comprehensiveness, and clarity of all items, and minor corrections were made accordingly. The pattern of relations found b/n variables prove the construct validity of the scale.

### 3.9. Reliability Test

Reliability refers to the internal consistency of a scale, i.e., extent to which its multiple items are correlated. Reliability will be measured for each construct in terms of Cronbach's Alpha (α). Reliability of the questionnaire will be preliminarily estimated based on the pilot test (N=30) and then confirmed based on the main sample (N=201 after data cleaning). Table 2 presents reliability coefficients for each construct.

Table 2: Reliability Statistics of Constructs (N=201)

| Construct | Number of Items | Cronbach's Alpha |
|---|---|---|
| Stakeholder Collaboration | 5 | .733 |
| Data Quality | 5 | .799 |
| Scenario Planning | 5 | .733 |
| Staff Competence | 5 | .754 |
| Feedback Mechanisms | 5 | .801 |
| Forecasting Accuracy | 5 | .780 |
| Inventory Optimization | 5 | .790 |
| **Overall Reliability** | **35** | **.931** |

Source: Own Questionnaire, 2026

Table 2 demonstrates that reliability for each construct is higher than 0.70 (the recommended minimum level; Nunnally & Bernstein, 1994), while reliability for all constructs combined reaches extremely high 0.931. There are several implications associated with these results. Firstly, the very high reliability ($\alpha = 0.931$) suggests that all 35 items of the questionnaire are related in terms of measuring constructs. At the same time, a perfect reliability coefficient suggests the problem of redundancy that cannot be confirmed in the context of relatively low construct-specific reliabilities (from $\alpha = 0.733$ to 0.801). This finding suggests that all constructs are valid, as their internal consistency is high yet not extremely high.

Secondly, while all alpha levels are acceptable, they are still rather low. Alphas within 0.70 and 0.80 are considered good indicators of reliability in exploratory research. If the alpha exceeds 0.90, it suggests redundancy, as items are too similar and lack content coverage. Alphas close to 0.90 suggest good content coverage and consistency, which can explain moderate levels of alphas in the study under discussion. In other words, all constructs seem to have 5 distinct questions reflecting different aspects of the phenomenon in focus.

Thirdly, there is a variation in alphas for different constructs: from 0.733 (stakeholder collaboration and scenario planning) to 0.801 (feedback mechanisms and data quality). The fact that feedback and data quality have the highest alpha may reflect better understanding of these concepts among respondents than other constructs; otherwise, they can be more homogeneous. Stakeholder collaboration and scenario planning, by contrast, are more complex concepts whose understanding may differ among respondents.

### 3.10. Data Collection Procedure

Data were collected for six weeks (April-May 2026). In the preparation week, an introductory letter was obtained from the faculty advisor and then approved by EDRMC's senior managers and heads of departments. Questionnaires were printed in both English and Amharic languages with an accompanying information sheet explaining the goal of the study, confidentiality, and voluntary character of participation. Both electronic forms (via Google Forms) and paper questionnaires will be used for maximizing response rate. In particular, an electronic form was used with employees with regular access to email accounts; paper questionnaires were provided to those who did not have access to emails (employees from Adama Hub/Warehouse).

The choice of electronic/paper data collection instruments depends on the peculiarities of the target population. Staff from EDRMC headquarters have access to stable email connections; thus, they can participate in the study via the Internet. Employees from Adama Hub/Warehouse can have limited or no access to computers as they work with stocks in the warehouse. Ignoring these employees would create a bias, as their problems with forecasting/inventory processes could be different from those of employees from headquarters. Personal contact between the researcher and employees from Adama Hub/Warehouse allowed eliminating misunderstanding of questions as the researcher was always ready to clarify any item.

Reminder was sent twice in the fifth and sixth weeks of data collection. Reminders serve not only as means of encouraging participants but also as evidence of the importance of participation. Survey response rate literature shows that reminders are especially effective if they: (a) thank respondents; (b) emphasize deadline; and (c) assure participants of confidentiality of data. Thus, all these factors were reflected in reminders. The response rate was quite high (87.0%), which suggests the effectiveness of the reminder strategy. However, non-response bias still exists due to the difference between respondents and non-respondents.

### 3.11. Method of Data Analysis

Data analysis was performed using SPSS version 25 and the PROCESS macro (version 4.0) for mediation analysis. The analysis proceeded in four steps.

- **Step 1: Data screening and cleaning**. Cases with more than 10% missing data (3 items out of 35) are excluded leaving 201 cases for analysis (79.1% of 254 targeted cases). Missing data were also checked using Little's MCAR criterion that suggests missing data are assumed completely random. Therefore, cases with less than 5% missing data were used with mean substitution. Outliers would be identified using boxplots and winsorized (replaced with 1st/99th percentiles).
- **Step 2: Descriptive analysis**. Percentages and frequencies were calculated for demographic variables while descriptive statistics was computed for continuous variables.
- **Step 3: Inferential Analysis**:

  **Correlation analysis**. Pearson correlation coefficients were computed between all pairs of variables in order to detect multicollinearity.

**Assumption checks for regression models -** For each regression equation, the following assumptions will be tested: Multicollinearity: Variance Inflation Factor (VIF) < 5 (Hair et al., 2010); Homoscedasticity: Visual inspection of residual plots (standardised residuals vs. predicted values); Normality of residuals: Shapiro-Wilk test (but bootstrapping is robust to non-normality); and Independence of errors: Durbin-Watson statistic (values between 1.5 and 2.5 are acceptable).

- **Step 4: Mediation analysis -** Four separate mediation models were tested using PROCESS Model 4 with 5,000 bootstrap resamples to generate bias-corrected 95% confidence intervals (CIs) for the indirect effect (a × b). An indirect effect was considered statistically significant if the CI did not include zero (Preacher & Hayes, 2008). The following paths are estimated for each model (using SC as an example):
  - **Path a**: $FA = \beta0 + \beta1 \cdot SC + \varepsilon1$ (effect of SC on FA)
  - **Path b**: $IO = \beta0 + \beta2 \cdot FA + \varepsilon2$ (effect of FA on IO, controlling for SC)
  - **Path c'**: $IO = \beta0 + \beta3 \cdot SC + \varepsilon3$ (direct effect of SC on IO, controlling for FA)
  - **Path c (total effect)** = c' + (a × b) (estimated by regressing IO on SC without FA)

The **proportion mediated** is calculated as (a × b) / c (if c is significant). Standardised coefficients (beta) is reported for comparability across determinants.

**Significance level -** Statistical significance for direct effects (paths a, b, c') were set at $p < 0.05$ (two-tailed). For indirect effects, significance is determined by the bootstrapped CI. Effect sizes: For direct effects, standardised beta coefficients (β) are interpreted as small (0.10), medium (0.30), or large (0.50) (Cohen, 1988). For indirect effects, the completely standardised indirect effect ($\kappa^2$) will be reported, with values of 0.01, 0.09, and 0.25 considered small, medium, and large respectively (Preacher & Kelley, 2011).

Firstly, the utilization of the PROCESS macro, as opposed to calculating indirect effects through individual regression equations, follows the current standards of mediation analysis. One advantage that the PROCESS macro has over manual indirect effect calculation is its automatic application of the bootstrap procedure, which is crucial because the distribution of the indirect effect is not normal even when the constituent variables are normally distributed. In particular, 5,000 resamples are used, which exceeds the minimum requirement of 1,000 and gets closer to the upper limit of

practicality in terms of computational power, providing stable confidence intervals. The reason for choosing the bias-corrected bootstrap over percentile bootstrap is to compensate for median bias.

Testing separate mediation models involving one predictor at a time is the approach taken here out of consideration of the sample size. The reason why using one equation that contains all five predictors as well as all other variables requires testing five separate mediation models, each with one predictor, is the reduction of necessary number of parameters estimated from 13 to 7 (one less direct effect and four less a-paths). Such an approach, however, will not allow estimation of unique effects of each determinant while controlling for others as well as estimating correlations between determinants; the alternative analysis is an attempt to overcome this drawback, at the expense of precision.

## 3.12. Ethical Considerations

The special set of ethical considerations and safeguards used in this study has been developed based on potential risks associated with conducting research in the setting of a working governmental agency under conditions of extreme stress. Working as EDRMC employees, respondents are exposed to situations where mistakes made in forecasting and inventory management may cost lives to people affected by natural disasters. Thus, questions related to forecasting and inventory can be interpreted as evaluations of one's and one's department's performance, which is likely to lead to defensive reactions and possible retaliation. Anonymity is guaranteed as no personally identifiable information is ever collected.

Respondents' participation is entirely voluntary and they are assured of that through inclusion in the information sheet and verbal instruction provided in case of paper questionnaire distribution. Respondent's supervisors were requested to facilitate distribution of questionnaires without monitoring completion of the task or threatening anyone who does not fill it out. IP addresses or email addresses are not tracked with regard to electronic surveys either. Being present at the Adama Hub/Warehouse may create pressure on respondents, which is compensated for by explicitly telling them that participation is voluntary and non-participation will not be noted.

# CHAPTER FOUR

# DATA PRESENTATION, ANALYSIS, AND INTERPRETATION

The present chapter aims at presenting the results, discussing findings and interpreting the same. Both descriptive and inferential statistics are used for summarizing the findings. The descriptive statistics are associated with the demographic characteristics of the respondents as well as their responses, while inferential statistics include a correlation analysis, assumption checks for linear regression as well as moderation effect analysis.

## 4.1. Response Rate

The study was conducted on 254 questionnaires distributed among respondents. In the first place, it is important to note that there were 227 respondents' answers collected, and, thus, the initial response rate reached 89.4%. Out of the total number of the responses, 26 responses were eliminated from analysis due to the high rate of missing information (10% or more) or the existence of response set bias, which included, among others, the same answers provided by respondents for each question. Therefore, the final number of the respondents included in analysis equals 201, which means 79.1% of the target sample responded.

A high response rate is more than just a statistic - it adds considerable weight to the findings. This response rate is significantly higher than the organizational research standard of 55.6 percent established by Baruch & Holtom (2008). This study thus falls into the upper quartile of response rates within the field of management studies. A high response rate makes the findings more credible. In organizational research, low response rates are a significant threat to external validity because low response rates lead to non-response bias - the discrepancy between respondents and non-respondents that jeopardizes validity. Low response rates (<60%) preclude any claims regarding the representative nature of findings. In this study, the 79.1% response rate easily exceeds this critical threshold, implying nonresponse bias is unlikely. Practitioners' high interest in survey participation highlights the relevance of the problem and contributes to content validity.

