Mitigating Fashion Obsolescence Risk through Transit Time Reduction: An Agent Based Modeling Study of Apparel Supply Chain

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Abstract

The global fashion industry is experiencing rapid trend acceleration, with styles shifting every three to four months due to social media influence and fast fashion dynamics. This short lifecycle increase the risk of fashion obsolescence, especially for manufacturers in developing countries like Ethiopia, where delayed deliveries lead to missed market windows and financial loss.in the bole lemi special economic zone (BLSEZ), a major garment manufacturing hub, long transit times caused by inefficient logistics infrastructure, slow customs procedures, and underperforming logistics agents reduce the competitiveness of local manufacturers and threaten the zone's ability to retain global investment.

This study aims to mitigate the risk of fashion obsolescence by improving logistics responsiveness and reducing supply chain transit time within BLSEZ. A mixed methods approach was employed, including surveys, interviews, document review, and direct observation to assess the current logistics performance and stakeholder capacity. Based on this empirical data, an agent modeling technique was used to simulate and evaluate three improvement scenarios: introducing new logistics agents, improving the performance of existing agents by 10%, and combining both strategies. Each scenario was analyzed to determine its effectiveness in enhancing delivery speed and supply chain reliability.

The results showed meaningful improvements across all scenarios, with scenario 1 achieving a 40.52% transit time reduction, scenario 2 yielding a 34.45% improvement, and scenario 3 producing the most significant result with a 58.74% reduction. A phased implementation is proposed: short term (within 1 year) incentives to attract competitive logistics firms, followed by medium and long term improvements in customs clearance infrastructure, technology use, and production speed reduce 58.74% obsolescence risk. These findings highlight the critical of integrated logistics strategies in aligning Ethiopia's garment industry with the time sensitive demands of the global fashion market. The study provides evidence based insights for policymakers, and manufacturers seeking to enhance competitiveness through responsive supply chain systems.

***Keywords**: fashion trend, transit time, optimization, risk, ABM*

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Declaration

I, Mulugeta Fekade, declare that this thesis entitled "Mitigating Fashion Obsolescence Risk through Transit Time Reduction: An Agent Based Model Study of Apparel Supply Chain in Bole Lemi Special Economic Zone (BLSEZ)" is my original research work and no material has been submitted previously for the award of any other academic degree. The research work was done under the guidance of Dr. Ameha Mulugeta at Addis Ababa University, College of Technology and Built Environment, School of Mechanical and Industrial Engineering.

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This is to certify that the above declaration made by the author is correct to the best of my knowledge.

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Abbreviation and Acronyms

BLSEZ—Bole lemi special economic zone

GFA-- global fashion agenda

AI—Artificial intelligence

IoT—internet of things

LP—linear programming

MIP—mixed integer programming

DES—Discreet event simulation

ABM--Agent based modeling

ABS—Agent based simulation

UAE-- United Arab emirates

Hrs--Hours

CHAPTER ONE: INTRODUCTION

1.1 Justification of the study

The fashion industry operates within a dynamic and volatile environment, where product life cycles are increasingly short and consumer preferences shift remarkable speed. Today's fashion trends are often defined and redefined within weeks, driven largely by the rise of fast fashion, social media influence, and demand for constant novelty. As a result, apparel supply chain faces growing pressure to deliver products to the market within ever narrower windows of relevance. Failure to do so results in fashion obsolescence the rapid devaluation of fashion products due to missed selling seasons, leading to inventory surplus, markdowns, and financial losses.

In this time sensitive landscape, the ability of logistics system to ensure timely delivery has become a strategic priorities for garment manufacturers and retailers alike. Among various logistics performance indicators, transit time is a critical determinant of supply chai9n responsiveness. Delays at this stage can negate prior gains in production efficiency, resulting in product arriving after peak demand has passed.

Transit time, therefore, is not merely an operational concern but a strategic lever for risk mitigation in fast paced fashion supply chains. Reducing the time required to transport goods from manufacturing facilities to distribution hubs or ports of exit enhances a firm's ability to synchronize supply with market demand. This alignment is particularly vital in the global fashion industry, where relevance is fleeting, and consumer behaviors increasingly unpredictable. While this relationship between lead time and obsolescence risk is widely acknowledged in high efficiency supply chains of developed countries, there remains a significant research gap in how this dynamic plays out in emerging manufacturing regions such as sub Saharan region. In particular, Special economic zones (SEZs) across the continent are increasingly viewed as engines of industrial growth, yet their capacity to meet global speed to market expectations is still in question. This is especially true for Ethiopia, where despite substantial investment in SEZs such as Bole Lemi special economic zone (BLSEZ), logistical inefficiencies remain a persistent bottleneck.

This study is justified on the following grounds

1. Industry Relevance: Ethiopia, and specifically the Bole Lemi Special Economic Zone, has become a focal point for foreign direct investment in garment manufacturing due to its low labor costs, trade incentives, and expanding industrial infrastructure. However, logistics inefficiencies due to long or unpredictable transit times remain a barrier to achieving full integration with moving global fashion networks. Exploring compatible strategies to reduce transit time is therefore essential for competitiveness and reducing losses associated with product obsolescence.
2. Local contextual insight: there is limited empirical research on how logistics firms operating in Ethiopian SEZs manage time sensitive goods such as fashion apparel. By focusing on pave logistics plc, this study provides a context specific analysis that addresses this gap and contributes to localized knowledge in logistics and supply chain risk management.
3. Theoretical contribution : this study intersects with key theories in agile supply chain management and risk mitigation by utilize agent based modeling to realize the autonomous decision making activity of supply chain agents, offering a nuanced understanding of how operational interventions can influence strategic outcomes in fashion logistics.
4. Policy and managerial implications: finding from this study will inform both logistics management practices and policy frameworks in Ethiopia's SEZs. It provides actionable insights for logistics service providers, apparel manufacturers, and government agencies working to enhance the efficiency and sustainability of the country's export oriented textile garment sector.

1.2 Background

Logistics is one of the basic components in the supply chain management that focuses the transportation, warehousing, inventory management, order processing and distribution of goods, services and information from the point of origin to point of consumption (Christopher & Peck, 2012). Effective and efficient transportation selection and assigning optimize source and destination location reduce the transit time and improve meeting the market demands and maintaining the market competitiveness in the fashion industries. Recently the balance of cost, speed and reliability in the transportation processes directly impact on the transit time performance on the inventory management and customer satisfaction. (Liao et al., 2024)

Efficient transportation and optimized transit times are critical to meet the market demands and global competitiveness. Air freight is the fastest and expensive mode of transportation, it is used to low volume, high- value and time sensitive items (Chopra et al., 2016). While sea freight is the most cost effective mode of transportation for large volume and oversized items. But it is slower and influenced by the weather conditions (Harrison& van Hoek .2011).on the other hand rail transport balances speed and cost, is environmentally friendly and reliable to long distance in land transportation until the availability of rail infrastructure(Chopra et al., 2016). In addition road transport is the flexible, last mile delivery and affected by traffic delays (Harrison& van Hoek .2011).the optimization cost and efficiency of the transportation processes can improve by intermodal transport way, because it combining multi transportation modes depend on the product feature and the customer requirements(Chopra et al., 2016).

The Bole lemi special economic zone (BLSEZ) in Ethiopia is a critical hub for manufacturing and logistics, particularly for the garment industry. Established to attract foreign investment and boost local manufacturing. BLSEZ offers various incentives to business, including tax exemption and streamlined customs procedures. The logistics process within this zone done by Pave and pan Affric logistics plc, both companies are integral to the supply chain that supports garment production, yet they exhibit significant difference in service performance. Pave logistics plc specializes in the transportation of raw materials and finished products, facilitating the supply chain for garment manufacturing. The company sources raw materials primarily from suppliers in Shanghai, Vietnam and Thailand. Pave logistics is responsible for transporting these transporting these materials to various garment manufacturing customers in BLSEZ and exporting finished products to international markets.

Transit time is the time taken between to move goods from one point of origins to its destination. So, the performance of transit time is crucial for fashion industries to meet the market demands and improve competitiveness. The factors that affecting the performance of transit time are mode of transportation, geographic destination, route complexity, port congestion and customs clearance procedures (Harrison& van Hoek .2011). However, fashion industries faced with significant risks related rapid changing trends affected by market fluctuations, environmental changes, supply risks like material shortages and logistics, demand risks from inaccurate market prediction and internal risks related to production and workflow disruptions (textile learner, 2023).

1.3 PROBLEM STATEMENT

The global fashion industry is experiencing mounting challenges due to the rapid acceleration of fashion trend cycles, which now last as little as three to four months before being replaced by new styles (crane, 2022). This shortened trend life cycle significantly increases the risk of inventory obsolescence, leading to substantial financial losses across the fashion supply chain. A major contributor to this challenge is the prolonged and unpredictable transit times within the supply chain, which hinder the timely delivery of fashion goods. These delays are influenced by a range of factors, including inadequate transportation infrastructure, inefficient customs procedures, and limited technological integration, and logistical bottlenecks challenges that are particularly pronounced in developing economies.

The Bole lemi special economic zone (BLSEZ) in Ethiopia, a key hub for textile and apparel manufacturing, is significantly affected by these issues. Despite its strategic role in attracting foreign direct investment and promoting industrial growth, persistent transit time delays and misalignment with global fashion timelines reduce the competitiveness of manufacturers operating within the zone. According to pave logistics 2023 data 28% of its logistics operation had delays. the When fashion products arrive late to market, they often miss critical sales windows, leading to inventory markdowns or total loss due to obsolescence. As a result, investors and global brands increasingly perceive BLSEZ as a high risk location, promoting considerations to shift operations to countries with more agile and reliable supply chain ecosystems. This trend threatens the long term viability of BLSEZ as a competitive industrial zone and underscores the urgent need to enhance supply chain responsiveness to retain and attract investment in the fashion sector.

1.4 RESEARCH QUESTION

- How do current logistics processes in BLSEZ garment industries contribute to fashion obsolescence risks, particularly due to transit delays?
- How does the existing logistics agent serving BLSEZ perform in terms of transit time efficiency?
- What logistics strategies can a simulation model propose to reduce transit times for garment exports from BLSEZ?
- How do different logistics scenarios impact delivery reliability and fashion risk reduction in BLSEZ?

1.5 OBJECTIVES

1.5.1 GENERAL OBJECTIVES

- ➢ To mitigate fashion obsolescence risk in garment manufacturing companies within BLSEZ by reducing the transit time of the supply chain.

1.5.2 SPECIFIC OBJECTIVES

- ➢ To evaluate the existing supply chain processes of garment industries in the BLSEZ in relation to their contribution to the fashion obsolescence.
- ➢ To evaluate the capacity of existing logistic agent in terms of transit time efficiency.
- ➢ To design simulation model that supports decision making for improving logistics responsiveness.
- ➢ To assess the impact of different logistics scenarios and strategies on reducing transit time.

1.6 SCOPE OF REASERCH

This research focus on reducing transit time within the garment supply chain in bole special economic zone to mitigate the risk of fashion obsolescence. It focuses on key logistics processes between main raw material supplier location, garment manufacturer in BLSEZ and main retailer's location of the SEZ garment manufacturers, and it excluding detail production processes and warehouses operations.

1.7 SIGNIFICANCE OF THE RESEARCH

This research is significant for its focus on reducing transit time and mitigating fashion obsolescence risks within the garment supply chain, using the fashion period as a baseline for evaluating delivery performance for other SEZs. In the context of developing countries like Ethiopia, where export oriented industrial zones such as BLSEZ are central to industrial growth, delays in logistics can lead to missed market windows and economic loss. By examining how different logistics strategies affect the timely delivery of fashion products, this study offers practical guidance for improving supply chain responsiveness without imposing substantial in operational cost. The finding contribute to a deeper understanding of how time based competitiveness can be achieved in emerging economies and serve as a valuable resource for policymakers, manufacturers, and logistics providers aiming to align production and delivery timelines with the demands of fast changing global fashion markets.

1.8 LIMITATION OF THE RESEARCH

In this study, Questionnaires and interviews are used as data collection tools, supported by secondary data. This reliance on personal judgement data may introduce potential bias. Data availability was limited, and benchmarking within the Ethiopia context proved difficult due to a lack of similar research. Additionally, time and resource constraints restricted further data collection and validation processes. Stakeholder support during data collection was also limited, which affected the comprehensiveness of the study.

CHAPTER TWO: LITRATURE REVIEW

2.1 INTRODUCTION TO LOGISTICS IN THE GARMENT INDUSTRIES

Logistics in the garment industries is a main component to the effective movement of raw materials from suppliers to the manufacturers and finished or semi-finished products from manufacturers to consumers. Effective logistics management includes optimizing transportation, warehouse utilization and distribution system to minimize cost and delivery speed. Recent studies emphasize that integrating the logistics processes with advanced technology, such as internet of things and artificial intelligence for improving the supply chain transparency and enhancing the ability to quick respond to changing fashion trends (Basak et al., 2014; Colovic, 2016). Additionally, preparing strategic warehouses and proper inventory management based on data drive demand forecasting are essential to mitigate risks associated with fashion trend life cycle (Wonduante, 2019). By incorporating these advanced logistics practices, garment industries can significantly enhance their operational efficiency, enabling them to manage resources more effectively, reduce costs, and streamline processes.

The implementation of effective and efficient logistics management in particularly crucial in regions like bole lemi Special economic zone (BLSEZ) in Ethiopia had many logistics challenges, such as inefficient transport infrastructure, delayed costumes clearance and inadequate warehousing facilities are reduce market competitiveness. Overcoming these obstacles through the adoption of advanced technology, such as internet of things (IOT) for real time tracking and artificial intelligence (AI) for predictive for predictive analytics. It can lead to more reliable supply chains, reduced transit time, and better alignment with fast changing fashion trends. Consequently, these improvements not only enhance the logistics operation capability of the company but also contribute the overall growth and development of the garment industries (Abebe, 2020).

2.1 CHALLENGES ON THE GARMENT LOGISTICS SECTOR

The garment logistics sector faces with several significant challenges that impact their efficiency and competitiveness in global market. The logistics delays such as delays in raw material sourcing, transportation cost fluctuation, the complexity of coordinating the suppliers and buyers across different regions. These challenges are the global supply chain obstacles by varying either the cost of logistics or the speed of delivery (Beza, 2015).insufficient logistics infrastructure, which includes poor road conditions, limited rail way connectivity, lack of ships and properly organizing ports are contribute to increased lead times, higher operational cost and make it challenging for companies to maintain agility needed to follow the fast changing fashion trends (Yonas, 2022).

The costumes clearance delays and inadequacy warehousing facilities are the additional obstacles are common in Ethiopia. These logistic bottlenecks can lead to delays, the garment manufacturers unable to deliver products on time and meet market demands. The lack of advanced technology usages in the logistics operation limiting the potential real time tracking and efficient inventory management (Alvi & Gosavi, 2022).

2.3 FASHION TREND CYCLE

The fashion trend cycle is a dynamic process. This includes fashion trends emerge, gain popularity by consumers and eventually decline. This cycle consists of five stages: introduction, rise, peak, decline and obsolescence. Initially, new fashion trend introduced by designers or brands during the fashion weeks. (Jones, 2027). After the trends gain the visibility and acceptance directly enters to raise stage, where it becomes popular among consumers by using different methods of marketing methods. It increased until the peak stages when the trend reaches its highest level of popularity on the market (Kim &Johnson, 2018). However, when the trend becomes oversaturated the consumer interest declined and the trend cycle reached at decline stage. Finally the trend reached at obsolescence stage. It is not logger fashionable by their consumers and replaced by new fashion trends (Hines & Bruce, 2020)

The average fashion trend life cycle has significantly accelerated in recent years. According to Crane (2022), The traditional fashion trend cycle used to last around six month to one year duration time, whereas in the recent years the trend life cycle reduced from 3 to 4 months before replaced by new style. In addition, the fashion trend life cycle reduction and the introduction of new fashion were increase in recent years, fast fashion brands now introduced approximately 52 trends per year, which is equivalent to one new trend per week (Diantari, 2021). Several factors affecting the acceleration of the fashion trend life cycles. Such as rapidly producing trendy cloths by affordable prices, the companies utilize the agile supply chain and data driven design processes to quickly respond to consumer preference and market demand (Barnes & Lea-Greenwood, 2010). The second factor was the social media platforms and influencers has dramatically increased the speed the adoption of new trend to public (Khamis et al., 2017).

Source Akter, j. Stages of fashion cycle

Figure 2.1 stages of fashion cycle

2.4 THE IMPACT OF TRANSIT TIME DELAYS ON FASHION TREND RISK

Transit time delays can introduce several significant risks on the fashion trend on the overall performance and reputation of fashion brands. According to Christopher et al. (2004) transit time delays can lead to the supply chain disruption, causing stock out or overstock situations and when the products do not arrive on time, brands may face lost sales opportunity at high demand seasons and increased the inventory holding cost when the demand reduced, resulting financial strain and inefficiency.in addition, long transit delays can harmful to a brand or fashion reputation. Consumers today expect fast delivery, and delay can lead to consumer's disaffection, negative reviews and decrease a customer loyalty (Barnes & Lea-Greenwood, 2010).

The transit time delays can increased the cost of products and reduce the profit margin of the manufacturers (Bhardwaj & Fairhurst, 2010). And the fashion industries must have ability to quickly adapt to new brands. Delays in the transit time reduce the market responsiveness, this reduce agility can lead to missed opportunities and loss of competitiveness (Ferdows et al., 2004). Sometimes the delays of the transit time happened by the logistic agent followed long transportation routine from the manufacturer location to destination or from raw material suppliers to manufacturers. According to Matuszak (2024), prolonged transit time often involved long-distance transportation, contributing to higher carbon emissions and environmental degradation.

2.5 MODELS OF SUPPLY CHAIN IN TRANSIT TIME REDUCTION

2.5.1 MATHIMATICAL MODEL

2.5.1.1 HISTOTYOF MATHEMATICAL MODELING

The foundation of mathematical modeling optimization can be traced back to ancient mathematical problems, but its formal development began in the 17th century with the work of Pierre de Fermat, who developed methods for maxima and minima (Bazaraa, Sherali, & Shetty, 2013). However the major leap occurred with the invention of calculus by Isaac Newton and Gottfried Wilhelm Leibniz, powerful tools for optimizing continuous functions. The 17th and 18th centuries saw further advances with contributions from mathematicians like Joseph-Louis Lagrange, who developed the methods of Lagrange multipliers for constrained optimization problems.

The 20th century witnessed a revolution in the optimization driven by the advert of computers and the development of new algorithms. Linear programming emerged as a powerful tools for solving optimization problems with linear objective functions and linear constraints, largely due to the work of George Dantzig, who developed the simplex algorithm in the 1947 (Dantzig, 1963. The development of non-linear programming (NLP) techniques followed, allowing for the optimization of more complex more complex function (Nocedal & Wright, 2006). Integer programming (IP) also become a critical areas, enabling the modeling and solution of optimization with discrete decision variables. The increasing availability of computational power and optimization software has made mathematical optimization a pervasive tool in numerous fields.

2.5.1.2 APPLICATION OF MATHEMATICAL MODELING

Mathematical modeling based optimizations are now integral to countless application across diverse domains. In engineering, optimization used for structural design, process control, and resource allocation. I.e. Aerospace engineers optimize the aircraft designs for fuel consumption efficiency and performance, while civil engineers optimize bridge designs for strength and stability (Arora, 2017). Optimization also play a crucial roles for industrial engineers to design the supply chain system to optimize the transportation cost, time, inventory levels and schedule deliveries.

In finance, optimization used for portfolio optimization, risk management, and algorithmic trading. Portfolio managers used mathematical optimization models to allocate assets in the way that maximizes return while minimizing risks (Markowitz, 1952). Furthermore it is used in machine learning for training models and selecting optimal parameters. Algorithms like gradient descent are used to minimize the error function of the machine learning models and improving its predictive accuracy. The increasing reliance on the data driven decision making has further amplified the importance of mathematical optimization in a wide range of industries and research areas.

2.5.1.2.1 APPLICATION AREA OF MATHEMATICAL MODELING IN TRANSIT TIME REDUCTION

Mathematical optimization model, encompassing techniques like linear programming (LP), Mixed-integer programming (MIP), and Network-flow optimization, plays a crucial roles in the strategic and tactical design of the global supply chain system. According to Goetschalckx, Vidal, and Dogan (2002), a compressive review of integrated strategic and tactical models and design algorism, emphasizing their application in determining optimal facility locations, transportation routes, and inventory levels within complex global networks. This model allowed for the minimization or optimizations of the logistics cost, transit times, and other related key performance indicators (KPI), while simultaneously considering various constraints such as, capacity limitations, demand fluctuations and service level requirements.

The application of mathematical model optimization in the global supply chain/ logistics system utilized by other researchers. I.e. according to Chopra and Meindl (2016), highlights the importance of considering both strategic and tactical decision within integrated frameworks, advocating for the utilization of optimization mathematical model to balance responsiveness and efficiency in the global supply chain systems. They emphasize that decisions regarding network design, inventory management and transportation planning should be made in a coordinated manner to achieve optimal performance. Furthermore the effectiveness of mathematical optimization models are applicable in mitigating risks and enhancing resilience in the global supply chains, particularly in the face of disruptions like natural disasters or geopolitical events by incorporating risk factors into optimization models, logistics companies or other stockholders can design more robust and adaptable logistics networks that can withstand unforeseen challenges (Simchi et al., 2008).

2.5.2 QUEUING MODEL

2.5.2.1 HISTOTY OF QUEUING MODEL

The development of queuing models originated with Agner Krarup Erlang's work in the early 20thcentury (Jensen, 1995), he driven by the practical needs of the Copenhagen telephone exchange facing increasing telephone traffic. Erlarg sought to understand and predict call congestion. His initial models, most notable the Erlarge-A (Erlarg loss) and Erlarg-B formulas, provided to calculate the probability of call being blocked due to all lines being busy, or, alternatively, the probability of the call having to wait. These models, while relatively simple, rested in the key assumptions such as passion distribution used for the arrival of the processes and exponential distribution for service time of the processes. This foundational work established the queuing models as a quantitative approach to understanding waiting line phenomena (Elldh & Olsson, 2000).

The mid-20th century saw a surge in queuing model development spurred by operations research and system engineering. David G. Kendall's introduction of the A/B/C notation, where A represents the arrival processes, B the service time distribution, and C the numbers of servers allowed for the systematic categorization and analysis. This framework spurred the creation of models beyond the simple M/M/C (Markovian arrival and service, C servers) that were initially developed. This notation facilitated the systematic study and classification of queuing models, leading to the development of models for various arrival processes (e.g. passion, deterministic, general) and the service processes (exponential, Erlarg, general). Advanced techniques for all types of queuing system also developed (Gross, Shortle, Thompson, & Harris, 2018).

2.5.2.2 APPLICATION AREA OF QUEUING MODEL

Queuing models have become indispensable tools across wide spectrums for industries application. In telecommunication, beyond Erlang's initial focus on the telephone exchange, queuing models are used to design and optimize the modern cellular networks, internet routers, and cloud computing systems (Kleinrock, 1975). M/M/C/K models, which incorporate a finite queuing capacity (K), are used to analyze systems where customers may be blocked or balk if the queue is full. In the healthcare, queuing model extend beyond optimizing patient flow in to the emergency room to encompass scheduling surgeries, managing organ transplant waiting list, and optimizing the allocation of medical resources during pandemics (Green, 2006).

Manufacturing and logistics system leverage queuing models for diverse purposes. I.e. optimizing the production line balancing, managing the warehouse operations, designing efficient transportation network, and analyzing supply chain disruption. Queuing network model, combined with simulation, are used to analyze the complex flow of materials and information in the modern supply chains (Hopp & Spearman, 2011). In the service industries, queuing models have evolved to addresses the queuing challenges of online service platforms, call centers and customer service operations. Models that incorporate customer abandonment behavior are used to understand and mitigate the impact of long within time on the customer satisfaction and revenue (Haviv & Ritov, 2021).

2.5.2.2.1 APPLICATION AREA OF QUEUING MODELING IN TRANSIT TIME REDUCTION

Queuing models offer an invaluable framework for analyzing and ultimately reducing transit time across the supply chain networks by addressing the persistent issue of waiting line and delays. According to Hopp and Spearman (2011), in their seminal "factory physics", established the critical understanding that variability in arrival and service rates directly precipitates congestion, there by prolonged transit time. Their work underscores the imperative of strategically managing capacity and proactively mitigating variability to not only enhance throughput, but also directly minimize the transit time within production and logistics systems. This is because if a material is waiting to another, the overall time increases.

Building upon this foundation, researchers have increasingly adapted and extended the queuing modeling techniques to specifically target transit time reduction. According to Lee and Billington (1992), in their analysis if the bullwhip effect, compellingly demonstrate hoe amplified the demand variability, propagating upstream within the supply chain, leads to increased queuing delays at various stages, thereby inflating the overall transit time of the system. The advocate for implementing enhanced information sharing and collaborative decision-making protocols to mitigate this effect, emphasizing the strategic importance of reducing demand-side variability to achieve substantial transit time reduction.

The careful considering of the trade-off between responsiveness and efficiency when optimizing the supply chain networks for reduction of transit time are significant for managing transit time and possible bottlenecks within the system performance(Chopra and Meindl, 2016). According to Zipkin (2000), presents the compressive overview of a diverse queuing model application within the supply chain contexts, with specific focus on reducing transit time of the system. Examples including the strategically optimizing the transportation routes, meticulously managing the inventory levels at key nodes, and efficiently design the service operations to minimize waiting time at critical touch points. Models may take into consideration complex relationships that can make it hard to measure by hand.