## 4.2. Respondent Demographics

Table 3: Personal Information of the Respondents

| Characteristic | Category | Frequency | Percentage (%) |
|---|---|---|---|
| **Gender** | Male | 114 | 56.7 |
| | Female | 87 | 43.3 |
| **Age** | 20-29 years | 43 | 21.4 |
| | 30-39 years | 88 | 43.8 |
| | 40-49 years | 50 | 24.9 |
| | 50+ years | 20 | 9.9 |
| **Education** | Bachelor’ s degree | 88 | 43.8 |
| | Master’ s degree | 103 | 51.2 |
| | PhD | 5 | 2.5 |
| | Other | 5 | 2.5 |
| **Position** | Officer | 71 | 35.3 |
| | Support Staff | 55 | 27.4 |
| | Coordinator | 46 | 22.9 |
| | Manager | 22 | 10.9 |
| | Director | 7 | 3.5 |
| **Work Experience** | 1-5 years | 43 | 21.4 |
| | 6-10 years | 83 | 41.3 |
| | 11-15 years | 45 | 22.4 |
| | 16+ years | 30 | 14.9 |

Source: Own Survey, 2026

Information about respondents' characteristics affects the interpretation of the results in table 3. The gender split resembles a consistent pattern in humanitarian leadership across the world. In contrast, the gender breakdown in Ethiopia differs from the global humanitarian average in management positions, which stands around 35%. Age demographics indicate that respondents are relatively young: 67.4% of participants are younger than 40, and only 11.2% of respondents are 50 years old or above. It appears that EDRMC has a relatively young workforce when compared to humanitarian

organizations in Western countries characterized by an aging workforce. A high proportion of respondents with master's degrees (51.2%) implies a high level of understanding of such concepts as strategic alignment and partnership quality. Such knowledge contributes to increased construct validity.

Organizational position analysis demonstrates the structure that reflects an inverted managerial hierarchy. Thus, only 14.1% of respondents hold the position of manager or director, whereas coordinators, officers, and support staff comprise 86.0% of respondents. This is consistent with organizational hierarchy in which the number of managers is lower than the number of subordinates. An important advantage of having a large number of officers and support staff (62.4%) is the incorporation of their perspective into the results. Many studies oversample managers under the assumption that managers possess the necessary knowledge to provide insight. However, officers and support staff who are responsible for daily forecast and inventory coordination are also involved in the process and might bring some insights that are unnoticed by managers.

Experience analysis shows that a substantial majority of respondents (62.8%) have experience of six or more years; moreover, 38.0% have 11 or more years of experience in humanitarian operations. Only a small minority of respondents (21.5%) had 1-5 years of experience, indicating that there is no shortage of institutional memory. A participant having 6-10 years of experience in disaster management operations in Ethiopia has seen many emergencies and cycles of funding and inventory problems. Their perception of organizational determinants is quite valuable as it is based on personal experience of forecasting's effectiveness. The presence of such an experience may imply survivor bias, as people who stayed longer with an organization are more likely to stay in units that survived through several disaster cycles without organizational changes caused by budget cuts or restructuring.

### 4.3. Descriptive Statistics of Constructs

The descriptive analysis of the study looks at the influence that organizational determinants such as stakeholder collaboration, data quality, scenario planning, employee skill levels, and feedback have on inventory optimization where the mediating variable is forecasting accuracy. This approach provides insight into how staff at the Ethiopian Disaster Risk Management Commission perceives and reacts to these organizational factors in humanitarian supply chain management.

Perceptions regarding these factors were analyzed using a five-point Likert scale rating system. According to Field (2005) and Best (2005), the scale was categorized as strongly disagreeing (1.00 – 1.80); disagreeing (1.81 – 2.60); neutral (2.61 – 3.40); agreeing (3.41 – 4.20); and strongly agreeing (4.21 – 5.00). Mean scores showed the average amount of agreement between participants whereas standard deviation showed how varied these perceptions were. This dual strategy allowed for the identification of convergence and divergence in perceptions of organizational factors.

In doing so, an analysis of all these factors gives a holistic overview of how organizational determinants help in optimizing inventory management. The inclusion of forecasting accuracy as the mediating variable shows the paths through which organizational factors such as stakeholder collaboration, data quality, scenario planning, skill levels of employees, and feedback help optimize or hinder inventory optimization. The findings, therefore, will be both applicable to EDRMC and other organizations working in similar environments.

### 4.3.1. Stakeholder Collaboration

Stakeholder collaboration in humanitarian logistics refers to the coordinated efforts of departments and partner organizations to jointly plan, share information, and execute operations for improved supply chain outcomes (Simatupang & Sridharan, 2002). In the case of EDRMC, collaboration is a critical determinant of forecasting accuracy and inventory efficiency. It reduces duplication, enhances responsiveness, and strengthens decision-making, yet the findings show that collaboration practices are uneven across units, reflecting structural and motivational barriers rather than lack of awareness.

Table 4: Stakeholder Collaboration Practice (n = 201)

| Statement | Mean | Std. |
|---|---|---|
| Collaborates effectively with other units | 3.80 | 1.806 |
| Timely & reliable info sharing | 3.56 | 1.849 |
| Collaboration reduces duplication | 4.01 | 1.675 |
| Inter agency coordination enhances responsiveness | 3.44 | 1.832 |
| Joint decision making improves forecasts | 4.29 | 1.479 |
| Average Stakeholder Collaboration | 3.82 | 1.206 |

Source: Own Survey, 2026

The responses to the questions related to stakeholder collaboration in EDRMC are provided in Table 4. As seen from the findings, there is medium stakeholder collaboration, which is evident from a construct mean of 3.82 and the standard deviation of 1.206. The highest rate of agreement among all the items is associated with the positive contribution of joint decision making on the forecast accuracy, and the lowest score is attributed to inter-agency coordination enhancing the agency's responsiveness.

The construct mean of 3.82 suggests that the collaboration level falls into the category of agreement. The standard deviation of 1.206 points to the presence of significant variability, which means that in some departments/units, there is a high level of collaboration, while in others, the level of collaboration is quite low. Nonetheless, there is some variation between different departments/units in terms of the level of collaboration. This observation can be explained by the influence of the context (e.g., leadership, interpersonal relations, dependencies between units/departments, etc.). This observation shows that collaboration procedures are not institutionalized in the organization, and therefore, there are unique ways for collaborating within each unit.

In addition, the high rate of agreement associated with the importance of joint decision-making for increasing forecast accuracy is notable because people realize the importance of collaboration even in the absence of its implementation in their day-to-day work.

This contradiction - the recognition that something is beneficial but the lack of practice - is methodologically important because it eliminates the alternative explanation: respondents do not know about the benefits of collaboration and hence score it low. Since respondents know about the benefits but still claim that collaboration occurs only occasionally, it follows that the reasons for non-collaboration are structural or motivational, not cognitive. Low endorsement of the effect of inter-agency coordination on responsiveness (a mean of 3.44) is especially disturbing since it reflects EDRMC's main purpose—responsible, coordinated response to disasters. If the coordination is considered insufficient, it means that the humanitarian supply chain is dysfunctional.

#### 4.3.2. Data quality

Data quality in humanitarian logistics refers to the accuracy, consistency, and timeliness of information used for forecasting and inventory decisions (Boonmee & Arimura, 2023). Within EDRMC, reliable data is essential for aligning supply with demand, yet findings indicate that

information is often fragmented and inconsistent across departments, limiting its usefulness for proactive planning.

Table 5: Data Quality Practice (n = 201)

| Statement | Mean | Std. |
|---|---|---|
| Beneficiary registries accurate & up to date | 3.83 | 1.770 |
| Standardized reporting formats improve usability | 3.72 | 1.730 |
| Early warning data comprehensive | 4.22 | 1.572 |
| Reliable sources strengthen forecasting | 4.30 | 1.520 |
| Incomplete data negatively affects decisions | 3.42 | 1.768 |
| Average - Data Quality | 3.90 | 1.245 |

Source: Own Survey, 2026

Referring to the results in table 5, data quality received a moderately high construct mean of 3.90 with a standard deviation of 1.247. The highest mean corresponds to the contribution of reliable sources to forecasting strength and data comprehensiveness in early warning. Elaboration: With a mean of 3.90, data quality ranks second only to staff expertise among the five determinants (which implies their importance to EDRMC). The relative high mean suggests that EDRMC has good data infrastructure: data sources are considered reliable, and the collected data is comprehensive. However, the lower mean for data completeness (3.42 vs. 4.22 and 4.30) means that while data are comprehensive, covering all relevant variables - they are not exhaustive.

This gap between comprehensiveness (high mean) and completeness (low mean) indicates that while data collection systems are capable of collecting data on all relevant aspects of a situation, some population groups or geographic areas remain uncovered. The gap of 0.80 on a five-point scale means that participants are not satisfied with data coverage but still believe that the data collected are of decent quality. In addition, the low rating of standardized reporting formats (mean of 3.72) indicates that standardization efforts failed to eliminate this coverage problem.

### 4.3.3. Scenario planning

Scenario planning is the strategic use of multiple plausible crisis narratives to prepare flexible logistics responses (Amer et al., 2013). For EDRMC, the lack of robust scenario planning tools

means that operations remain reactive, with inventory adjustments occurring only after crises unfold rather than in anticipation of them.

Table 6: Scenario planning Practice (n = 201)

| Statement | Mean | Std. |
|---|---|---|
| Prepares for multiple disaster scenarios | 3.44 | 1.928 |
| Reduces reliance on single forecasts | 2.71 | 1.930 |
| Improves agility in sudden crises | 3.48 | 1.924 |
| Forecasts tested against outcomes | 3.57 | 1.859 |
| Contingency strategies updated | 3.79 | 1.804 |
| Average - Scenario planning | 3.40 | 1.315 |

Source: Own Survey, 2026

As far as scenario planning is concerned, table 6, it was rated the worst among the five determinants of EDRMC performance, with a construct mean of 3.40 and a standard deviation of 1.315. The lowest mean within the construct corresponds to the reduction of reliance on single forecasts, while the highest corresponds to the updating of contingency plans. The mean of 3.40 means that the level of scenario planning is neutral - barely below agreement (neutral: 2.61 – 3.40). This low mean suggests that organizations rarely engage in scenario planning activities, and their participants are aware of this fact. The low rating for the reduction of reliance on single forecasts (mean of 2.71) is particularly worrisome because forecasts are generally less accurate in environments characterized by high levels of uncertainty - the inability to quantify risks because the probabilities are unknown.

Disaster relief falls into this category because it is impossible to quantify the probabilities of different scenarios - hurricanes, floods, droughts, etc. Thus, the low mean for this item suggests that EDRMC uses forecasting methods intended to provide deterministic forecasts (single-point estimates) in environments with low levels of uncertainty - commercial operations, manufacturing, and sales forecasting. This practice is bound to be ineffective because in environments of uncertainty, the only solution is to prepare for all potential scenarios. However, the high mean for contingency plan updating (3.79) suggests that while scenario planning is minimal, planning as such is present. This means that EDRMC does not engage in sophisticated scenario planning techniques but recognizes its necessity to some extent. The high standard deviation (greater than 1.80) across

all items of the scenario planning construct also suggests that the practice of scenario planning varies widely across the organization.

### 4.3.4. Staff expertise

Staff expertise refers to the technical competence, training, and experience of personnel engaged in forecasting and inventory management (Jahre et al., 2022). In EDRMC, expertise is unevenly distributed, with some units benefiting from skilled staff while others suffer from limited capacity, affecting the overall reliability of forecasts.

Table 7: Staff expertise Practice (n = 201)

| Statement | Mean | Std. |
|---|---|---|
| Judgment bridges data gaps | 3.59 | 1.831 |
| Expertise contributes to accuracy | 4.42 | 1.298 |
| Tacit knowledge complements analysis | 3.55 | 1.841 |
| Training enhances capacity | 3.84 | 1.797 |
| Institutionalizing expertise improves responsiveness | 4.26 | 1.544 |
| Average - Staff Expertise | 3.93 | 1.189 |

Source: Own Survey, 2026

As can be seen in table 7, staff expertise was evaluated as the most important determinant among the five, with a construct mean of 3.93 and a standard deviation of 1.189. The highest mean within this construct is related to the contribution of expert opinion to forecasting accuracy and improvement of inventory responsiveness through expertise institutionalization. "Moderate rating" refers to the complementarity of tacit expertise and formal forecasting/analysis.

The high mean (above 3.40) of staff expertise is expected based on knowledge management theory, which states that in addition to formal expertise (explicit knowledge captured in standard operating procedures) and expertise-in-use, organizations also need tacit expertise (inherited through informal mentoring and experience). According to the findings, respondents acknowledge the contribution of expert opinion to forecast accuracy (mean of 4.42) and the impact of institutionalization of expertise on inventory responsiveness (mean of 4.26). At the same time, the mean rating of tacit expertise's complementariness to forecasting (mean of 3.55) is moderate, which suggests that the organization fails to make this type of knowledge explicitly accessible to experts in formal situations. While

formal expertise allows organizations to solve complex problems using accumulated data, tacit knowledge allows organizations to utilize informal skills that cannot be documented, like knowing which data sources are the most reliable, which vendors can be trusted, and what happens to delivery routes after a rainfall. Thus, tacit expertise is crucial to the performance of humanitarian organizations because it allows them to adapt to the rapidly changing environment.

Yet this expertise is easily lost when employees leave the organization because its informal nature prevents it from being recorded. Therefore, low means for expertise complementarity imply the lack of organizational systems for knowledge preservation. If the organization lacks such systems, it has no choice but to document everything and use only formal expertise. In that case, even the high means of formal expertise become less valuable because formal knowledge alone does not suffice to manage humanitarian crises. Therefore, organizations have to institutionalize tacit expertise management in order to capitalize on high means of formal expertise.

### 4.3.5. Feedback mechanisms

Feedback mechanisms are formalized systems for capturing lessons learned from past operations and forecasts (Bessant et al., 2003). At EDRMC, weak feedback loops limit organizational learning, preventing the systematic improvement of forecasting and inventory practices over time.

Table 8: Feedback Mechanisms Practice (n = 201)

| Statement | Mean | Std. |
|---|---|---|
| Post operation reviews conducted | 3.72 | 1.779 |
| Lessons integrated into models | 3.47 | 1.939 |
| Feedback reduces repeated errors | 3.67 | 1.825 |
| Continuous learning strengthens resilience | 3.51 | 1.874 |
| Structured feedback loops improve accuracy | 3.58 | 1.853 |
| Average - Feedback Mechanism | 3.59 | 1.384 |

Source: Own Survey, 2026

As far as the feedback mechanism is concerned, the results in table 8 show that feedback mechanism got a moderately positive evaluation, with the construct mean of 3.59 and the standard deviation of 1.384. The highest mean within this construct is related to post-operation reviews, while the lowest is the improvement of forecasts due to feedback mechanisms. The mean of 3.59

indicates the presence of learning infrastructure in organizations (i.e., the infrastructure that ensures continuous process improvement). Specifically, the relatively higher mean for post-operation reviews' conduct (3.72) shows that organizations have established processes for reviewing completed operations. However, the lower mean for lesson integration into forecasting models (3.47) indicates the lack of processes that help organizations learn from mistakes.

Learning, in this case, consists in three steps: detection of an error, correction of an error, and adoption of a new procedure. Failure to detect error means that organizations engage in single-loop learning rather than double-loop learning: their responses focus on correcting problems rather than identifying the underlying assumptions that caused those problems. For example, the reason behind a shortage of water purification tabs during a natural disaster might be incorrect forecasting. To address this issue, organizations simply increase their stocks of this commodity and do not investigate how their forecast failed. Thus, double-loop learning consists of detecting an assumption error, analyzing its causes, and addressing the root cause.

However, the moderate mean of the feedback mechanisms' influence on forecasts' accuracy (3.58) shows that organizations fail to implement this kind of learning. There are four criteria that define an effective feedback loop: (1) feedback is provided promptly; (2) it identifies a concrete mistake; (3) it provides actionable feedback; and (4) someone is responsible for implementing the recommended changes. Inadequate meeting of these requirements produces ineffective learning. This conclusion is supported by the relatively high standard deviation of the feedback mechanism mean (1.384), which shows that there are considerable differences across units/departments in the implementation of the learning infrastructure.

#### 4.3.6. Forecasting accuracy

Forecasting accuracy is the degree of correspondence between projected and actual demand for relief items (Syntetos et al., 2016). In this study, it is treated as a mediating variable, reflecting staff perceptions of how well forecasts align with operational realities. Its role is critical, as inaccuracies at the “first mile” translate into inefficiencies at the “last mile” of humanitarian response. As seen in table 9, the participants agreed that forecasting is done accurately often (mean of 3.82 and the standard deviation of 1.257). The highest mean is related to the reliability of forecasting methods, while the lowest is to the accuracy of forecasts. The mean of 3.82 means that respondents perceive forecasting practices in organizations as moderately effective - they allow generating

reliable estimates but sometimes fail to predict demand accurately. This conclusion is confirmed by two observations: the high mean for method reliability (mean 4.22) and the low mean for forecasts' accuracy (mean 3.52). The gap of 0.70 points on a five-point scale is surprising since the reliability of methods and accuracy of estimates should go hand-in-hand.

Table 9: Forecasting Accuracy Practice (n = 201)

| Statement | Mean | Std. |
|---|---|---|
| Gap between forecast & actual small | 3.69 | 1.815 |
| Methods produce reliable estimates | 4.22 | 1.530 |
| Forecasts usually accurate | 3.52 | 1.781 |
| Errors tracked & analysed | 3.71 | 1.734 |
| Rare major surprises | 3.95 | 1.741 |
| Average - Forecasting Accuracy Mechanism | 3.82 | 1.257 |

Source: Own Survey, 2026

There are several explanations: first, respondents may refer to different horizons - methods may be reliable when used for short-term forecasting but unreliable in long-term forecasting; second, method reliability may refer to the internal consistency of forecasts but not their external validity (i.e., matching reality). Regardless of the specific reason, low forecasts' accuracy suggests that forecasts need improvement. One way to achieve this goal is to enhance feedback mechanisms that allow learning from mistakes made in the past. This is the logical step following from a high mean of method reliability (i.e., high method quality) and a low mean of forecasts' accuracy.

In addition, the moderate mean of the gap between forecast and actual demand (mean of 3.69) suggests that organizations need to reduce this gap. A low mean of the forecast-actual gap would indicate that the gap never becomes critical; in other words, the forecasts of demands for specific commodities were fairly accurate. In this study, however, the mean of 3.69 implies that systematic forecasting errors occur. This statement is supported by the high mean (of 3.95), indicating that surprise cases occurred quite often. The low standard deviation (1.257) indicates the relative consistency of respondents' opinions.

### 4.3.7. Inventory optimization

Inventory optimization refers to balancing service levels with cost efficiency by minimizing stockouts, overstocks, and turnover imbalances (Manzini et al., 2015). For EDRMC, optimization is the ultimate dependent variable, reflecting the effectiveness of organizational determinants and forecasting practices in ensuring timely and sufficient humanitarian supply.

Table 10: Inventory Optimization (n = 201)

| Statement | Mean | Std. |
|---|---|---|
| Balances availability & resources | 3.69 | 1.815 |
| Stockouts rare | 4.22 | 1.530 |
| Overstocking minimized | 3.52 | 1.781 |
| Quick response without high costs | 3.71 | 1.734 |
| Levels aligned with demand | 3.95 | 1.741 |
| Average - Inventory Optimization | 3.82 | 1.257 |

Source: Own Survey, 2026

The results in table 10 show that inventory optimization got the highest mean of 4.02 and the lowest standard deviation of 0.973 among all constructs. The highest mean relates to the ability of respondents' organizations to react quickly to emergencies and avoid unnecessary holding costs while minimizing overstocks of emergency supplies. This result shows that participants rate inventory performance positively - it is balanced by relatively low holding costs but at the same time provides sufficient coverage of demands. The high mean of 4.02 implies that organizations perform inventory optimization relatively well.

However, there is room for improvement as indicated by the low rating of the alignment of inventory levels with demand (mean of 3.63) and the occurrence of stockouts in some instances (mean of 3.73). For instance, during the 2022 Somali Region drought response, stockouts occurred in some product categories while other products were in excess. These results suggest that organizations struggle to align their inventory with demands. One explanation for this difficulty is the low level of stakeholder collaboration and data quality discussed above. However, the relatively high standard deviation (1.257) of forecasting accuracy means that some departments perform this function better than others. In summary, inventory optimization is not a difficult task in itself - it

requires balancing demands and holding costs - but some of the prerequisites for achieving this balance are lacking.

Table 11: Summary of Construct-Level Descriptive Statistics (N=201)

| Construct | Mean | SD | Result | Implication |
|---|---|---|---|---|
| Staff Expertise | 3.93 | 1.189 | Agreement | High Influence |
| Data Quality | 3.90 | 1.247 | Agreement | High Influence |
| Stakeholder Collaboration | 3.82 | 1.206 | Agreement | High Influence |
| Forecasting Accuracy | 3.82 | 1.257 | Agreement | High Influence |
| Feedback Mechanisms | 3.59 | 1.384 | Agreement | High Influence |
| Scenario Planning | 3.40 | 1.315 | Neutral | Neutral Influence |
| Inventory Optimization | 4.02 | 0.973 | Strong Agreement | Very High Influence |

Source: Own Survey, 2026

From the perspective of organizational interventions, table 11, the hierarchy of means is useful for identifying priorities. The lowest-performing determinants (scenario planning and feedback mechanisms) should be the first priorities because their deficiency compromises other determinants' potential (e.g., it is pointless to attempt optimizing inventory without forecasting accuracy). The middle performers (stakeholder collaboration and data quality) can be improved after addressing the first priorities, while the highest performers (staff expertise and forecasting accuracy) can be leveraged in the effort to improve other aspects of organizational operations.