More advanced models that include simulation have been developed to demonstrate how the queuing system can improve and enhance the results of transportation. If there is unbalances in the distribution and network processes the whole processes will be slowdown. Simulation would also allow this to be tasted before implementation (Cruz, 2016). On the other hand even more advances have been used to analyze the queuing processes used the machine learning for dynamic queue routing. The key aspect of using those is that those have very robust control and allow adaptation based on multiple parameters (Wang et al., 2019)

Queuing models and simulation allows the strong optimization of times and materials. It offer a powerful and flexible toolkits for analyzing and optimizing diverse aspects of the supply chain management, from managing inventory to improving logistics and transportation networks, facilitating enhanced efficiency, responsiveness and, critically, reductions in the transit time.

2.5.3 STATISTICAL AND ECONOMETRIC MODELING

2.5.3.1 HISTOTY OF STATISTICAL AND ECONOMETRIC MODELING

The development of statistical and economic models is deeply rooted in humanity's quest to understand uncertainty, quantify relationships, and predict outcomes. The origins of statistical thinking can be traced to the 17th century, when mathematicians like Blaise Pascal and Pierre de Fermat pioneered probability theory to solve gambling problems(Hacking, 2006). Their work laid the groundwork for understanding chance and risk, concepts that remain central to modern statistics .This foundation was expanded by Jacob Bernoulli's Law of large numbers in the early 18th century, which formalized the idea that repeated trials stabilized around expected values, providing mathematical basis for inferring population characteristics for samples(Bernoulli, 1713).

The 19th century, Carl Friedrich Gauss introduced the normal distribution and the method of least squares, revolutionizing error analysis in the astronomy and geodesy (Gauss, 1809). Gauss's contribution became the core stone of regression techniques, enabling scientists to model the relationships between variables with unprecedented precision. Francis Galton's work in the regression in 1886 marked a turning point, shifting the focus from mere description to prediction (Galton, 1886). His studies on heredity demonstrated how quantifiable relationships between variables could explain complex phenomena, such as the inheritance of traits. Karl Pearson later systematized these ideas, developing correlation coefficients and chi-square test, which becomes pillars of modern statistical inference (Pearson, 1900). Pearson's establishment of the journal Biometrika in 1901 future institutionalized statistical methods across driplines from biology to economics.

The 20th century witnessed the formulation of econometrics as a disciplines. The establishment of Econometrics society in 1930 by Ragnar Frisch, Jan Tinbergen, and others institutionalized the integration of Economics, Mathematics, and Statistics (Bergholt & Dupont-Kieffer, 2009). Frisch's work on dynamic economic modes and Tinbergen's macroeconomic forecasting frameworks set the stage for empirical economic analysis, a paradigm shift occurred with Trygve Haavelmo's probability approach Econometrics (1944), which argued for probabilistic models to address causality, moving beyond deterministic frameworks. Haavelmo's insistence on stochastics models transformed econometrics into a tool for testing hypothesis rather than mere curve-fitting. This era also saw breakthroughs in time series analysis, such as the Box-Jenkins methodology for ARIMA modeling in the 1970s (Box & Jenkins, 1976). Which enabled researchers to decomposed trends, seasonality, and noise in the economic data? Robert Engle's ARCH model (1982) introduced a way to forecast volatility in financial markets, revolutionizing risk management. The late 20thand early 21th centuries brought computational advancement, with machine learning techniques like LASSO regressions (Tibshirani, 1996) and Bayesian hierarchical models merging traditional econometrics with predictive analytics (Gelman et al., 2013).. Toady's, big data and AI-driven tools enable real-time analysis of the complex systems, from financial markets to global supply chain (Athey, 2018).

2.5.3.2 APPLICATION AREA OF STATISTICAL AND ECONOMETRIC MODELING

Statistical and economic models are indispensable tools across diverse fields, offering frameworks to decode complexity and drive evidence based decisions, in economics, these models underpin policy evaluation and development strategies (Card & Krueger, 1994). For instance, difference-in-difference (DID) models and instrumental variables (IV) techniques have been pivotal in assessing the impact of minimum wage laws or trade policies on employment (Angrist & Pischke, 2008). Multivariate regression models are central to poverty studies, helping organizations like the World Bank identify determinants of inequality through initiatives such as living standards measurement study (Deaton, 1997). These model parse socioeconomic variables from education levels to access to healthcare to isolate factors perpetuating poverty. In development economics, computable general equilibrium (CGE) models simulate policy impacts on entire economies, guiding decisions on tax reforms or infrastructure investments.

In healthcare, survival analysis models like Cox proportional hazards have transformed patient's outcome predictions, particularly in oncology, by quantifying the effect of treatments while adjusting for covariates such as age sand genetic markers (Cox, 1972). Randomized collected trials (RCT), the gold standard in medical research, rely on ANOVA and Bayesian methods to validate drug efficiency (Berry, 2006). For example Bayesian adaptive trials allow for dynamic sample size adjustments, reducing costs and ethical concerns in drug development. The COVID-19 pandemic highlighted the role epidemiological models, such as SIR (Susceptible-infected-Recovered) frameworks, in forecasting infection rates and guiding public health responses (Kermack & McKendrick, 1927). Special econometrics has also been critical in mapping disease spread, as seen in studies correlating malaria incidence with climatic variables in sub-Saharan Africa.

Finance and risk management heavily depend on econometric tools. GARCH models are ubiquitous in predicting stock market volatility (Bollerslev, 1986).While logistics regression and decision trees form the backbone of credit scoring systems Thomas et al., 2002). Value-at-Risk (VaR) models, which estimate potential portfolio losses, integrate Monte Carlo simulations to account or tail risks. Environmental economics leverages spatial econometrics to assess climate change impacts, such as Mendelsohn's Ricardian approach, which correlates agricultural productivity with climate variables (Mendelsohn et al., 1994). Beyond these domains, statistical models drive innovations in marketing (e.g., conjoint analysis for customer preference) (Green &

Srinivasan, 1990), sports analytics (e.g., player performance prediction using mixed-effects models)(Albert, 2009), and even criminal justice (e.g., recidivism risk assessment via propensity score matching) (Berk et al., 2009). The versatility of these models lies in their adaptability to structured and unstructured data, making them vital in an increasingly data-driven world. For instance, natural language processing (NLP) techniques now analyze social media sentiment to predict consumer behaviors, blending econometrics with machine learning.

2.5.3.2.1 APPLICATION AREA OF STATISTICAL AND ECONOMETRIC MODELINGIN TRANSIT TIME REDUCTION

In global supply chain, transit time reduction is a critical for cost efficiency and competitiveness, and statistical models plays a transformative role in achieving this. Route optimization, a cornerstone of logistics, employs linear programming and operational research models like the vehicle routing problems to minimize travel distances and fuel consumption (Danzig & Ramser, 1959). Advanced algorisms, such as genetic algorisms and ant colony optimization, solve complex routing challenges with multiple constraints, such as vehicle capacity and time windows. Geospatial analytics, enhanced by GIS and Poisson regressions, identifies congestion hotspots and optimizes delivery corridors (Ghiani et al., 2013). For examples, UPS's ORION systems use advanced algorisms to reroute drivers in real time, saving millions of miles annually (Vidal et al., 2020). Similarly, FedEx's network design tools integrate spatial autoregressive models to balance warehouse locations with demand patterns.

Delay prediction models are equally vital. Survival analysis, traditionally used in the healthcare, has been adapted to estimate the probability of shipment delays (Kleinbaum & Klein, 2012). Parametric models like the Weibull distribution analyze hazard rate of the delays caused by customs inspections or port congestion (Lawless, 2003). Machine learning techniques, such as random forests and neutral networks, process historical shipping data (e.g., AIS vessels tracks) to predict delays with high accuracy. According to Xu et al., (2021) study the integrating weather data and port throughput metrics into natural networks reduced prediction errors by 30% in maritime logistics. Reinforcement learning models are now being tested to dynamically adjust shipping schedules based on real-time disruptions, such as storms and labor strikes.

2.5.4 SIMULATION MODELING

2.5.4.1 HISTOTY OFSIMULATION MODELING

Simulation modeling is a computational methodology that replicates real-world systems to analyze their behavior, predict outcomes, and test decision making strategies in a controlled virtual environment. It serves as a cost effective alternative to physical experimentation, particularly in scenarios where real world testing is impractical, risky, or ethically challenging (Banks et al., 2010). The foundational principle of simulation lies in abstraction simplifying complex systems into logical components (e.g., entities, resources, events) while preserving their core dynamics. For instance, a manufacturing plant might be modeled as a network of machines, workers, and inventory flows to identify bottlenecks.

The evolution of simulation modeling is deeply tied to advancements in computing. Early applications in the 1940s, such as the Monte Carlo method developed for nuclear physics research, laid in the groundwork for the modern techniques (Metropolis & Ulam, 1949). Today, simulation integrates interdisciplinary knowledge from mathematics, statistics, and computer science, enabling its use in fields as diverse as epidemiology and supply chain management. However, critics highlights limitations, such as the black box nature of the models, where oversimplification or biased assumptions can skew results (Saltelli et al, 2008). Despite these challenges, simulation remains indispensable for systems with inherent uncertainty, such as financial markets or climate change projections.

2.5.4.2 TYPES OF SIMULATION MODELING

Simulation methodologies are categorized based on their treatment of time, system components, and randomness. According to this the following are the type of simulation modeling.

1. **Discrete-Event Simulation (DES)**

Discrete event simulation (DES) models system where state changes occur at specific, discontinuous points in time. Originating in the 1940s with operations research during Second World War, DES was initially used to optimize military logistics and manufacturing assembly lines. The development of programming languages like GPSS in the 1960s formalized DES frameworks, enabling modular modeling of queues, resources, and stochastics events challenging

(Banks et al., 2010). By the 1990s software like Arena and Simio democratized DES for industries such as healthcare and telecommunications. Today, DES is pivotal in optimizing supply chains, hospitals workflows, and telecommunication networks, for example, Walmart uses DES to streamlines inventory management, reducing stock outs by 15%(Smith & Smith, 2020). However challenges persist in scaling DES for global systems and ensuring data accuracy.

2. **Continuous Simulation**

Continuous simulation models systems that evolve smoothly over time, governed by different equations. Its roots trace back to analog computers in the 1930s, which solved equations for engineering systems like electrical circuits. Jay Forrester's system dynamics framework in the 1950s expanded its use to socio-economic systems, such as urban growth and resource management (Forrester, 1961). Modern tools like Vensim and MATLAB support high-fidelity simulation of climate change, pharmacokinetics, and energy grids. The international panel on the climate change (IPCC), For instance, relies continuous models to project global warming impacts (IPCC, 2021). Despite its strengths, continuous simulation struggles with computational cost and modeling discrete distributions (e.g., sudden equipment failures).emerging include coupling continuous models with machine learning to refine predictions and deploying them in real-time systems.

3. **Agent-Based simulation**

Agent-Based simulation (ABS) focuses on autonomous agents, individuals entities with decision making rules to study emergent behaviors. Emerging from cellular automata theory in the 1940s and complexity science in the 1980s, ABS gained traction with simulated societal dynamics (Epstein & Axtell's Sugars cape, 1996). Which simulated societal dynamics. The 2000s saw open-source tools like Netlogo and Repast democratize ABS for social sciences and ecology. During the COVI-19 pandemic, ABS become critical for modeling disease spread and evaluating lockdown policies (Ferguson et al., 2020). Applications now span urban planning, ecology, and economics, such as simulating pedestrian movement in smart cities or species migration due to climate change. Key challenges include calibrating agent behavior rules and managing computational loads for large populations.

4. **Monte Carlo simulation**

Monte Carlo simulation uses random sampling to estimate probabilistic outcomes, rooted in its namesake casino's randomness. Developed during the 1940s Manhattan project to modern neutral diffusion, it expanded with digital computing into finance, engineering and project management. Today, it underspin risk analysis tools, enabling applications such as finance portfolio optimization and stress-testing engineering designs (Rubinstein & Kroese, 2016). For example, Pfizer employed Monte-Carlo methods to assess risks in COVIC-19 vaccine trails (Mahase, 2021). While powerful, it requires thousands of iterations for accuracy and struggles with dynamic interactions. Innovations include GPU acceleration for real-time risk assessment and quantum computing integration to solve complex probabilistic problems.

5. **Hybrid simulation**

Hybrid simulation merges methodologies (e.g., DES, ABS, continuous) to model multi- scale systems. Emerging in the 2000s, it addresses a complex systems like healthcare, where patient flow (DES) intersects with staff behavior (ABS). Tools like any logic pioneered hybrid frameworks, enabling applications such as smart city planning combining traffic flow (continuous) with driver decisions (ABS) and manufacturing systems integrating production lines(DES) with market demand (system dynamics). For instance, Singapore's hybrid traffic models reduced congestion by 20% (Chong et al., 2020). Challenges include synchronizing simulation clocks and standardizing development processes.

The evolution of simulation methodologies indicates that technological advancements and interdisciplinary demands. DES and continuous simulation remain foundational, while ABS and Hybrid approaches address modern complexities in human centric and multi scale systems. In addition, Monte Carlo simulation methods dominate risk analysis.