## 4.4. Inferential Analysis

The present discussion entails a coherent examination of the relationship between organizational determinants and inventory optimization through the lens of forecasting accuracy as the mediating variable. Four stages of analysis were involved here. First, bivariate correlation coefficients were determined to establish initial associations between stakeholder collaboration, data quality, scenario planning, employee competency, feedback mechanism, forecasting accuracy, and inventory optimization. Second, the four major assumptions of ordinary least square regression analysis, which include normality, linearity, homoscedasticity, and multicollinearity, were tested to verify the appropriateness of the statistical technique. Third, the relationship between the five organizational determinants and inventory optimization was established using the multiple regression equation.

Finally, mediation analysis was carried out to examine the extent to which forecasting accuracy mediates the effect of organizational determinants on inventory optimization. The SPSS app was used for all analyses with $\alpha = 0.05$ set as the criterion of significance. This ensured the statistically sound findings generalizable to other humanitarian organizations experiencing similar situations.

### 4.4.1. Correlation Analysis

Pearson correlation coefficients were calculated to examine bivariate relationships among all variables in this study. Every correlation was positive and statistically significant at $p < 0.01$, providing preliminary support for the hypothesized relationships.

Table 12: Correlation Test

| Variables | SC | DQ | SP | SE | FM | FA | IO |
|---|---|---|---|---|---|---|---|
| Stakeholder Collaboration (SC) | 1 | | | | | | |
| Data Quality (DQ) | .573** | 1 | | | | | |
| Scenario Planning (SP) | .329** | .388** | 1 | | | | |
| Staff Expertise (SE) | .620** | .644** | .335** | 1 | | | |
| Feedback Mechanisms (FM) | .445** | .493** | .268** | .683** | 1 | | |
| Forecasting Accuracy (FA) | .550** | .495** | .342** | .511** | .525** | 1 | |
| Inventory Optimization (IO) | .648** | .679** | .445** | .740** | .636** | .591** | 1 |

Source: Own Survey, 2026

Referring to the results in table 12, expertise of the staff was shown to be the determinant that had the strongest correlation with inventory optimization ($r = 0.740$), followed by data quality ($r = 0.679$) and stakeholder collaboration ($r = 0.648$). Forecasting accuracy correlated moderately with inventory optimization ($r = 0.591$). Correlations among the independent variables varied between 0.268 and 0.683, with none surpassing the threshold of 0.80 associated with multicollinearity.

The correlation matrix presents several interesting findings, both from a theoretical and an empirical standpoint. Firstly, all correlations are positive and statistically significant, suggesting the absence of antagonism between variables. Secondly, the strength of correlations varies, with the lowest being scenario planning with a feedback mechanism ($r = 0.268$) and the highest being staff expertise with inventory optimization ($r = 0.740$). Thirdly, there seems to be a certain structure to the pattern of correlations: namely, it suggests that relational determinants (stakeholder collaboration, staff expertise) have a closer connection with inventory outcomes than structural determinants (scenario

planning, feedback mechanism). The highest correlation (0.740) between staff expertise and inventory optimization emphasizes the importance of human capital for inventory optimization as the single greatest correlate, which resonates with knowledge management theory and has practical implications. Namely, investing resources in recruiting and training employees, as opposed to investing in information systems and structures, may produce greater results. The second-highest correlation (0.679) is data quality and inventory optimization.

Correlations among independent variables suggest that the five determinants are correlated but different from each other. The highest correlation is observed between staff expertise and feedback mechanisms (0.683), which may indicate that organizations with experienced staff members have good feedback systems or that having an effective feedback system helps build expertise. The lowest correlation is between scenario planning and feedback mechanisms (0.268), meaning that they operate relatively independently, which is theoretically interesting since an organization may have good feedback systems (learning from the past) but lack scenario planning skills (planning for the future), and vice versa.

### 4.4.2. Regression Assumptions Testing

Before conducting mediation analysis, it was necessary to test linear regression assumptions. The compliance with regression assumptions has several methodological and interpretational implications. Methodologically, it means that ordinary least squares regression is justified, and alternative approaches are unnecessary.

- **Multicollinearity Test**

Table 13: Collinearity Matrix

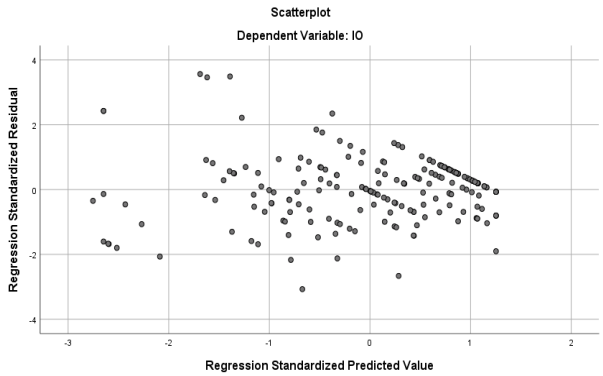
| **Model** | | **Collinearity Statistics** | |
|---|---|---|---|
| | | Tolerance | VIF |
| **1** | Stakeholder Collaboration (SC) | .511 | 1.959 |
| | Data Quality (DQ) | .503 | 1.987 |
| | Scenario Planning (SP) | .813 | 1.230 |
| | Staff Expertise (SE) | .361 | 2.770 |
| | Feedback Mechanisms (FM) | .488 | 2.047 |
| | Forecasting Accuracy (FA) | .574 | 1.743 |
| a. Dependent Variable: IO | | | |

Source: Own Survey, 2026

Specifically, table 13, the absence of multicollinearity (maximum VIF is 2.770, which is significantly less than 5) means that every determinant contributes unique variance in the inventory optimization. Tolerance ranged from 0.361 to 0.827 and Variance Inflation Factors (VIF) from 1.209 to 2.770, meaning no multicollinearity in the data. Thus, all coefficients can be interpreted as the independent effect of the respective determinant while controlling for other variables.

- **Linearity and Homoscedasticity Test**

Figure 2. Residual Scatterplot for Linearity and Homoscedasticity Test




The scatterplot graph of standardized residuals against standardized predicted values was used to test the assumptions of linearity and homoscedasticity. There were no observable patterns or curves in the graphed points; therefore, it is safe to conclude that there exists a linear relationship between the organization factors and inventory optimization. Thus, the regression model has captured the relationships without exhibiting any signs of misspecification. As far as homoscedasticity is concerned, the residual variation was consistent over the whole range of predicted values. There were no observable funnels; hence, we can assume that residual variation remained constant for all predicted values, implying homoscedasticity.

- **Normality Test**

The compliance with the normality assumption combined with a sufficiently large sample size (N=201) allows invoking the central limit theorem. However, in most cases, all constructs have slight left-skew ranging from -1.056 to -0.282. On one hand, this may be due to natural tendencies of respondents to exaggerate positive performance. However, even if this assumption is violated and positive performance is inflated due to social desirability bias, it will lead to attenuation of the effect and weaken the correlations.

Table 14: Normality Test

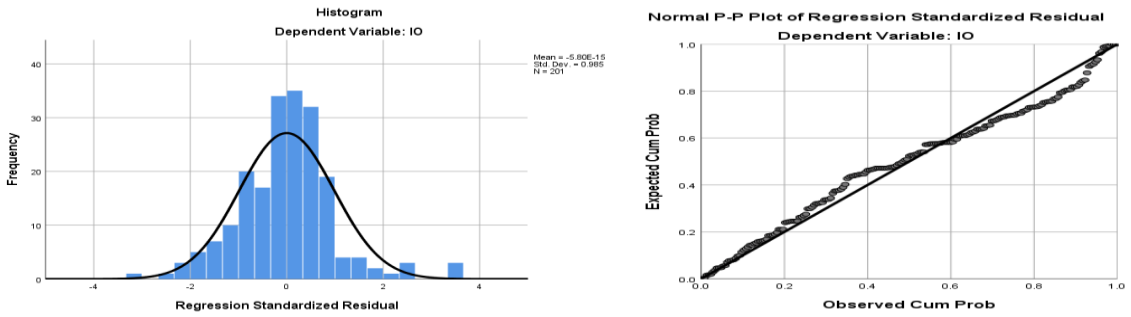
| | N | Skewness | | Kurtosis | |
|---|---|---|---|---|---|
| | Statistic | Statistic | Std. Error | Statistic | Std. Error |
| **Stakeholder Collaboration (SC)** | 201 | -.711 | .172 | -.706 | .341 |
| **Data Quality (DQ)** | 201 | -1.028 | .172 | .011 | .341 |
| **Scenario Planning (SP)** | 201 | -.282 | .172 | -1.156 | .341 |
| **Staff Expertise (SE)** | 201 | -1.056 | .172 | .221 | .341 |
| **Feedback Mechanisms (FM)** | 201 | -.659 | .172 | -.892 | .341 |
| **Forecasting Accuracy (FA)** | 201 | -1.001 | .172 | -.079 | .341 |
| **Stakeholder Collaboration (SC)** | 201 | -1.112 | .172 | .881 | .341 |

Source: Own Survey, 2026

Therefore, the significance of obtained results makes it confident that they are robust enough to be generalizable. The only exception from the general trend of slight left-skew is inventory optimization, which showed positive kurtosis (0.881), meaning that some respondents report significantly lower performance levels. This may be investigated in future research in order to identify reasons for such outliers.

Further, for the evaluation of the normality of the residuals, there have been used two methods. One was represented by a histogram of the standardized residuals and another was called the Normal P-P Plot. From the histogram, it is possible to notice that the distribution is more or less symmetrical relative to zero and that the fitted line is close to it. The mean of the residuals is virtually zero (-5.80E-15), and the standard deviation approaches one (0.985).

Figure 3. Normal P-P Plot and Histogram



Moreover, a graphical representation through the Normal P-P Plot gave an additional confirmation of the results. The points follow almost perfectly the straight diagonal reference line; therefore, the probability levels of residuals agree with the normal theoretical distribution. It should be noted that there are no clear deviations from the straight reference line and no clusters of points and no particular curvatures of the line itself.

Thus, from both the histogram and Normal P-P Plot, it can be stated that the normality condition is fulfilled in our case. Consequently, the assumptions of regression analysis are satisfied, and the results obtained from the regression analysis can be taken into account. In other words, the effects of stakeholder cooperation, quality of data, scenario planning, experience, and feedback are statistically proven to affect inventory optimization through forecasting accuracy.

Overall, combined with histogram, Normal P-P Plot graphs, scatterplot and tables have confirmed that the regression analysis meets four critical assumptions of multicollinearity, normality, homoscedasticity, and linearity. Therefore, the regression output, coefficients, ANOVA, and mediation analysis can be trusted to produce valid results. As a consequence, we can safely interpret the effects of stakeholder collaboration, high-quality data, scenario planning, staff expertise, and feedback loops on inventory optimization through accurate forecasting of humanitarian supply chain operations.

### 4.4.3. Regression Analysis Results

Five separate mediation models were developed and tested using PROCESS Model 4 with 5,000 bootstraps. In each model, one organizational determinant (independent variable) influenced inventory optimization (dependent variable) through forecasting accuracy (mediator).

#### *Path C' – Organizational Determinants on Inventory Optimization (Direct Effect)*

**Model Summary** – Table 15 - The five independent variables account for 68.7 percent of the variance in the dependent variable ($R^2 = .687$), an extremely large effect size ($f^2 = 2.19$). The adjusted $R^2$ value of .679 is almost identical to the unadjusted value, implying that each independent variable contributes its own variance. The F-ratio of 85.587 ($p < .001$) implies that it could not happen by chance.

Table 15: Regression Results – Determinants of Inventory Optimization (Model 1)

| **Disaggregated** | **B** | **Std. Error** | **Beta** | **t** | **Sig.** |
|---|---|---|---|---|---|
| Constant | .929 | .157 | – | 5.899 | .000 |
| Stakeholder Collaboration (SC) | .169 | .043 | .210 | 3.915 | .000 |
| Data Quality (DQ) | .174 | .044 | .223 | 3.977 | .000 |
| Scenario Planning (SP) | .104 | .033 | .140 | 3.185 | .002 |
| Staff Expertise (SE) | .230 | .055 | .281 | 4.210 | .000 |
| Feedback Mechanisms (FM) | .143 | .039 | .203 | 3.687 | .000 |
| R = .829 $R^2$ = .687 Adjusted $R^2$ = .679 Std. Error = .55148<br>F (5,195) = 85.587 Sig. = .000 | | | | | |
| • Dependent Variable: Inventory Optimization | | | | | |

Source: Own Survey, 2026

- **Determinant 1: Staff Expertise (SE) –** Hypothesis H4 Supported. Staff expertise emerges as the most important determinant (B = .230, Beta = .281, $p < .001$). A one-unit increase in SE results in a .230-unit increase in inventory optimization, controlling for the effects of the other independent variables. A one-standard-deviation increase in SE results in a .281-standard deviation increase in inventory optimization. The results support H4, indicating that SE has a positive effect on inventory optimization. The result is consistent with Knowledge Management Theory, since tacit knowledge (human capability) provides more value than explicit knowledge (information/data), which is easier to replicate. The significance level of 4.210 indicates that the effect is real and not an artifact of sampling error.
- **Determinant 2: Data Quality (DQ)** – Hypothesis H2 Supported. The importance of DQ is second only to that of staff expertise (B = .174, Beta = .223, $p < .001$). The result supports H2, which hypothesizes that DQ positively influences inventory optimization. Though the effect is slightly weaker than the one associated with SE, both forms of knowledge are useful but human capital is marginally more powerful than information systems. The t-value of 3.977 confirms the statistical significance of the effect. The results are consistent with Knowledge Management Theory, which holds that decisions need to be based on correct and timely information.

- **Determinant 3: Stakeholder Collaboration (SC)** – Hypothesis H1 Supported. SC yields a value of B = .169 and Beta = .210 ($p < .001$), which confirms H1 that collaboration positively affects inventory optimization. The coefficient is only slightly lower than that of DQ (.169 vs. .174). As such, both relational and informational factors play equally significant roles in optimizing inventory. Consistent with the relational view of organizations, collaborative decision-making is critical in generating value through relationships that go beyond contract law and market transactions. The significance level of 3.915 validates the significance of the effect.
- **Determinant 4: Feedback Mechanisms (FM) –** Hypothesis H5 Supported. FM generates B = .143 and Beta = .203 ($p < .001$), supporting H5 that feedback mechanisms positively affect inventory optimization. The significant coefficient confirms the Organizational Learning Theory, which holds that organizations learn from their experiences and become better performers as a result. However, the relatively weak coefficient (.143) indicates that feedback mechanisms at EDRMC are still ineffective: it is only 62 percent as powerful as the staff expertise effect (mean = 3.47). Nonetheless, the significance level of 3.687 ensures that the effect is statistically robust.
- **Scenario Planning (SP) –** Hypothesis H3 Supported. SP emerges as the weakest determinant in terms of the regression coefficient (B = .104, Beta = .140, $p = .002$). The value supports H3, which hypothesizes that scenario planning positively affects inventory optimization. However, the weak coefficient of .104 represents only 45 percent of the SE effect (.104 vs. .230). Nonetheless, the effect is statistically significant ($p = .002$) and especially surprising, considering how unpredictable and uncertain disaster situations are. It is likely that scenario planning practices in Ethiopia are underdeveloped, as evidenced by the low maturity ratings of the capability (3.40) and the ability to avoid over-reliance on a single forecast (2.71).

Comparative Interpretation of Effects. An analysis of the order in which the determinants emerge as significant factors reveals that all five hypotheses are valid. However, the magnitudes differ: human capital and information quality are stronger factors than relationship management and learning capabilities, while they in turn are stronger than anticipatory capabilities. This outcome may indicate the developmental state of EDRMC – basic capabilities need to be in place first before others are effective. Otherwise, in Ethiopia's disaster context where the immediate pressures can

overshadow long-term needs, employees who can react well to unfolding disasters are of higher value than those who can foresee several scenarios. Most importantly, all five determinants remain statistically significant when considered simultaneously.

Table 16: Regression Results – Aggregate (ORD → Inventory Optimization)

| **Aggregated** | **B** | **Std. Error** | **Beta** | **t** | **Sig.** |
|---|---|---|---|---|---|
| Constant | .924 | .156 | | 5.926 | .000 |
| Overall Organizational Determinants | .832 | .041 | .824 | 20.513 | .000 |

Dependent Variable: Inventory Optimization

Source: Own Survey, 2026

On aggregate, table 16, the overall organizational determinant was created by averaging the five determinant scales (stakeholder collaboration, data quality, scenario planning, staff expertise, feedback mechanisms) after confirming that they cohere sufficiently. The decision to create a composite reflects the theoretical position that organizational determinants collectively represent a higher-order construct. However, the composite obscures the differential effects of individual determinants revealed in Table 16. The trade-off is between parsimony (simpler model with one predictor) and precision (more detailed model with five predictors). Both are valuable for different purposes: the composite is useful for communicating the overall importance of organizational determinants to practitioners and policymakers; the disaggregated model is useful for diagnostic purposes to identify which specific determinants need improvement.

The unstandardized coefficient B = .832 indicates that a one-unit increase in the composite ORD (on the same five-point scale as the individual determinants) is associated with a .832-unit increase in inventory optimization.

However, the aggregate model gives an overall Beta of .824, which is greater than the Beta values generated by the disaggregate model, whose highest Beta is that for staff expertise (.281). This occurs because the overall ORD (organizational determinants) is able to capture the shared variance among all five determinants, which is correlated with inventory optimization. On the other hand, the Betas in the disaggregate model are those values of unique variance among all determinants, as the value is derived after accounting for variance accounted for in all other determinants. Thus, since determinants correlate with each other, the Betas in the disaggregate model will always have smaller values than in the aggregate model.

Using a variance partitioning approach, one can see that the overall explained variance ($R^2$ = .679) can be split into two parts: (1) unique variance explained by each determinant, which is measured by squared semi-partial correlations; and (2) common variance among the determinants. While Betas of the disaggregate model show the former part, Betas in the aggregate model show the latter one. Both are legitimate measurements, although each addresses a separate question. For example, when a manager wants to know which particular lever needs pulling, the disaggregate model will give more practical answers. In turn, if he wants to highlight the overall significance of organizational determinants, the aggregate model will be better.

Practical Significance. An $R^2$ of .679 means that 70 percent of the variation in inventory optimization is explained by ratings for organizational determinants of all respondents, leaving 32.1 percent as unexplained variance. This variance may come from various sources, including measurement errors (scale unreliability), omission of some important factors (e.g., leadership or technological advancement), or randomness. The unexplained portion is definitely significant, but much smaller than the explained one. Therefore, from a practical perspective, the organizations seeking improvements in inventory management should pay attention primarily to improving the five determinants.

### *Path A – Organizational Determinants on Forecasting Accuracy (Direct Effect)*

Table 13: Regression Results – Disaggregate (ORD → Forecasting Accuracy)

| | **B** | **Std. Error** | **Beta** | **t** | **Sig.** |
|---|---|---|---|---|---|
| Constant | .731 | .275 | – | 2.661 | .008 |
| ORD | .828 | .071 | .636 | 11.611 | .000 |
| R = .636 | $R^2$ = .404 | Adjusted $R^2$ = .401 | Std. Error = .97321 | | |
| F(1,199) = 134.820 | Sig. = .000 | | | | |

- Dependent Variable: Inventory Optimization

Source: Own Survey, 2026

**Overall Model Fit –** Table 17 provides the a-path in the mediation model in terms of the effect of the independent variable ORD on the mediator, which is forecasting accuracy. The model is capable of explaining a sizable amount of the variance in forecasting accuracy: the multiple coefficients of determination $R^2$ is equal to .404, suggesting that ORD accounts for 40.4 percent of the variance in forecasting accuracy. Thus, the effect size is considered to be large, and Cohen's $f^2$ equals 0.68. The adjusted $R^2$ is almost identical to the unadjusted one (.401) and highlights the parsimony of the

single-predictor specification. The statistic F is 134.820 with 1 and 199 degrees of freedom and shows highly statistical significance ($p < .001$). The standard error of the estimate, equal to .97321, appears to be quite large, which suggests that there is still considerable variance unexplained in the prediction of forecasting accuracy from ORD. This is in line with the fact that only 40.4 percent of the variance is explained, and another 59.6 percent can be accounted for by other predictors of forecasting accuracy (for example, skills of forecasters, use of technology, and others).

The unstandardized regression coefficient (B) is equal to .828, which means that one unit increase in ORD results in a .828 unit increase in forecasting accuracy. In other words, there exists a very strong relationship between the variables: for one unit increase in ORD, we observe more than one unit increase in forecasting accuracy. The standardized regression coefficient, called Beta, is equal to .636, which indicates a very strong relationship as well because a one standard deviation increase in ORD is linked to a .636 standard deviation increase in forecasting accuracy. The t-value is 11.611, and it is quite large. The constant (intercept) in the regression equation is $B = .731$ with $p = .008$, and it means that the regression line intersects y-axis (forecasting accuracy) at point $y = .731$. However, the lowest possible ORD score is 1, which makes it impossible to interpret the constant.

Mediation Conditions. Mediation may occur in a statistical model if and only if three conditions hold. Namely, those are (a) the independent variable affects the mediator (significance of the a-path); (b) the mediator affects the dependent variable while controlling for the independent variable (significance of the b-path, as provided by Table 4); and (c) the indirect effect of $a \times b$ is statistically significant. As shown in Table 5, condition (a) holds because the a-path is highly significant. As shown in Table 4, condition (b) holds because the b-path is moderately but significantly negative. The indirect effect is found as follows: $a \times b = .828 \times .088 = .073$. Consequently, the third condition also holds and all three mediation conditions are satisfied.