Hybrid modeling integrates two or more simulation methodologies such as discrete event simulation and system dynamics to address complex systems than cannot adequately captured by a single approach. Originated in the early 2000s, hybrid modeling emerged in response to the need for analyzing multi scaling systems where macro level dynamics e.g., supply chain flows interacts with micro level behaviors e.g., human decision making (Brailsford et al., 2019). For instance, healthcare systems combines DES for patient flow management and ABS for modeling clinical behavior. Enabling holistic optimization of the hospital workflows. Hybrid models excels excel in scenarios with heterogeneous components, such as smart cities traffic flow + pedestrian movement, or pandemic response disease spread + policy enforcement. Despite their versatility, challenges like computational complexity and synchronization of simulation clocks persist. This review examines hybrid modeling types, applications and specialized uses in reducing transit time.

2.5.4.3APPLICATION AREA OF SIMULATION MODELING

Simulation's versatility enables its adoption across industries. In healthcare, DES optimizes patient flow in emergency departments, reducing waiting time by 30% in studies at Johns Hopkins hospital (Ahmed & Alkhamis, 2009). ABS has also been critical in modeling disease spread, such as the Ferguson team's COVID-10 projections that informed UK lockdowns policies (Ferguson et al., 2020).

Manufacturing relies heavily on DES for lean production. Toyota's digital twin of assembly lines reduced defects by 20% through virtual testing (Tao et al., 2018). Similarly transportation systems use simulation for traffic management; Singapore's AI-driven traffic lights, modeled via continuous simulation, cut congestions by 15% (Chong et al., 2020).

In defense, war-gaming simulation like the U.S army's One SAF train soldiers in virtual battleground, saving millions in field exercise costs (Neyland, 1997).Environmental science employs ABS to predict deforestation impacts, such as the world wildlife Fund's Amazon basin models (Grimm et al., 2005). Emerging domains includes smart cities, where hybrid simulations integrate energy grids, public transport, and IoT sensors for sustainable urban planning (Batty, 2018).

2.5.4.3.1 APPLICATION AREA OF SIMULATION MODELING IN TRANSIT TIME REDUCTION

Discrete- Event simulation (DES) is a cornerstone for optimizing transit time in a logistics and transportation. By modeling Discrete events such as vehicle arrivals, loading and unloading processes, and traffic delays, organizations can identify inefficiencies in supply chains and delivery networks. For example, FedEx utilized DES to redesign its hubs and spoke logistics networks, reducing packaging transit time by 20% through optimized sorting processes and route prioritization (Banks et al., 2010). Similarly, urban freight delivery systems leverage DES to test dynamic routing algorithms that adopt to real-time traffic conditions, cutting last-mile delivery times by 15-30% (Chong et al., 2020). Agent- based simulation (ABS) complements DES by modeling interactions between autonomous agents such as, delivery trucks and drones. Agent-based modeling (ABM) is the valuable tool for optimizing supply chain networks by simulating the behaviors and interactions of individual agents, such as suppliers, manufacturers and distributers with in the complex system. ABM allows for researchers and practitioners to explore emergent behaviors, test different scenarios and identify optimal strategies for improving the supply chain performance. It can provide valuable outcomes in the dynamic nature of supply chains, enabling more effective and efficient supply chain processes (Adedirana, 2019). A study on port operations demonstrated how ABS reduced cargo transit time by 25% by improving coordination between docking schedules and truck movements (Lee & Kim, 2019).these methodologies highlight how simulation uncovers bottlenecks and enables data-driven route optimization. The integration of ABM into supply chain management helps address these challenges by allowing stakeholders to simulate different transit scenarios, predict potential delays and devise strategies to mitigate risk associated with long transit time (Bhardwaj & Fairhurst, 2010).

Hybrid simulation (combining DES and ABS) is a pivotal in streamlining public transit systems. For instance, Singapore's land transport authority employed hybrid models to redesign bus routes and schedules, reducing average commuter transit time by 18% during peak hours (LTA, 2021). By simulating passenger behavior (ABS) alongside bus/train scheduling (DES), transit agencies balance demand and capacity. Tokyo's metro system used DES to synchronize train timetables with passenger flow patterns, reducing wait times by 22% (Nakamura& Keto, 2018). These applications underscore simulations role in harmonizing infrastructure planning with used behavior to minimize delays.

Monte Carlo simulation plays a critical role in emergency logistics by quantifying risks such as road closures or whether disruptions. The federal emergency management agency (FEMA) reduced ambulance response times by 30% during hurricane evacuations by simulating probabilistic scenarios of blocked routes (Mohmoudi et al., 2020). Meanwhile, agent- based simulation (ABS) optimizes crowd evacuation strategies. A study of London stadium evacuations used ABS to redesign exit gate allocations, slashing evacuation transit time by 40% (Helbing et al., 2000). These approaches demonstrate how simulation prepares responders for uncertainty and enhances life-saving efficiency.

Continuous simulation models traffic flow dynamics to optimize signal timing. Los Angeles automated traffic surveillance and control (ATSAC) system reduced intersection transit time by 25% by adjusting signal phases in real time using continuous simulation (Choe et al., 2017). DES further enhances this by evaluating signal coordination during peak hours. In Mumbai, a DES-based study prioritized flood prone routes during monsoons, cutting average vehicle transit time by 18% (Patil & Kulkarni, 2019). These applications illustrate how simulation balances real-time adaptability with long-term infrastructure planning.

Hybrid simulation merges ABS for vehicle/drone behavior and DES for traffic flow to optimize autonomous systems. Amazon's drone delivery simulations reduced rural package transit time by 35% by refining flight paths and battery management (Amazon prime air report, 2022). Similarly, Waymo uses ABS to simulate interactions between autonomous vehicles and human drivers, mitigating urban traffic conflicts and reducing transit delays by 20% (Weymo, 2021). These innovations highlight simulation's role in advancing next- generation mobility solutions.

DES and Monte Carlo simulations synergize to streamline supply chains. Walmart reduced across border shipping time by 22% by simulating customs clearance processes and rerouting shipments probabilistically (Walmart logistics, 2020). Agent based simulation (ABS) also optimizes suppliers retailer coordination. ABS used to reduce raw material transit time by 30% in multi-tier supply chain (Procter & Gamble, 2021). These examples emphasize simulation's capacity to mitigate risks and synchronize global logistics networks.

In maritime and cargo handling, hybrid simulations synchronize ship/plan arrivals, cargo handling, and customs processes. The port of Rotterdam reduced ship docking to departure transit time by 28% using a hybrid DES and ABS model to coordinate crane operations and truck movements (Port technology, 2022). Similarly, Dubai international airport slashed cargo handling time by 20% by simulating ground crew workflows with DES (IATA, 2021).

2.6 COMPARISIONS OF DIFFERENT SUPPLY CHAIN MODELS

2.6.1 MATHEMATICAL MODELING

Mathematical modeling employs deterministic equations e.g., linear programming, network optimization to minimize transit time through route and resource allocation optimization. While effective for static systems with predictable variables. While it struggles account for dynamic uncertainties inherent in the garment industry, such as sudden supplier delays or volatile customer demand driven by fast fashion trends. For example, linear programming can optimize shipping routes between suppliers and manufacturers, but it cannot adapt to real time disruptions like port strikes or unexpected raw material shortages. The rigidity limits its ability to mitigate obsolescence risk, as it fails to model human decision making or behavioral factors e.g., logistics agents, rerouting shipments (Bonabeau, 2002).

2.6.2 QUEUING MODELING

Queuing modeling identifies bottlenecks at specific supply chain nodes, such as raw material queues at suppliers or production delays at manufacturing plants. While useful for optimizing single node processes e.g., reducing waiting times in the factories. It lacks a holistic view of end to end supply chain interactions. For instance, it cannot model how a retailer's panic order during a trend surge impacts raw material procurement or logistics workforces. This narrow focus makes it inadequate for addressing systematic transit time delays that accelerate fashion obsolescence (Choi et al., 2018).

2.6.3 STATISTICAL AND ECONOMIC MODELING

Statistical modeling using historical data e.g., time series forecasting, regressions to predict demand and transit patterns. While it helps align production schedules with seasonal trends e.g., forecasting holiday demand for winter apparel, it is inherently reactive rather than prescriptive. Statistical models cannot optimize processes or simulate what if scenarios, such as how a viral social media trend might disrupt supply chain timelines. This reactive nature limits its utility in mitigating obsolescence risk, as it cannot prescribe actionable strategies to accelerate transit during trend shifts (Helbing et al., 2000).

2.6.4 SIMULATION MODELING

2.6.4.1 Discrete-Event Simulation

DES models sequential events e.g., raw material delivery, production, shipping to test workflows and identify delays. While effective for optimizing processes like manufacturing timelines or warehouses turnover, DES treats entities e.g., supplies, retailers as passive components rather than autonomous decision makers. For example, it can simulate the impact of a logistics delay but cannot model how suppliers might renegotiate contracts or how retailers might alter orders in response to trends. This limits its ability to address behavioral risks that drive obsolescence (Macal & North, 2010)

2.6.4.2 Agent based modeling (ABM)

ABM simulates autonomous agents e.g., suppliers, logistics firms retailers customers and their interactions, capturing emergent behaviors and decentralized decision making. In the garment industries, ABM can model

- Raw material suppliers-Negotiation behaviors, reliability and response to demand spikes.
- Logistics Agents- dynamic rerouting decisions during disruptions e.g., port closures.
- Manufacturers- Adaptive production scheduling based on real time retailers order.
- Retailers – Panic ordering during trend surges and markdown strategies for obsolete inventory.
- Customers- trend driven purchasing patterns and social media influences.

ABM excels in simulating how delays propagate through supply chain and how agents adapt to mitigate risks. For example, it can reveal how a supplier's delay triggers a retailer's shift to alternative suppliers, preventing production halts and reducing transit time (Choi et al., 2018).

2.6.4.3 Monte Carlo simulation

Monte Carlo simulation assesses probabilistic risks. For example delays, demand fluctuations but it does not model interaction between supply chain actors. While useful for stress- testing strategies e.g., estimating the likelihood of missing a product launch deadlines. It cannot simulate adaptive behaviors like logistics agents rerouting shipments or retailers collaborating with manufacturers to expedite orders (Bonabeau, 2002).

2.6.4.4 Hybrid simulation

Hybrid models combine ABM for agent interactions, DES for processes optimization and statistical forecasting for demand trends. While powerful, they introduce complexity in synchronizing methodologies and require extensive computational resources. For instance, simulating a hybrid model of a fast- fashion supply chain would involve synchronizing DES timelines with ABM agent behaviors and statistical trend forecasts, which may be impractical for small firms. In addition to this hybrid modeling offers a compressive approach, agent based modeling (ABM) is the most effective method for reducing time and mitigating fashion obsolescence risk in the garment industries. Because ABM can uniquely captures the decentralized, adaptive behaviors of a supply chain actors i.e., suppliers, logistics agents, manufacturers, retailers and customers enabling a granular understanding of how a trends, disruptions, and decisions propagate through the system (Macal & North, 2010). By simulating human interactions and emergent risks, ABM provides actionable insights to accelerate transit, optimize inventory, and respond dynamically to fast fashion trends, making it the superior choice for an industry where agility and adaptability are paramount (Choi et al., 2018)

2.7 LITERATURE SUMMERY

From the journal articles and books reviewed conclusion is given here. Logistics in the garment industry plays a critical role in ensuring timely delivery of raw materials, efficient production and rapid distributions. However, the sector faces significant challenges, including volatile demand, short product lifecycle, and complex global supply chains. Fast changing fashion trends, driven by social media and seasonal shifts, further exacerbate these challenges, making agility and responsiveness essential. Delays in the transit time can lead to missed trend windows, resulted in obsolete inventory, markdowns and financial losses. The industry must balance speed, cost and sustainability while navigating disruptions like port congestion and supplier delays.

To address these challenges, various supply chain models are employed. Mathematical models, such as linear programming and network optimization, help optimize routes and resource allocation but struggle with dynamic uncertainties. Statistical and econometric models use historical data for demand forecasting but may fail to predict sudden trend shifts. Queuing models identify bottlenecks in specific nodes e.g., production delays but lack a holistic view of the supply chain. Simulation models, particularly Agent based modeling, offer a more dynamic approach by simulating interactions among suppliers, manufacturers and retailers, enabling proactive risk mitigation. These models help analyze how delays propagate and test adaptive strategies like dynamic rerouting or supplier diversification.

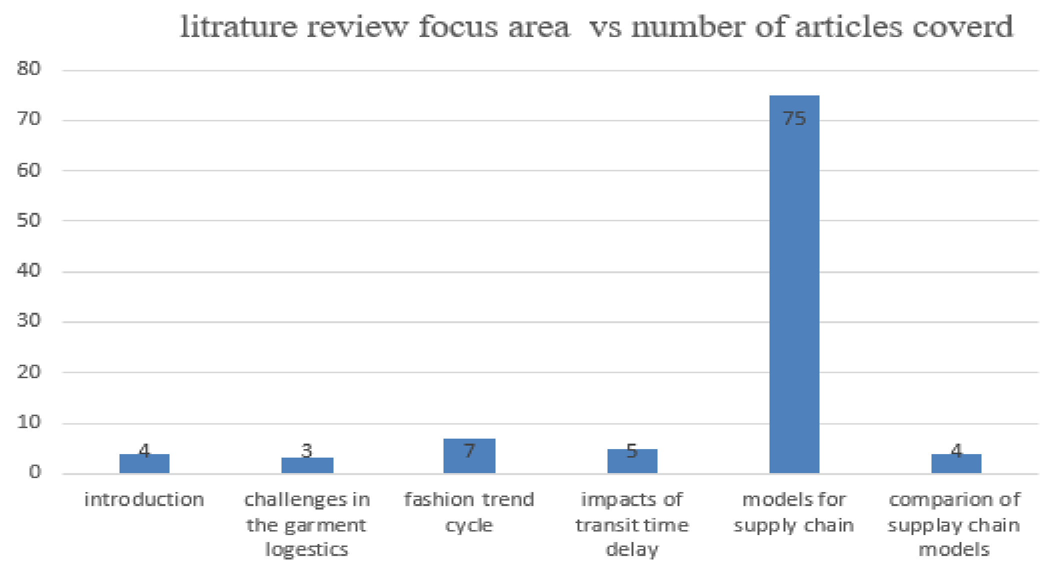

Figure 2.2 specific focus areas of selected articles

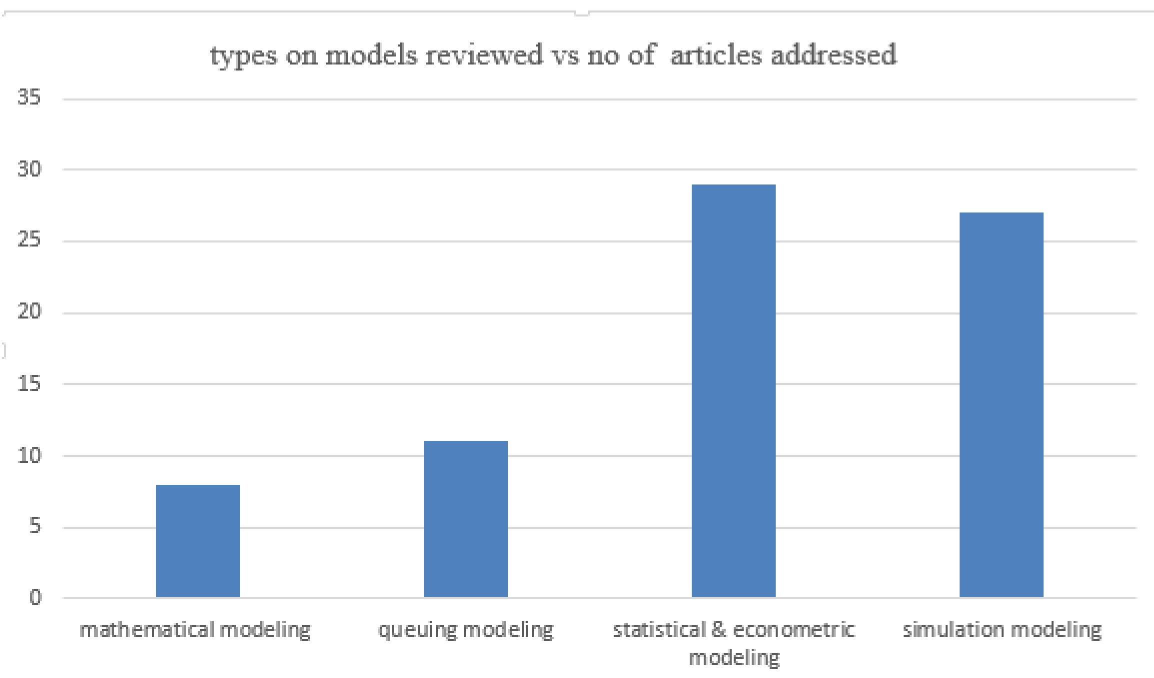

Figure 2.3 detailed focused areas on type of models related to supply chain management

2.7 LITRATURE GAP

Existing Agent based modeling (ABM) studies often simplify supply chains by isolating stockholders e.g., manufacturers, retailers rather than modeling their interconnected behaviors (Macal &North, 2010). For instance, raw material supplier's delays are rarely linked to downstream impacts like retailer stock outs or markdowns of obsolete inventory. This oversight limits the ability to simulate collaborative strategies such as dynamic supplier diversification or retailer manufacturer partnerships to expedite production. A holistic ABM framework could model how suppliers adjust lead time based on the retailers demand signals or how logistics agents reroute shipments during disruptions. Without such integration, models fails to capture systematic risks, such as Bullwhip effects, where delays amplify across the chain (Lee &Lee, 2018).

In addition to this, the rest literatures have the following gaps

- Limited research specifically addresses transit time reduction in the Ethiopian fashion industry. Most studies focus on developed economies.
- Studies on transit time often focus on cost optimization, neglecting the unique impact of speed on fashion obsolescence.
- Some research explores supply chain optimization in Ethiopia, few studies integrate agent-based modeling (ABM) for simulating the complex dynamics of fashion logistics.
- Few studies explore the combined impact of transit time and other factors (e.g., fluctuating demand, customs procedures) on fashion obsolescence in Ethiopia**.**

2.8 CONCEPTUAL FRAMEWORKS

This study's conceptual framework explores the relationship between logistics performance and the risk of fashion obsolescence in Ethiopia's garment manufacturing sector, particularly within the Bole Lemi Special Economic Zone (BLSEZ). It emphasizes how improving transit time through enhanced logistics operations can reduce the likelihood of fashion products becoming obsolete before reaching the market. The framework consists of five interconnected components:

1. Logistics Performance Factors

Key logistics-related variables logistics agent efficiency**,** customs processing time, infrastructure capability, and technology integration are directly influence the overall performance of the supply chain. Each factor contributes to delays or improvements in the flow of goods and collectively determines how fast and reliably fashion products move from production to market.

2. Transit Time

At the core of the framework is transit time, which serves as the central mediating variable. It reflects the cumulative effect of logistics operations and infrastructure on delivery speed. Reducing transit time is critical for aligning product availability with the short life cycles of modern fashion trends. Improvements in upstream logistics performance are expected to significantly decrease transit time.

3. Fashion Cycle Duration (Moderating Factor)

The fashion cycle duration, which is increasingly compressed due to social media and fast fashion acts as a moderating variable. Even small delays in the supply chain can render products obsolete in such a fast-moving environment. Thus, the shorter the fashion cycle, the greater the risk posed by transit delays.

4. Fashion Obsolescence Risk

The ultimate dependent variable in the framework is fashion obsolescence risk. When transit time exceeds the active period of a fashion trend, products lose relevance upon arrival at the market. This leads to increased markdowns, inventory loss, and reduced profitability for manufacturers and retailers. The framework establishes that lowering transit time is directly linked to reducing this risk.

5. Stakeholder Influence

External stakeholders including manufacturers**,** customs officials**,** logistics coordinators**,** and policymakers play a critical role in enabling or hindering improvements to logistics performance. Their collaboration is essential to implementing strategies that enhance efficiency, streamline customs operations, and integrate modern technologies across the supply chain.

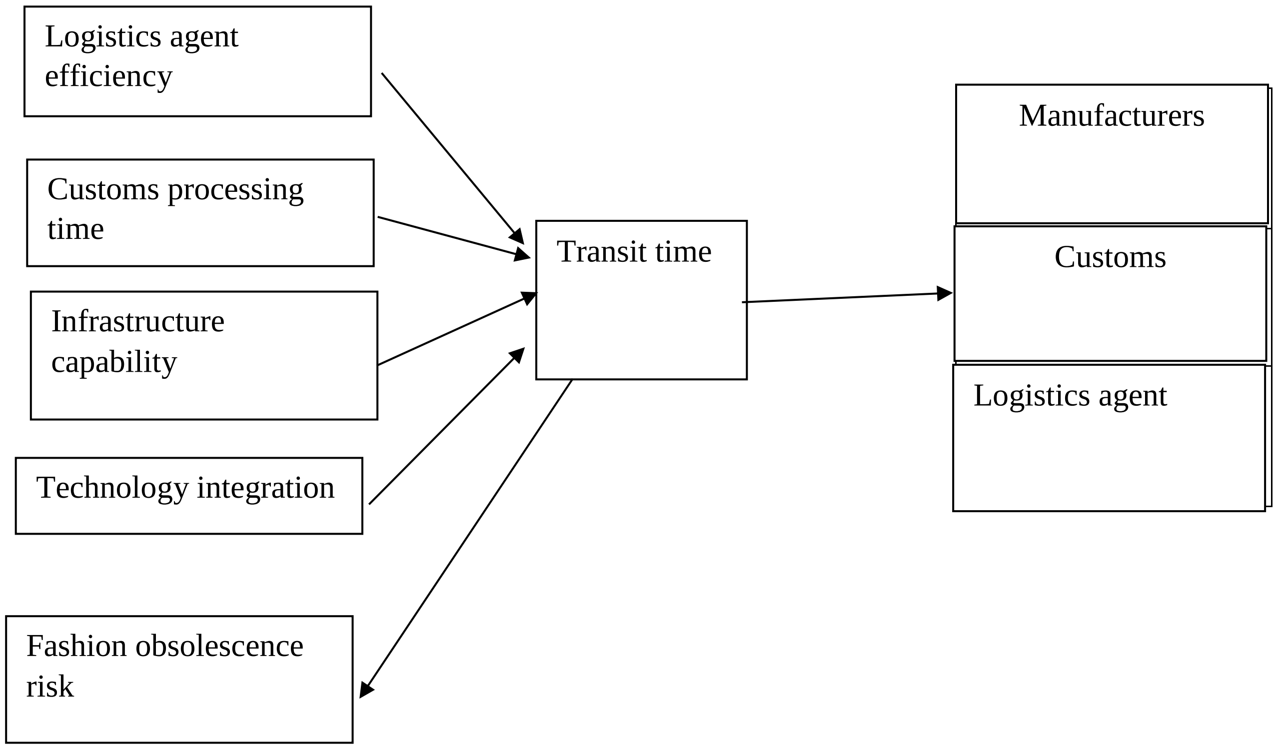

Figure 2.4 conceptual framework diagram

CHAPTER THREE: REASEARCH METHODOLOGY

3.1 STUDY AREA

This research is focused on Logistics operations of bole lemi special economic zone (BLSEZ), located in Addis Ababa, Ethiopia. The BLSEZ is the key industrial, trade and logistics zone dedicated to promoting garment industries development. This location significantly aimed to manufacture export standard and global competitive products, which faces significant pressures from fast changing fashion industry and customer demand. The specific focus on the highly performing existing logistics agent operating within BLSEZ makes it a suitable case study for investigating transit time reduction and fashion risk mitigation.

3.2 STUDY DESIGN

This research adopts a mixed methods approach to explore strategies for reducing transit time and mitigating fashion obsolescence within the garment supply chain at BLSEZ in Ethiopia. The process begins with a compressive literature review, aimed at identifying the main factors contributing fashion obsolescence and transit time delays in the context of global and regional supply chains. This review provides the theoretical foundation for the study and informs the design of the data collecti0n tools, particularly the questionnaire.

The next phase involves collecting primary data through a structured survey. The purpose of this survey is to gather the export opinions of manufacturers operating in BLSEZ regarding the most influential factors that lead to fashion obsolescence and logistics related inefficiencies. By aggregating expert insights from the field, the study aims to prioritize which factors are perceived as most critical from an operational and strategical perspective.

Once the survey results have been analyzed, the research will move to modeling design phase. The appropriate modeling approach will be chosen base on the nature and structure of the key variables identified through the survey. The model will aim to simulate the flow of garments through the supply chain from sourcing raw materials to export, incorporating delays, inventory flow, and fashion shelf life. To support the model's accuracy and contextual relevance, the study will also conduct a document review of performance data from the main logistics agent at BLSEZ.

In addition to document review, semi structured interviews will be conducted with stockholders across the supply chain, including logistics personnel, customs officials, and selected representatives from manufacturing firms. These interviews will provide deeper insights into the workflows, bottlenecks, and decision making processes that impact transit time and responsiveness to fashion cycle. The combination of survey, documentary evidence, and stakeholder interviews will ensure that the model reflects both qualitative and quantitative operational procedures.

The validation phase will be done to ensure that the agent based simulation model is accurate representation of the real-world logistics agent supply chain performance and to confirm that the data generated by the simulation can be a valid inferences by comparing the simulation output with historical data, after alternative scenarios will be use a verity of different simulated innervations to test how transit times can be reduced. The finding will provide actionable recommendations for policymakers, manufacturers, and logistics providers in BLSEZ, supporting more efficient and fashion aligned supply chain in Ethiopia's emerging garment industries.

3.3 DATA COLLECTION

Both primary and secondary data will be employed in proper manner to complete this investigation.

3.3.1 PRIMARY DATA

The primary data for the study will be gathered by surveys, observation and interviews with the Pave logistics plc and its stockholders.