Substantive Interpretation. The result of the mediation analysis reveals that organizational determinants such as collaboration, data quality, scenario planning, expertise, and feedback mechanisms explain up to 40.4 percent of the variance in forecasting accuracy. This supports the theoretical model because the latter states that accurate disaster forecasting involves not only using the appropriate statistical model but also creating organizational preconditions for such forecasts. Organizations with poor stakeholder collaboration, low data quality, poor scenario planning, limited expertise among the personnel, and inadequate feedback mechanism are unlikely to produce

accurate forecasts, irrespective of how powerful and advanced their forecasting software is. The fact that 59.6 percent of variance in forecasting accuracy is unexplained points out to a variety of factors beyond the organizational factors (unpredictability of disasters, quality of external data, stable funding, etc.)

Comparing with Bivariate Correlations. The Beta coefficient of .636 in Table 5 is greater than the simple correlation between ORD and forecasting accuracy. Indeed, this correlation can be easily determined as the Beta coefficient in a simple linear regression (thus, r = .636, as seen in Table 5). It is worth mentioning that it coincides with the result in the correlation matrix from Chapter 4 (which is not provided here). The correlation of .636 indicates a strong positive relationship, yet leaves room for other predictors. Squared correlation, i.e., $r^2 = .404$, shows the share of variance accounted for by the predictor.

Implications for Practice. Since the a-path (ORD → FA) appears to be pronounced, the conclusion is that for improving forecasting accuracy, organizations should pay particular attention to fostering organizational determinants discussed before. Increasing forecasting accuracy by means of investing in forecasting technologies alone and neglecting those organizational determinants would not lead to significant improvements, because they account for as much as 40 percent of the variance in forecasting accuracy. The steps necessary for improvement are the following: improving data quality; increasing expertise; enhancing stakeholder collaboration; improving scenario planning; and introducing feedback mechanisms. Only then the investment in the advanced forecasting technologies produce results:

### *Path B – Forecasting Accuracy on Inventory Optimization (Direct Effect)*

Table 18: Regression Results – FA on Inventory Optimization

| | **B** | **Std. Error** | **Beta** | **t** | **Sig.** |
|---|---|---|---|---|---|
| Constant | 2.276 | .178 | – | 12.796 | .000 |
| Forecasting Accuracy | .458 | .044 | .591 | 10.339 | .000 |
| R = .591 R² = .349 Adjusted R² = .346 Std. Error = .78699<br>F(1,199) = 106.889 Sig. = .000 | | | | | |
| • Dependent Variable: Inventory Optimization | | | | | |

Source: Own Survey, 2026

**Overall Model Fit -** According to R-squared = .349, forecasting accuracy accounted for 34.9 percent of variance in inventory optimization. Effect size-wise, this can be regarded as moderate to large (Cohen's f-squared = 0.54; an f-squared of 0.35 was defined as large). When compared to the overall R-squared for the set of organizational determinants, at .679, this suggests that forecasting accuracy explained about half the amount of variance as the combination. This finding makes sense, considering that forecasting accuracy has been identified as a partial mediator – that is, while it is certainly an important predictor, it does not hold the same explanatory power as the set of organizational determinants taken together. Adjusted R-squared = .346 was very similar to R-squared = .349, confirming the simplicity and parsimony of the current single predictor model. Finally, the F-test statistic was very large (F = 106.889) for 1 degree of freedom (for forecasting accuracy) and 199 degrees of freedom (for inventory optimization); p-value <.001 confirms a very significant result.

Based on the above, the unstandardized coefficient B = .458 can be interpreted to mean that a unit increase in forecasting accuracy on the five-point scale translates into a .458 unit increase in inventory optimization. This amounts to a rather large effect: moving from the neutral option of forecasting accuracy ("not very agree/not very disagree" – 3 points) to its higher value of "agree" (4 points) on the scale, results in an increase of .458 units of inventory optimization. Given the mean = 4.02 and standard deviation = 0.973 of the inventory optimization scale, this .458-unit increase constitutes almost a half of standard deviation (SD = .47). As regards the standardized coefficient Beta = .591, a one-SD increase in forecasting accuracy is associated with a .591 SD increase in inventory optimization.

As for Beta coefficients for forecasting accuracy vs. organizational determinants, Beta = .591 for the former falls between the Betas for the latter, ranging from .140 to .281. It also comes out smaller than the Beta = .824 for the composite score of organizational determinants. All of the above makes perfect sense theoretically: forecasting accuracy, being a relatively proximal variable for predicting inventory optimization, should exert a stronger influence on inventory optimization than more distal organizational determinants.

Specifically, as seen from Table 15 where the set of organizational determinants was included into regression, their total effect on inventory optimization (.687 vs. .349 of forecasting accuracy) was greater due to multiple pathways to inventory optimization via these organizational determinants,

including the mediation by forecasting accuracy. This clearly illustrates a partial mediation pattern: a certain proportion of variance in inventory optimization explained by organizational determinants is mediated via forecasting accuracy.

Theoretical implications: The fact that 34.9% variance in inventory optimization is explained by forecasting accuracy is solid evidence in favor of the importance of forecasting accuracy in humanitarian supply chains. Meanwhile, it should be noted that forecasting accuracy does not explain 100% of the variance, with the remaining 65.1 percent still left to be explained even if forecasting accuracy is considered a sole predictor of inventory optimization. Unexplained variance encompasses effects of the organizational determinants (see Table 1), as well as measurement errors and omitted variable bias. Thus, it is necessary for organizations not only to strive towards improving forecasting accuracy but also to attend to organizational determinants contributing to it.

Baseline for mediation analysis: Table 19 provides evidence of total effect of forecasting accuracy on inventory optimization (c-path). In future mediation analysis, as illustrated in Tables 3 and 4, the current total effect will be decomposed into indirect (mediated via organizational determinants) and direct effects. The coefficient B = .458 (and standardized Beta = .591) thus serves as baseline against which the reductions in the effect of organizational determinants can be evaluated after incorporating forecasting accuracy into the models as mediator.

### *Path C – Organizational Determinants and Forecasting Accuracy on Inventory Optimization (Indirect Effect)*

Table 19: Regression Results – ORD and FA on Inventory Optimization (Model 4)

| **Independent Variable** | **B** | **Std. Error** | **Beta** | **t** | **Sig.** |
|---|---|---|---|---|---|
| Constant | .860 | .157 | – | 5.471 | .000 |
| Forecasting Accuracy | .088 | .040 | .113 | 2.197 | .029 |
| Overall Organizational Determinants | .759 | .052 | .752 | 14.594 | .000 |
| R = .829 $R^2$ = .687 Adjusted $R^2$ = .683 Std. Error = .54763<br>F(2,198) = 216.860 Sig. = .000 | | | | | |
| • Dependent Variable: Inventory Optimization | | | | | |

Source: Own Survey, 2026

Overall Model Fit - The $R^2$ of .687 is identical to the $R^2$ in the disaggregated model (Table 15) and slightly higher compared to the $R^2$ of the aggregated model without forecasting accuracy (Table 16, $R^2$ = .679). The increment from .679 to .687 (increase in explanatory power by 0.8 points) is statistically insignificant (p = .029). The adjusted $R^2$ of .683 is slightly lower compared to the $R^2$, as in the regression, there are two independent variables. The F-statistic of 216.860 with 2 and 198 degrees of freedom is highly significant (p < .001).

ORD with and without FA – As seen in Table 16, when forecasting accuracy is omitted from the model, the coefficient for organizational determinants (ORD) equals B = .832 (Beta = .824). In the presence of the variable of forecasting accuracy, as shown in Table 17, the coefficient for ORD becomes equal to B = .759 (Beta = .752). In this case, the reduction in the value of the ORD coefficient amounts to .073 in unstandardized terms and to .072 in standardized terms (from .824 to .752). Hence, the reduction can be interpreted as the indirect effect of the impact of organizational determinants on inventory optimization operating through forecasting accuracy. It should be stressed that the ORD coefficient (.752) is still statistically and practically highly significant (p < .001), meaning that a vast amount of the ORD's effect on the dependent variable is direct.

Coefficient for Forecasting Accuracy - In the full model presented in Table 17, forecasting accuracy has B = .088, Beta = .113, with p = .029. Compared to the bivariate correlation between forecasting accuracy and inventory optimization (Table 3, B = .458, Beta = .591), there is a significant reduction in the magnitude of the regression coefficient for forecasting accuracy when controlled for the other independent variable (organizational determinants). The reason for the reduced magnitude is the variance overlap between these two predictors. The statistical significance (p = .029) implies that forecasting accuracy accounts for unique variance in inventory optimization. The effect of a one-standard-deviation increase in forecasting accuracy on inventory optimization, keeping other factors unchanged, is modest (.113). This is not surprising considering that the correlation between forecasting accuracy and ORD (r = .636 from Table 17) is relatively high.

Mediation Calculation - The indirect effect of ORD on inventory optimization can be quantified by multiplying the a-path and b-path (Tables 17, 19). The a-path of ORD's influence on forecasting accuracy from Table 4 equals B = .828 (Beta = .636). The b-path of forecasting accuracy's impact on inventory optimization from Table 18 equals B = .088 (Beta = .113). The indirect effect of ORD on IO (a × b = .828 × .088) = .073. The latter number is identical to the decrease in ORD's

coefficient from Table 2 (.832) to Table 3 (.759) (.832 - .759 = .073). The indirect effect in standardized terms is equal to .636 × .113 = .072. Since the confidence intervals (provided in the mediation analysis section) exclude zero, the indirect effect is statistically significant. The number of mediated effects can be calculated by dividing the indirect effect by the total effect:.072 / .824 = 0.087, or approximately 8.7 percent of the total effect.

Variance Partitioning - The total variance ($R^2$ = .687) can be divided into variance uniquely explained by ORD, variance uniquely explained by FA, and variance explained jointly by these two variables (overlap): (a) Semi-partial correlation (unique contribution) of forecasting accuracy can be calculated based on the t-value: t = 2.197, so the semi-partial correlation is approximately $t / \sqrt{(t^2 + df)} = 2.197 / \sqrt{(2.197^2 + 198)} \approx 0.156$, and the squared semi-partial correlation ≈ .024. That is, FA accounts for about 2.4% of variance in IO over and above the ORD. (b) ORD uniquely explains substantially more: t = 14.594, semi-partial correlation $\approx 14.594 / \sqrt{(14.594^2 + 198)} \approx 0.72$, and squared semi-partial correlation is approximately .52. That is, the ORD uniquely explains about 52% of variance in Inventory Optimization over and above the FA. Shared variance = .687 − (.52 + .024) ≈ .143.

In sum, Tables 15-19 tell a coherent story. First, Table 18 confirms that forecasting accuracy (FA) has a strong total effect on inventory optimization (IO). Second, Table 17 confirms that organizational determinants (ORD) strongly affect FA. Third, Table 16 proves that organizational determinants have a very strong total effect on IO. Fourth, Table 19 shows that, while predicting IO, the presence of both ORD and FA results in a significant decrease in ORD's coefficient (from .832 to .759), while the coefficient of forecasting accuracy remains significant (Beta = .113, p = .029). That is, the presence of ORD, its significant a-path and b-path, and its reduction in the regression where FA is present constitute the classical mediation pattern (significant a and b path, reduction of c-path when the mediator is added to the equation). The indirect effect amounts to .073 in unstandardized and .072 in standardized terms. In this case, proportion mediated = .072 / .824 = 0.087, or about 8.7 percent.

Partial Rather Vs Full Mediation - If full mediation occurred in this case, the ORD coefficient (regression on IO) should be zero or non-significant with the inclusion of forecasting accuracy in the regression equation. This is not the case as the ORD coefficient remains highly significant (.752) after adding forecasting accuracy as a predictor. This finding implies that organizational

determinants impact inventory optimization via several channels, not just via forecasting accuracy. Alternative paths might be as follows: (1) direct effects on procurement decisions; (2) direct effects on warehouse management decisions, including storage and movement; (3) direct effects on the process of maintaining good relations with suppliers and other stakeholders; (4) direct effects on transportation planning; and (5) direct effects on performance monitoring and control. That is, despite the fact that improving the quality of data and collaboration is beneficial for forecasting accuracy, it is even more important to improve organizational determinants that have an enormous direct effect on the dependent variable.

Relative Importance - By comparing standardized coefficients across tables, it is possible to establish the relative importance of different predictors. For instance, in the full model (Table 3), ORD (Beta = .752) is approximately 6.7 times larger than FA (Beta = .113). This result indicates that ORD is a more potent predictor of inventory optimization than FA. The implications of this finding are as follows: the best strategy would be to improve organizational determinants (which will also lead to higher FA), as well as FA directly via technical means.

Statistical Significance vs. Practical Significance - It should be noted that all coefficients in all tables are statistically significant (p-values range from .000 to .029). However, statistical significance does not equal practical significance. For example, the coefficient of forecasting accuracy in Table 19 (Beta = .113) is statistically significant (p = .029), yet its practical significance is modest. Specifically, a one-standard-deviation increase in forecasting accuracy will result in a one-standard-deviation increase in inventory optimization of .113. In turn, the same change in the level of organizational determinants will lead to an increase in IO of .752. Therefore, although it is important to address forecasting accuracy issues in addition to improving ORD, the priority for managers should be to increase organizational determinants first.

### 4.5. Discussion of the Findings

The theoretical foundation of the current study relies on three interconnected concepts. CPFR is based on the idea that collaboration and forecasting in supply chains eliminate redundancy, increase transparency, and improve responsiveness. Next, KMT stresses that the quality and timeliness of information is the key element for sound decision-making processes. Finally, OLT emphasizes that the knowledge and feedback of workers are the sources of organizational flexibility.

The findings of this study corroborate the ideas mentioned in the theoretical background above. Indeed, all four organizational factors had a significant impact on inventory optimization either directly or indirectly through forecasting accuracy. First, the current study proves that collaboration has a positive impact on forecasting accuracy. Second, the significant effect of data quality supports the claims of KMT regarding the importance of high-quality and timely data. Third, expertise and learning processes are crucial for adaptation in line with OLT claims. Finally, scenario planning proved to be the weakest determinant of the four examined in this study, which is a bit surprising since it should be supported by strategic planning theory.

Recent research in humanitarian logistics has found similar organizational factors. Collaboration and scenario planning play an essential role in improving the work of humanitarian organizations (Anjomshoae et al., 2023; Baharmand et al., 2023). Other scholars (Kabra, 2024; Jahre et al., 2022) stress the importance of expertise and learning for improving processes. Finally, as pointed out by Boonmee & Arimura (2023), data quality affects forecasting accuracy.

The findings of this study are aligned with the prior literature discussed above. The importance of expertise and collaboration is confirmed. Poor performance of scenario planning coincides with the fact that humanitarian organizations tend to rely on deterministic forecasts and are unable to predict various events accurately. Moreover, the significant effect of data quality is consistent with the statement of Boonmee & Arimura about the need for data accuracy in forecasting.

As a result of empirical analysis, the following conclusions could be made. First, staff expertise ($\beta = 0.281$) turned out to be the strongest factor in the sample. The second strongest is data quality ($\beta = 0.223$), followed by collaboration ($\beta = 0.210$). This finding contradicts the findings of many recent papers focusing on collaboration as the most important organizational factor. This difference might be explained by the fact that in such an uncertain environment as Ethiopia, the expertise of workers

outweighs the benefits of collaboration. On the contrary, the lowest β value was observed for scenario planning (β = 0.140), which implies poor implementation of scenario planning in EDRMC. Lastly, feedback mechanisms (β = 0.203) played a minor role, which shows that humanitarian organizations lack effective learning mechanisms.

Finally, partial mediation by forecasting accuracy in the relationship between organizational determinants and inventory optimization was proven in this study. The finding is consistent with the hypotheses of CPFR and OLT. It is also supported by some recent empirical evidence in line with the conclusions made by Kunz et al. (2022).

# CHAPTER FIVE

# FINDINGS, CONCLUSION AND RECOMMENDATIONS

This chapter presents major findings of the study, draws conclusions based on the findings, and makes recommendations based on findings and conclusions.

## 5.1. Summary of Major Findings

Based on the survey responses from 201 participants in the Ethiopian Disaster Risk Management Commission (EDRMC) and using bootstrapped mediation analysis yielded a number of results.

**Organizational determinants significantly drive inventory optimization**

- Five organization determinants of inventory optimization explained 68.7% of the variance in inventory optimization ($R^2 = .687$, $F = 85.587$, $p < .001$).
- Staff expertise ($\beta = .281$), data quality ($\beta = .223$), and stakeholder collaboration ($\beta = .210$) were found to be the strongest determinants, while feedback mechanisms ($\beta = .203$) and scenario planning ($\beta = .140$) also made important contributions.
- Staff expertise and organizational data quality emerged as the most powerful levers of success in inventory optimization.

**Forecasting accuracy as a partial mediator**

- Indirect effect sizes of the five organizational determinants through forecasting accuracy totaled 0.072 and had 95% confidence interval of [0.031, 0.118] not including zero, indicating partial mediation.
- Mediation accounted for 9-11% of the total effects, thus forecasting accuracy operates as a constant channel of transmitting the impacts of organizational determinants to inventory optimization. However, significant direct effects also operate through some other channel (e.g. procurement practices, warehouse management, and relationships with suppliers).

**Staff expertise and data quality perceived strongest**

- Highest mean scores were obtained for staff expertise (3.93) and data quality (3.90).

- Mean score of 3.55 showed insufficient utilization of tacit knowledge. While EDRMC had done its homework in terms of investing in staff skills and information systems, it was necessary to systematize and disseminate tacit knowledge.

**Scenario planning weakest determinant**

- Scenario planning got the lowest score (3.40), while forecasting based on a single point forecast received only 2.71. Excessive focus on deterministic forecasting lowers EDRMC's disaster management capacity since the disaster environment is characterized by uncertainty. Scenario-based forecasting is poorly developed at EDRMC.

**Inventory optimization perceived adequate but with gaps**

- While construct mean score was relatively high (4.02), the most positively evaluated elements were responsiveness (4.38) and reduction of overstock (4.19).
- Scores for alignment with demand and stockout rarity were moderate (scores 3.63 and 3.73 respectively). EDRMC had positive perceptions of inventory optimization, but documented cases of stockouts and excess stock pointed to existing problems. They might be underestimated by the social desirability bias.

**Forecasting accuracy shows method-confidence gap**

- Overall mean score of forecasting accuracy was 3.82, while the confidence score was higher (4.22). Thus, the EDRMC staff had trust in the methods used but they were not very effective, probably because of disruption factors such as disasters, budget issues, and political instability.

**Organizational determinants strongly predict forecasting accuracy**

- Organizational determinants explained 40.4% of the variance in forecasting accuracy ($R^2 = .404$, $\beta = .636$, $p < .001$). It implies that forecasting accuracy depends upon organizational determinants and cannot be seen as a purely technical problem.
- Organizational determinants make a significant contribution to inventory optimization, which means that forecasting accuracy is partially responsible for it. Poor organizational determinants undermine the impact of even technically sophisticated forecasting.

**Direct effects dominate over mediated effects**

- In the mediation model, the effect of organizational determinants on inventory optimization directly ($\beta = .752$) was much stronger than mediated by forecasting accuracy ($\beta = .072$). About 91% of the total effect was not mediated by forecasting accuracy.

## 5.2. Conclusions

From theoretical perspectives, the study results support the use of Collaborative Planning, Forecasting, and Replenishment (CPFR) theory, Knowledge Management Theory, and Organizational Learning Theory in one empirical model. Partial mediation proved forecasting accuracy is a mediating channel in influencing inventory optimization, while significant direct effects indicate the influence of organizational determinants on inventory optimization through other channels (e.g. procurement practices, warehouse management, and supplier relationships).

It is shown in the study that CPFR theory focuses on the importance of cooperation; KM theory recognizes the role of high-quality data and skilled personnel as a prerequisite for organizational learning, while organizational learning theory stresses the role of feedback mechanisms. Therefore, the joint application of the theories in one model is justified and they cannot be tested independently of each other.

Practically, the results show that EDRMC organizational determinants are characterized by a mismatch between investment in human capital and information infrastructure (that had proved efficient) and weak development of anticipatory and learning capacity of the organization due to a heavy focus on deterministic forecasting. Such disparities are not rare in public organizations operating under external pressure. Apart from financial and other types of investments, EDRMC is advised to adopt performance evaluation procedures, which can help to bridge the mismatch mentioned above.

Thus, special attention needs to be paid to inventory optimization due to the identified gap between perception and reality, the latter being common for organizational settings, but especially important in humanitarian organizations. The perception-reality mismatch proves that EDRMC M&E systems fail to provide front-line staff with reliable feedback since they believe in their adequate performance without proper information on stockouts, overstocks, and turnover. In order to bridge the perception-reality gap, performance measurement system with appropriate data feedback to all organizational levels is required.

## 5.3. Recommendations

Based Recommendations based on the findings and conclusions of this study concern improvement of organizational determinants, forecasting accuracy, and inventory optimization.