3.3.1.1 SURVEYS

Surveys will be used to collect the opinions of garment manufacturing experts at BLSEZ on the key factors of fashion obsolescence identified through the literature review, with a particular focus on transit time delays. Structured questionnaires featuring rating scale and close ended will be developed to assess responsiveness; the survey aims to determine which factors most affect timely delivery and how they influence the competitiveness of manufacturers within the zone.

3.3.1.2 INTERVIEWS

Semi structure interviews will be conducted to gather rich, qualitative data from representatives of the main logistics agents operating in BLSEZ, customs officials and manufacturing companies. The interviews will explore decision making processes related to supply chain, as well as perceived bottlenecks and current logistics practices.

3.3.1.3 DIRECT OBSERVATION

Direct observation will gather the operational processes and work flows of logistics stakeholders operation in BLSEZ i.e., logistics procedure, customs clearance procedures, loading/unloading procedures and inventory and warehousing etc. Provides firsthand knowledge of the operational context and validates findings from surveys and interviews.

3.3.2 SECONDARY DATA

3.3.2.1 DOCUMENT ANALYSIS

Document analysis will be used to collect both qualitative and quantitative data from existing records such as historical shipment logs, transportation contracts, financial records, and logistics performance reports. These documents will provide accurate and reliable information to support the identification of current operational conditions, transit time patterns, and supply chain bottlenecks, contributing to a realistic performance at BLSEZ

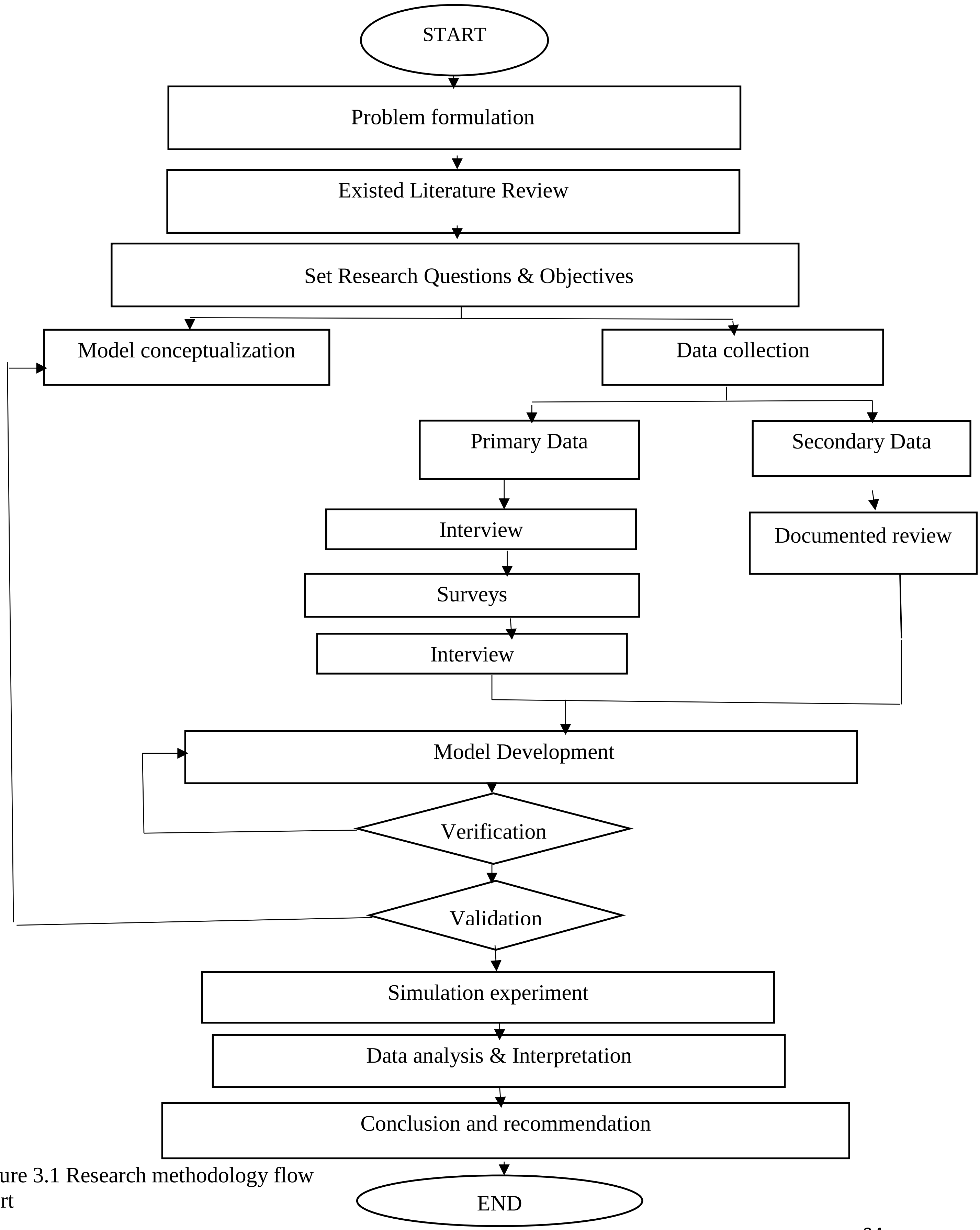

Figure 3.1 Research methodology flow chart

3.3.3 STUDY SUBJECTS

This study will be done based on the following study subjects.

1. Logistics agent personnel: including branch coordinator, logistics staffs and operational workers.
2. Garment manufacturing customers: selective garment manufacturing employees on supply chain and production related position.
3. Customs officials; selective officials at BLSEZ on managerial and senior experts level.

3.3.4 ELIGIBILITY CRITERIA

This research will be follow the following eligibility criteria to select the eligible data source personals.

- Participant personnel from logistics agent must be included from coordinator to operational workers in the transportation and logistics processes in BLSEZ branch.
- Participant personnel from garment manufacturing industries must be key personnel evolves in planning, logistics and production processes.
- Experts involving in this research must have substantial experience in logistics, supply chain or the fashion industry.

3.4 SAMPLE SIZE

3.4.1 Interview sample size

This research will be make 5 interviews for proper data saturations for the representatives for each logistics agent personals personnel, garment manufacturing companies employees and managers and customs officials (Guest et al., 2006).

3.4.2 Survey sample size

The sample size of the survey will be include all supply chain managers, supply chain experts and related employees of manufacturers in BLSEZ

3.4.3 Observation sample size

Observations of the logistics activity in BLSEZ are intended to supplement the interview and the survey data. This research will be used at least three site visit such that logistics agent operation, BLSEZ garment manufacturing companies and customs operation at BLSEZ.

3.6 Sampling Methods

This research will be used purposive sampling method to select key personnel in the logistics agent, garment manufacturing companies and officials of costumes in the process of supply chain managements.

3.7 Description of variables

3.7.1 Independent variables

- transportation mode: different mode of transportation (i.e. air, sea and land)
- logistics reliability: the probability of delay in the transit time
- fashion trend cycle: the expected lifespan for fashion trends
- Transit routes: different paths used for the transportation of materials.

3.7.2 Dependent variables

- Total Transit time: total times goods spend from the source to final destination.
- Fashion obsolescence risk

CHAPTER FOUR: DATA ANALYSIS AND ORGANAZATION

4.1 Background

Bole lemi special economic zone (BLSEZ), located in Addis Ababa, Ethiopia represents a core stones of the Ethiopian government's ambitious strategy to shift the national economy away from agriculture towards export-oriented manufacturing. Established to attract foreign investment direct investment (FDI) and facilitate rapid industrial growth, BLSEZ is one of several special economic zones designed to serve as a catalysts for economic transformation.

The establishment of BLSEZ is rooted in the broader Ethiopian growth and transformation plan (GTP), which prioritizes industrial development and export diversification by attracting FDI and fostering a conductive business environment.

4.2 Garment industries in BLSEZ

BLSEZ accommodates a range of export oriented garment manufacturing enterprises that contributes significantly to the country's industrialization objectives through employment generation, foreign exchange earnings and technology transfer.

These manufacturing firms primarily produce garments for international markets, leveraging Ethiopia's competitive labor costs, supportive industrial policies, and access to preferential trade agreement. The investment landscape within BLSEZ is international in nature, with companies originating from South Korea, Sri Lank, China, United Arab Emirates and Hong Kong. These firms benefit from various incentives offered under Ethiopia's industrial park framework.

The garment factories vary in scale and operational capacity, with some occupying extensive facilities equipped for large scale production. While each firm specializes in different market segment, collectively, they produce a wide range of apparel products including, adult ware, sport ware, children ware and safety ware products.

Most manufacturers operate under vertically integrated or semi integrated models, importing raw materials and exporting finished garments in line with buyer specifications. The main garment industries are BLSEZ are the following

4.3 Logistics agent in BLSEZ

4.3.1 Pave logistics plc

Pave logistics plc is a leading Ethiopian logistics and supply chain Management Company established in 2015, with its headquarters located on Churchill road, Addis Ababa. The years, the company has over expanded its operations its operations both locally and internationally, providing services such as customs clearance, freight forwarding (air and sea), inland transportation, warehousing, port handling, and door to door delivery. Domestically, pave logistics has built a strong presence with 10 operational branches across Ethiopia, including key locations such as Addis Ababa (head office), bole lemi special economic zone, Ethiopian airlines cargo and logistics, kality, dukem, adama, modjo, Dire Dawa, and Hawassa. This wide network enables efficient cargo handling and optimized service delivery nationwide. Internationally, the company has established liaison offices in strategic global hubs Including Djibouti, china and Dubai, Kenya and Uganda. These branches support seamless global logistics operations, helping pave logistics operations helping pave logistics connect businesses with international markets.

Pave logistics offers a comprehensive suite of logistics solutions, including

- Customs clearance: efficient handling of import/ export documentation and procedures
- Transportation: reliable land transport services across Ethiopia
- Air and Sea freight: Global freight forwarding services via air and sea
- Port handling: management of cargo at port facilities.
- Door to door delivery: End to end logistics solutions.
- Consultancy: expert advice on logistics and supply chain management

4.3.2 Pan Affric logistics plc

Pan Affric logistics plc is one of the logistics service providers operating in Bole lemi special economic zone. The company plays a key role in supporting the efficient movement of goods for export oriented garment manufacturers located in the zone. It offers a range of services including freight forwarding, customs clearance, inland transportation, and coordination with regulatory bodies.by facilitating timely cargo handling and delivery.

4.3 Factors Affecting Fashion Obsolescence in the Garment Industries

Potential factors that are identified from the literatures that accelerated fashion obsolescence are five main factors. According to Joy et al.(2012), the fast fashion model has intensified obsolescence by encouraging frequent design turnovers, rendering older style undesirable. Long transit time and production time exacerbate this issue, as delay prevent timely market entry, increasing the risk of unsold inventory (Gupta &Gentry, 2018). Additionally, poor fashion forecasting accuracy leads to over production, further contributing to fashion obsolescence (Thomassey, 2014).

Transit time delays significantly impact fashion obsolescence by extending the time between production and retail availability. According to Fernie and sparks (2018, inefficient logistics, customs bottlenecks and poor supply chain coordination prolong lead times, increasing the risk of products arriving too late to meet trend demand. In Bangladesh's garment sector, export processing delays further aggravate this issue, as product s may miss key selling windows (aziz & Rahman, 2021). Fast- fashion brands like Zara mitigate this by localizing production and using air freight for time- sensitive shipments (Tokatli, 2008).

Production time is another critical factors influencing fashion obsolescence. Long production cycles, often due to inefficient manufacturing processes or supplier delays, reduce a product's relevance upon arrival in stores (Bruce &Daly, 2016). In addition according to Taplin (2014), the brands with shorter production lead time, such as H&M and Uniqlo, experience lower obsolescence rates due to quicker replenishment cycle.

The shortening of the fashion trend cycle has intensified obsolescence, as styles now lose relevance faster than ever. According to Barnes & Lea-Greenwood (2006), social media and influencer culture have compressed trend life spans, forcing brands to adapt quickly. Fast- fashion retailers like Shein on this by releasing thousands of new designs weekly, pressuring traditional manufacturers to accelerate their cycle (Payne, 2021). However, this hyper-speed trend turns over increases the risk of unsold inventory for slower-moving brands (Caniato et al., 2014).

Fashion forecasting and customer behavior analysis plays pivotal roles in mitigating obsolescence. According to Thomassey (2014), accurate forecasting helps brands align production with anticipated demand, reducing overstock. However, consumer behavior is increasingly unpredictable due to digital influence and sustainability corners (Kozlowski et al., 2018).

4.4 **Factors Affecting Fashion Obsolescence in the Garment Industries**

Transit time delays represent a critical challenge in the global garment supply chain, particularly for export- oriented manufacturing hubs link Bangladesh. These delays not only disrupt lean inventory systems but also escalate risks of fashion obsolescence in an industry where product life cycles continue to compress. Existing literature identifies multiple interdependent factors that collectively determine transit efficiency, ranging from physical infrastructure limitations to administrative bottlenecks.

4.4.1 Mode of Transportation Utilization

Unstructured transportation mode selection and utilization amplifies transit time delays through systematic inefficiencies. Maritime shipping suffers from port congestion and vessel bunching when exporters fail to align booking with port schedules, forcing circuitous detours through oversubscribed hubs (Notteboom $ Rodrigue, 2008). According Aziz & Rahman (2021), Road transport delays are driven by infrastructure and whether dependency. Air freights speed advantage is negated by reactive deployment, where last- minute booking face cargo space shortage or indirect flight paths, while poor multimodal coordination create handover delays between ships, planes and trucks due to mismatched schedules and incompatible documentation (Rodrigue, 2020).

4.4.2 Geographic and Infrastructure constraints

Geographic and infrastructure constraints inherently disrupt transit time efficiency through interconnected physical and systematic limitations. A Region’s topography like landscape restricts route diversity by forcing road and rail networks to coverage around natural barriers (Rodrigue, 2020). Urban density compounds this issues, as a industrial zones cluster factories without proportional road expansion, leading to chronic gridlock (Aziz & Rahman, 2021).

4.4.3 Customs clearance efficiency

Customs clearance inefficiencies disrupt transit timelines thorough bureaucratic and procedural complexities inherent to cross-border logistics. Manual processing of physical documentation forces officials to verify each shipment's paperwork individually, creating sequential bottlenecks where cargo waits days for basic approvals (Grainger, 2021). Overlapping regulatory jurisdictions such as separate inspections by customs, tax authorities and standard agencies multiply processing steps, as shipments must satisfy disconnected approval workflows. Outdated technology exacerbates delays as paper based system lack automated validations, requiring manual error correction for even mirror discrepancies (Rodrigue, 2020).

4.4.4 Documentation Accuracy and completeness

Inaccurate or incomplete documentation disrupts transit timelines by embedding administrative friction into cross-border logistics. Errors in critical paperwork such as, mismatched commercial invoices, incorrect harmonized code (HC) or expired certificate of origin trigger iterative correction cycles where shipments stall at customs checkpoints until revisions are approved (Grainger, 2021). Paper based documentation systems exacerbate these issues, as manual data entry increases typographical errors and slows verification, particularly when physical papers must be couriered between stakeholders. Regional discrepancies in documentation requirement such as varying invoice formats or conflicting labeling rules create confusion, leading to avoidable rejections even for technically compliant shipments (Rodrigue, 2020).

4.4.5 Route Selection

The selection of transportation routes amid multiple options introduces delays when decision making fails to account for dynamic logistical variables. Over- reliance on a staticde4fault routes, such as primary highways or fixed shipping lanes, leads to congestion as multiple carriers coverage on limited infrastructure, creating bottlenecks that idle freight for hours (Rodrigue, 2020).

4.4.6 Loading and unloading efficiency

Inefficiency in loading and unloading operations prolongs transit timelines through labor intensive work-flows and skill gaps. Manual handling by untrained personnel slows cargo transfers, as improper stacking techniques or equipment misuse force network to secure unstable loads (McKinnon, 2018).

4.4.7 Technology Utilization

The complete lack of technology utilization in logistics operations entrenches transit delays by perpetuating manual, disjointed and error-prone processes. Manual documentation handling forces customs official to physically verify paper based bills of lading, invoices and certificates creating sequential bottlenecks where shipments queues for days waiting approvals(World bank, 2020). Without GPS and RFID tracking, logistics teams remain blind to real time shipment location, allowing distributions like truck breakdowns or route blockages to escalate undetected until delivery deadlines are irreparably missed (Rodrigue, 2020). Inventory management reliant on the paper logs leads to mismatches between warehouse stock and actual cargo availability, causing trucks to idle for hours while workers manually search for misplaced consignment (McKinnon, 2018).

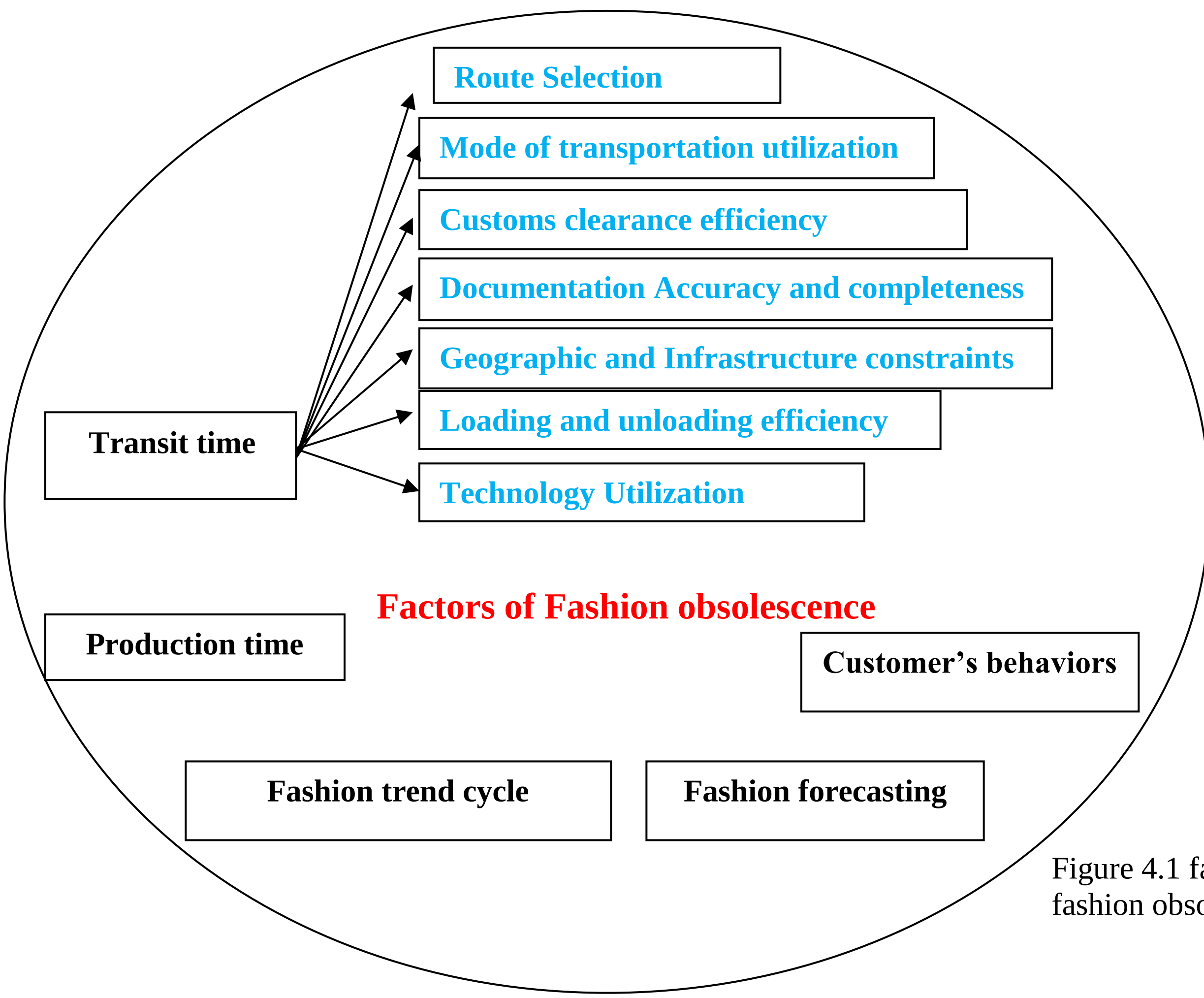

Figure 4.1 factors of fashion obsolescence

4.5 Data interpretation and presentation

The main factors of fashion obsolescence listed above, including transit time delays and their contributing factors are identified from literature review, are measured and elaborated in detail taking the case of pave logistics plc at BLSEZ. Responses from questionnaire completed by employees of manufacturing industries provide critical input for analyzing the impact of these factors on their logistics performance relative to fashion obsolescence risk. Additionally, document review was conducted at logistics agent for performance attribute of supply chain agents. Furthermore, insights from interviews with customs officials, logistics personnel and manufacturing company leaders for their behavior and rules are also discussed below.

The garment manufacturing sector within the BLSEZ plays a pivotal role in Ethiopians textile and apparel industry, serving as a key driver of export growth and employment. The seven companies included in this study are the following most active manufacturers.

- Shintes ETP Garment plc
- Jay Jay textile plc
- Ashton apparel manufacturing plc
- Ever top sports ware Plc
- Shan tex Garment Manufacturing Ethiopia plc
- Top New Garment manufacturing plc and
- Vestis Garment production plc

These companies collectively represent a significant portion of the garment production capacity in the region and directly impacted by the challenges of fashion obsolescence, supply chain inefficiencies and rapid changing market demands. To gain a comprehensive understanding of these challenges, a structured questionnaire was administered to employees across the supply chain and related function within these companies. The survey targeted all personnel involved in supply chain operational, managerial, and strategically roles only, ensuring a wide spectrum of insights into the factors influencing fashion obsolescence risk. A total of 15 respondents participated and distributed as follows.

Table 4.1 selected garment manufacturing company and respondent

No.	Company Name	Number of respondent
1.	Shintes ETP Garment plc	4
2.	Jay Jay textile plc	4
3.	Ashton apparel manufacturing plc	3
4.	Ever top sports ware Plc	3
5.	Shan-tex Garment Manufacturing Ethiopia plc	2
6.	Top New Garment manufacturing plc	2
7.	Vestis Garment production plc	2

This respondent profile captures a diverse range of expertise and experience, encompassing supply chain managers, experts, and production managers. Their collective input forms the foundation for analyzing key challenges and opportunities related to mitigating fashion obsolescence in the BLSEZ garment industry.

The sample consists of seven garment manufacturing companies located in BLSEZ an important industrial hub in Ethiopia. Among these companies 57% produce adult ware, 21% manufacturing children's wear, 21% focusing on Sportswear and lastly 21% focusing on work wear. This product distribution reflects the regional specialization in basic apparel, which trends to be highly sensitive to fashion obsolesce due to fast changing consumer preferences and competitive pressures.

Table 4.2 BLSEZ garment manufacturing company products

No	Main product	No of company manufactured	Percentage
	Adult ware	4	57%
	Children ware	1	14.3%
	Sport ware	1	14.3%
	Work ware	1	14.3%

Respondents include 33.33% supply chain managers and 60% supply chain expert, with remaining 6.33 % being production managers. This balance indicates that insights are capture from professionals deeply involved in both strategically and operational aspect of supply chain management. The experience profiles show that 53.33% have 4-6 years of experience, indicating the personnel's responses may based on a matured understanding of industry operations, while 33.33% and 13.33% fall into the 1-3 and 7-10 year of experiences respectively, providing a blend of fresh perspectives and seasoned expertise.

Educationally, the group is highly qualified 60% holding bachelor's degrees and 40% master's degrees. This suggests that the respondents possess both theoretical knowledge and practical skills, potentially influencing the depth and quality of their responses.

4.5.1 Factors influencing Product Obsolescence

Respondents assessed five key factors affecting product obsolescence on a 5-point Likert scale. The results reveal critical insights.

1. **Delays in transit time**

Transit time delays stand out as the most critical factor influencing product obsolescence 73.3%of respondent rating it as Very High and additionally 6.7% as high risk. This highlights the vulnerability of supply chain of transportation between inefficiency between sources and destination during logistics operation in BLSEZ garment manufacturing company context. This can disrupt the timely delivery of the products to market. Given the fast paced nature of the fashion industry, even minor delays can result in missed sales opportunities and increased inventory obsolescence. Therefore, addressing transit delays is paramount for companies seeking to maintain competitiveness and reduce lose.

2. **Longer Production Times**

The impact of longer production times on obsolescence risk appears to be perceived with moderate concern by majority of respondents, as 53.3% rated it as moderate. Meanwhile, 20% rated this factor as Very High, and another 20% as high, indicating that a minority still considers production delays a serious risk. A small portion, 6.7%, rated it as Low, suggesting that for some companies, production lead times are less problematic. This distribution reflects a mixed but generally cautious attitude toward production speed, implying that while many companies manage to keep production relatively stable, any extensions in lead times can still contribute meaningfully to the risk of the risk products becoming obsolete before reaching the market.

3. Rapid Fashion Trends

Rapid fashion trends are perceived as a highly significant factor contributing to fashion obsolescence risk, with 60% of respondents rating it as very high and additional 20% rating it as High. This overwhelming majority underscores the intense pressure on the companies to keep pace with fast changing consumer preferences and market dynamics; meanwhile, 6.7% rated this factor as moderate and 13.3 % as low, indicating that a smaller segment of respondents considers fashion volatility less critical possibly reflecting differences in product categories and market strategies

4. Unpredictable customer demand

Unpredictable customer demand and forecasting ambiguity present a significant challenge for managing obsolescence risk, as 47.7% of respondents rated this factor as high risk and 13.3% as a very high risk, together constituting the majority concerned about demand volatility. Meanwhile, 26.7% rated it as moderate risk, reflecting some uncertainty but less critical impact, and another 13.3% considered it low risk, indicating that a smaller portion of companies may have more stable or predictable demand patterns. These results emphasize the importance of improving demand forecasting accuracy and incorporating flexibility in supply chain planning to better align production with market needs and minimize the risks associated with demand fluctuations.