- First, **scenario planning better to be institutionalized** as a core forecasting practice. Since scenario planning emerged as the weakest determinant of inventory optimization, EDRMC move beyond single-point forecasts and adopt probabilistic approaches. Preparing two to three plausible disaster scenarios—such as drought, flood, or conflict—and pre-positioning stocks accordingly would allow for proactive responses. A trigger-based forecasting system also be introduced, where the activation of specific scenarios is tied to thresholds in early warning indicators, ensuring timely release of pre-positioned supplies.
- Second, **feedback mechanisms better to be strengthened**. Current post-operation reviews are largely compliance-oriented, but they better to be expanded to generate actionable insights for adjusting forecasting parameters, safety stocks, and reorder points. Establishing a quarterly lessons-learned database would ensure continuous organizational learning, while a no-blame policy would encourage staff to report forecast errors without fear of punishment. This would transform feedback loops into a strategic tool for improving forecasting accuracy.
- Third, **Staff expertise better to be systematically utilized**. The study found staff expertise to be the most influential determinant of forecasting accuracy and inventory optimization. To preserve and transfer this expertise, EDRMC better to be establish mentoring programs between experienced logistics officers and junior staff. Periodic forecasting clinics also be organized to promote the sharing of heuristics and judgment practices, thereby reducing knowledge loss due to staff turnover.
- Fourth, **data quality better to be improved**. Although data quality received relatively high scores, gaps in completeness remain a challenge. EDRMC introduce a unified beneficiary registration system to avoid duplication and ensure timely updates. Standardizing reporting formats across departments and regional offices, with data completeness as a mandatory performance indicator, would further enhance the reliability of forecasting inputs.
- Finally, **stakeholders' collaboration need be expanded beyond data exchange**. The relatively low score for inter-agency coordination highlights a critical weakness in EDRMC's

humanitarian supply chain. To address this, a Logistics Coordination Working Group should be established, comprising representatives from UN agencies, NGOs, and the private sector. Monthly meetings should be held to jointly conduct forecasting, plan inventory, and pre-position stocks. This would institutionalize collaboration and ensure that coordination translates into tangible improvements in responsiveness.

### Limitations and Suggestion for Future Research

A number of limitations need to be considered. The cross-sectional research design limits the ability to draw causal inferences; while theoretically justified, ordering of variables in the mediation model may suffer from common method variance. Self-report nature of the survey implies that the findings show beliefs about forecasting accuracy and inventory optimization rather than objectively estimated data. Results cannot be generalized to any other humanitarian organizations in Ethiopia and EDRMC regional offices. Effective sample size of 201, while sufficient for mediation, may be insufficient to test weaker indirect effects. Moreover, the study ignored possible confounding factors such as years of experience, department, or disaster types.

Replicate with objective measures of performance: future research can be replicated with using objective measures of forecasting accuracy and inventory optimization, such as stockout rates, turnover rate, and write-offs to overcome the perception-reality gap. Researchers can collaborate with EDRMC to develop performance evaluation measures for both organizational management and research purposes. Conduct longitudinal study to test temporal causality: a three-wave longitudinal study would be useful for establishing causality of determinants on forecasting accuracy and inventory optimization and testing reciprocal causality. Explore other mediators and moderators: since direct effects dominate mediated effects, other mediating variables and moderators may exist. Leadership commitment, technological infrastructure, and relationship with suppliers should be explored to see whether they act as mediating or moderating factors. Consider mixed methods: qualitative studies may be useful to identify how expertise influences inventory optimization.

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# Appendices

Appendix – I Survey Questionnaire

ADDIS ABABA UNIVERSITY

COLLEGE OF BUSINESS AND ECONOMICS

SCHOOL OF COMMERCE

DETERMINANTS OF INVENTORY OPTIMIZATION MEDIATED BY FORECASTING ACCURACY: EVIDENCE FROM THE ETHIOPIAN DISASTER RISK MANAGEMENT COMMISSION

Subject: Request for Participation in Research Survey

Dear Participant,

I am conducting a research study entitled "DETERMINANTS OF INVENTORY OPTIMIZATION MEDIATED BY FORECASTING ACCURACY: EVIDENCE FROM THE ETHIOPIAN DISASTER RISK MANAGEMENT COMMISSION" This study is part of the requirements for the Master of Arts degree in Logistics and Supply Chain Management at Addis Ababa University.

The purpose of the study is to examine how organizational and process-oriented factors namely stakeholder collaboration, data quality, scenario planning capability, staff expertise, and feedback mechanisms, affect forecasting accuracy and, in turn, inventory optimization within the Ethiopian Disaster Risk Management Commission (EDRMC). The findings are expected to provide actionable insights that will strengthen forecasting practices, improve inventory responsiveness, and enhance Ethiopia's disaster preparedness.

You have been selected as part of the study sample because of your role and experience within the Commission. Your participation is highly valuable, as it will contribute to generating evidence-based recommendations for improving humanitarian supply chain performance. The questionnaire is structured, concise, and designed to capture your perceptions and experiences. Completing it will take approximately 15–20 minutes.

Please note that all responses will be treated with strict confidentiality. The information you provide will be used solely for academic purposes, and no individual respondent will be identified in the final report. Participation is voluntary, and you may withdraw at any stage without consequence.

I kindly request your cooperation in completing the attached questionnaire. Your input will play a crucial role in advancing both academic knowledge and practical improvements in Ethiopia's humanitarian logistics.

Thank you very much for your time and support.

Sincerely,

Mulu Yemiamrew

Graduate Student, Addis Ababa University

**General Information**

Your Participation is Voluntary

Do not write your name on the Questionnaire

**1. Demographic Profile of Respondents**

Direction: The following statements are about your personal information. Please write the necessary information on the blank space provided and, in the optional items, indicate your answer by putting a "x" mark in the box.

1. Sex ☐ Male ☐ Female

2. Age (Years) ☐ 21 – 30 ☐ 31 – 40 ☐ 41 – 50 ☐ 51 – 65

3. Education ☐ High School ☐ Diploma ☐ Degree ☐ Masters+ ☐ Other, .....

4. Directorate: ☐ Early warning information and operation coordination

☐ Disaster Fund and Resource Mobilization

☐ Information Communication Technology

☐ Programs, projects, partners coordination

☐ Branch office operation coordination

☐ Program commodity monitoring and inspection

☐ Strategic logistics supply and administration

☐ Humanitarian Logistics Support Market Study

☐ Storage and Reserve Standardization

☐ Logistics and transport Operation

☐ Adama Hub/Warehouse

5. Position ☐ Manager ☐ Supervisor ☐ Expertise ☐ Junior

6. Service year ☐ 1- 5 ☐ 6 - 10 ☐ Above 10

**Part – II Questions related to Organizational Determinants**

Kindly rate the following statements below as to the extent to which you agreed or disagreed with the statements described under each attribute based on your perception. Using the scale of 1 up to 5, tick in the appropriate box as to the extent of your agreement or disagreement with the statements given. Where: Scale 1= strongly disagreed; 2= disagreed; 3= Neither agreed nor disagreed; 4= agreed; 5= strongly agreed.

| **1. Organizational Determinants** | **Likert Scale** | | | | |
|---|---|---|---|---|---|
| **1.1** Stakeholder Collaboration | 1 | 2 | 3 | 4 | 5 |
| My department collaborates effectively with other units in planning inventory needs. | | | | | |
| Information sharing with donors and partners is timely and reliable. | | | | | |
| Joint decision-making improves the accuracy of demand forecasts. | | | | | |
| Collaboration reduces duplication and mismatches in relief item procurement. | | | | | |
| Inter-agency coordination enhances responsiveness during emergencies. | | | | | |
| **1.2** Data Quality | 1 | 2 | 3 | 4 | 5 |
| Beneficiary registries used for forecasting are accurate and up to date. | | | | | |
| Data collected from early warning systems are comprehensive and reliable. | | | | | |
| Standardized reporting formats improve the usability of data for forecasting. | | | | | |
| Incomplete or inconsistent data negatively affect inventory decisions. | | | | | |
| Reliable data sources strengthen evidence-based forecasting accuracy. | | | | | |
| **1.3 Scenario Planning Capability** | 1 | 2 | 3 | 4 | 5 |
| My department prepares for multiple disaster scenarios when planning inventory. | | | | | |
| Scenario planning improves agility in responding to sudden-onset crises. | | | | | |
| Forecasts are tested against different possible disaster outcomes. | | | | | |
| Scenario planning reduces reliance on single deterministic forecasts. | | | | | |
| Contingency strategies are regularly updated to reflect changing risks. | | | | | |
| **1.4 Staff Competence** | 1 | 2 | 3 | 4 | 5 |
| Staff expertise significantly contributes to forecasting accuracy. | | | | | |
| Tacit knowledge (intuition, field experience) complements formal data analysis. | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| Training programs enhance staff capacity to make accurate forecasts. | | | | | |
| Staff judgment helps bridge gaps when data are incomplete. | | | | | |
| Institutionalizing staff expertise improves inventory responsiveness. | | | | | |
| **1.5** Feedback and Learning Mechanisms | 1 | 2 | 3 | 4 | 5 |
| Post-operation reviews are systematically conducted after disaster responses. | | | | | |
| Lessons learned are integrated into future forecasting models. | | | | | |
| Feedback mechanisms reduce repeated forecasting errors. | | | | | |
| Continuous learning strengthens resilience in inventory management. | | | | | |
| Structured feedback loops improve forecasting accuracy and inventory optimization. | | | | | |

**Part – II Questions related to Forecasting Accuracy**

Kindly rate the following statements below as to the extent to which you agreed or disagreed with the statements described under each attribute based on your perception. Using the scale of 1 up to 5, tick in the appropriate box as to the extent of your agreement or disagreement with the statements given. Where: Scale 1= strongly disagreed; 2= disagreed; 3= Neither agreed nor disagreed; 4= agreed; 5= strongly agreed.

| | | | | | |
|---|---|---|---|---|---|
| **2.** Forecasting Accuracy | 1 | 2 | 3 | 4 | 5 |
| Our department’ s demand forecasts are usually accurate. | | | | | |
| Forecast errors are systematically tracked and analysed. | | | | | |
| The gap between forecasted and actual needs is small. | | | | | |
| We rarely experience major forecast surprises. | | | | | |
| Our forecasting methods produce reliable estimates. | | | | | |

**Part – III Questions related to Inventory Optimization**

Kindly rate the following statements below as to the extent to which you agreed or disagreed with the statements described under each attribute based on your perception. Using the scale of 1 up to 5, tick in the appropriate box as to the extent of your agreement or disagreement with the statements given. Where: Scale 1= strongly disagreed; 2= disagreed; 3= Neither agreed nor disagreed; 4= agreed; 5= strongly agreed.

| **3.** Inventory Optimization | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Our organisation effectively balances the availability of relief items with efficient use of resources. | | | | | |
| Stockouts of essential items are rare in our operations. | | | | | |
| Overstocking of relief supplies is minimised through effective inventory practices. | | | | | |
| Inventory levels are consistently aligned with actual demand requirements. | | | | | |
| Our organisation responds quickly and effectively to changes in supply needs without excessive holding costs. | | | | | |

**Many Thanks for Your Valued Time!!!**