5. Customer behavior changes

Customer behavior changes appear to be perceived as a relatively low to moderate risk factor for product obsolescence, with 46.7% respondents rating it as low risk and an equal 46.7% rating as moderate risk. Only small minority, 6.7% consider changes in customer behavior to pose a high risk. This distribution suggests that while shifts in consumer preference are acknowledged, most companies may view them as manageable or less volatile compared to other factors such as transit time delays or rapid fashion trends. Nevertheless, ongoing monitoring of customer behavior remains important to anticipate market shifts and adjust strategies accordingly.

Among the various factors influencing fashion obsolescence risk, transit time delays and rapid fashion trends stand out as the most critical. A significant majority of respondents highlight the severe impact that logistical inefficiencies have on timely product delivery and market relevance. Similarly, a large portion of respondents considers rapid fashion trends to be a major risk, reflecting the intense pressure on companies to keep pace with fast-changing consumer preferences. These two fast factors dominate because they directly affect how quickly products can reach the market and remain desirable, especially in fast-moving apparel segments.

In contrast, other factors such as longer production times, unpredictable customer demand, and changes in customer behavior and viewed as moderate or lower risks by most respondents. Longer production times tend to be seen as manageable, while unpredictable demand shows some concern, but still less than transit delays and fashion trends. Changes in customer behavior are generally considered less risky, with most respondents rating them as low or moderate. This comparison underscores that while internal production and market uncertainties matter, the major drivers of obsolescence risk are external pressures related to supply chain logistics and rapidly evolving fashion obsolescence.

4.5.2 Existing logistics operation in BLSEZ

The logistics data collected from the seven garment manufacturing companies operating in the bole lemi special economic zone (BLSEZ) reveals a critical insight; 86% of the respondents rely on pave logistics plc as their primary logistics agent for their logistics operation. Given that Pave logistics plc is a focal case company for this research. This high percentage underscores the appropriateness and depth of the study's focus. It confirms that the logistics challenges, strengths, and practices identified through the document review and interview are highly representative of the actual conditions faced by the majority of manufacturers in the zone. But, only one company in sport wear segment reported using alternative logistics provider.

A significant majority of respondents 93% reported experiencing shipment delays. This high prevalence clearly indicates that transit inefficiencies are a systematic issue affecting most garment manufacturers in the BLSEZ. The widespread nature of these delays underscores the critical need to understand their cascading impacts on business operations and competitiveness.

Among the consequences of these shipment delays, order rejection stands out as the most acute problem, affecting 71.4% of respondents. This reflects the stringent delivery deadlines imposed by retailers and buyers in the fashion industry, where timing is a crucial. Failure to meet these deadlines often results in outright rejection of shipments, leading to immediate lost sales and damaging the manufacturer's reputation with key clients. The high rate of order rejection illustrates the zero tolerance nature of the fashion market regarding late deliveries.

Additionally, 50% of respondents indicated that shipment delays negatively impacted their market share. This suggests that persistent logistical failures reduce a company's ability to complete effectively, possibly because customers turn to competitors who can deliver more reliably and faster. Market share erosion is a serious long term threat that can undermine a firms sustainability and growth prospects.

The loss of customers was reported by 35.7% of respondents, highlighting that shipment delays not only affect immediate sales but also customer loyalty and retention. In a highly competitive apparel market, losing customers due to poor delivery performance can have significant ripple effects, including reduced brand equity and diminished word of mouth recommendations.

Furthermore, 14.3% of respondents experienced increased inventory costs as a consequence of shipment delays. These increased costs may result from the need to hold buffer stock or expedited shipments to compensate for unreliable transit times, typing up capital and increasing warehousing expenses.

Similarly, 14.3% reported an adverse impact on the cash flow, which is critical financial metric for manufacturing firms. Delays in shipments can postpone revenue recognition, disrupt payment cycles, and strain working capital, thereby limiting the company's ability to invest in operations or growth initiatives.

Regarding fashion cycles, the data shows that 64.3 % of garment manufacturing companies operate on cycles of 2 to 5 months, while 21.4% have cycles shorter than 3 months, and only 14.4% operate with cycles longer than one year. The significant prevalence of short to medium length cycles highlights the critical need for timely and reliable logistics services. Even minor shipment delays can cause products to miss essential market windows, leading to increased risks of product obsolescence and financial losses.

4.5.3 Factors influencing Transit time delay

The analysis explores the primary factors and impacts contributing to transit time delays in garment manufacturing company in BLSEZ logistics operations are multimodal transportation utilization, geographic conditions, route complexity, customs efficiency, documentation practices and personnel training and technology adoption.

The use of multimodal transportation emerged as a widely accepted strategy for optimizing transit time. According to the responses, 53.3% of participants agreed and 20% strongly agreed that their companies effectively utilize a combination of road, rail, air and sea transport. Although 26.7% remained neutral, there were negative responses, indicating that a majority of firms recognize the logistical benefits of multimodal approaches. This reflects a degree of operational maturity and suggest that most organization are actively seeks a way to enhance flexibility and mitigate risk through transport diversification.

Geographic challenges such as urban congestion, poor road conditions and regional infrastructure limitations were also identified as significant barriers to timely delivery. Here, 60% of respondents agreed and 40% strongly agreed that such factors impact their transit times, showing unanimous acknowledge of these structural constraints. The data strongly suggests that companies are operating within physical environments that inhabit efficiency, highlighting the need for infrastructural investments and government led improvements in transport networks.

However, opinions diverged on the issue of route complexity. While 33.3% agreed that complex routing leads to increased delays, 46.7% of respondents remained neutral, and a combined 20% disagreed or strongly disagreed. This distribution of responses indicates a lack of uniform understanding or prioritization of routing strategies within organizations. The prevalence of neutral responses may reflect insufficient data tracking capabilities or a limited reliance in advanced route optimization technologies in daily logistics planning.

Customs clearance efficiency was another factor assessed in the survey and was met with a clear consensus regarding its significance. A substantial 73.3% of respondents strongly agreed and 20% agreed that customs bottlenecks substantially impact overall transit times. Only 6.7% strongly disagree. These findings highlight the critical role customs operations play in international logistics and underscore the necessity for modernization of customs procedures.

Despite concerns around the customs delays, the responses regarding documentation practices were more mixed. While47.7% agreed and 20% strongly agreed that their teams ensure timely and accurate submission of customs paperwork, 20% were neutral, and 13.4% disagreed or strongly disagreed. This indicates variability internal compliance practice across firms. For organizations that fall short in documentation accuracy or timing.

Another critical factor influencing delivery performance is the competency of logistics personnel, particularly in loading and unloading operations. Equal proportions of respondents 35.7% each strongly agreed and agreed and that staff skill levels directly impact efficiency. However, 21.4% of participants either disagreed or strongly disagreed; while 7.1 % remained neutral these results reveal that majority appreciate the value of skilled workers.

Technology adoption received a less favorable overall assessment compared to other factors. While 40% agreed and 20% strongly agreed that technology helps reduce transit times, 26.7% were neutral and 26.6% disagreed or strongly disagreed, these finding point to significant disparities in the extent and effectiveness of digital integration across surveyed manufacturing companies.

The survey results on the factors of transit time delays indicate that companies are largely aligned on the importance of proper utilization of multimodal transportation, geographic realities between sourcing and delivery sites, and customs clearance efficiency as central determinants of transit time performance. However, internal operational factors such as documentation accuracy, worker skill, route selection and technology utilization show varied levels of implementation and perception.

4.6 pave logistics plc logistics operation and performance

As part of this research objective to analyze the logistics operations of garment manufacturing companies within the bole lemi special economic zone (BLSEZ). It was essential to identify a representative logistics service provider whose operational data could reflect the broader supply chain realities in the zone. According to the survey conducted among garment manufacturing companies operating in BLSEZ, 86% of respondents reported that they utilize pave logistics plc as their primary logistics agent both for sourcing raw materials and for delivering finished products tom retailers. This overwhelming majority indicates pave logistics central role in the regional supply chain network and justifies its selection for an in-depth document review. By examining pave logistics actual operations shows the routes, transport modes, infrastructure use, and performance of a detailed and realistic logistics currently managed in the BLSEZ.

According to data obtained from pave logistics plc, the company employs a free on board (FOB) Incoterm for most of its interactions. This structure places the responsibility for overseas freight on the buyer while the company focuses on managing transport from international ports into Ethiopia, customs clearance, and final inland delivery to client warehouses when sourcing raw material, similarly to delivery finished products from its client ware house to retailers. The logistics chain begins predominantly at shanghai port, china, from which approximately 80% of raw materials are source to BLSEZ garment manufacturers. India's Mundra port accounts for 17% and UAE ports for the remaining 3% .on the outbound side, 86% of finished garments are shipped to the UAE, 11% to Germany, and 3% to other destinations. This sourcing and distribution pattern confirms a concentrated logistics network with defined corridors, reducing route complexity but also creating high dependency on specific international ports.

The transportation route used by Pave Logistics plc for to source raw material from main raw material supplier location at shanghai port, from where goods are shipped via sea to the port of Djibouti. Upon arrival, containers are cleared through Djibouti ports by Djibouti and Ethiopia customs and forwarded either by truck or rail through the Djibouti-Dire Dawa –Addis Ababa corridor, with final customs clearance completed at Mojo dry port and Addis Ababa. The final destination for the most inbound shipments is the BLSEZ warehouse. This sequence spanning sea freight, cross border processing, inland transport, and multi-point customs clearance forms the backbone of material flow into the zone.

Pave logistics demonstrates notable flexibility and responsiveness in fleet management. The company operates with 30 company-owned trucks and supplements this with outsourced vehicles depending on the on the demand levels. At the lowest demand levels, 60 trucks are deployed. During regular operations, this increases to an average of 70 are used. All trucks are capable of handling 40 feet containers, in line with international freight standards. The utilization of road and rail for inland transport is also informed by urgency, cargo type and route conditions. While trucks handle over 92% of Paves inland logistics, the Ethio-Djibouti railways accounts for approximately 8%, providing an alternatives where appropriate.

Transit speeds vary by mode. Trucks operate between 40-50km/h, while the recently improved rail network has increased average speeds to 60km/h, offering a modest efficiency gain. Sea transport remains the lowest segment, with ships averaging 22km/h on the 11,000km route from shanghai to Djibouti, and 4000km from Djibouti to UAE to deliver finished products to main retailers' location, conversely, air freight is used for urgent or small volume orders, covering 8,400 km from shanghai to BLSEZ at an average speed of 800km/h. Air shipments are typically reserved for sub-20 feet container loads, or when rapid delivery is requested by clients. In some case, pave logistics uses air uses consolidation for below 20 feet containers when the raw materials or finished products not urgent though this can introduce delays if containers are not filled quickly enough with compatible cargo.

Customs clearance is a critical node within the logistics chain. Data indicates that the impractical average customs clearance time estimated to four hours per 20 feet containers including delays at major point Djibouti port, Mojo port, and BLSEZ. Among these, Djibouti port emerges as the primary bottleneck frequently cited for congestion, slow processing, and inconsistent handling protocols. These findings align with broader regional concerns around port capacity and efficiency in the horn Africa logistics corridor.

The outbound logistics flow for finished product mirrors the inbound route in reverse. Finished products are consolidated, packed, and loaded at BLSEZ warehouses, then trucked to Mojo dry port, where customs documentations and clearance are completed. From there, goods travel via road or rail to Djibouti port, and are shipped primarily to the UAE. This outbound logistics chain is similarly structured but typically involves less delay due to better streamlined nature of export procedures than import procedures in Ethiopia.

Pave's logistics operations are governed by a customer centric transport mode selection model. Transportation decisions such as the use of air versus sea or rail versus rail are influenced primarily by customer urgency and shipment volume. In terms of logistics performance, the data from pave logistics allows us to classify three distinct operational performances.

1. **Minimum transit time**

This represents the best logistics performance achieved by pave logistics plc during the 2023/2024 operational period when sourcing raw materials from shanghai and delivering fished products to the UAE. These optimal delivery times were not limited to one specific transport mode. Instead, minimum transit time were recorded across air, sea, and land route, depending on favorable conditions such as low congestion, efficient customs clearance, available fleet capacity, and clear demand forecasts. For example, when air shipments were fully loaded without delay or when sea shipments faced minimal clearance rime at Djibouti port, transit was significantly faster. Similarly, efficient rail or truck movement along the Djibouti-Mojo-BLSEZ corridor contributed to minimal inland delivery time.

2. **Standard transit time**

Standard transit time reflects the most frequently achieved logistics performance by pave logistics over the course of 2023/2024. It captures the normal operating conditions encountered when sourcing raw materials from shanghai and delivering to UAE retailers via a mix of sea, road, and rail transport. Under these conditions, there may be moderate customs processing times, average port handling delays, and typical traffic patterns along the inland corridors. Therefore these logistics performance represents the major disruptions and peak demand, and was observed across diverse shipment sizes and transportation modes.

3. **Maximum transit time**

The maximum transit time indicates that the worst performing delivery conditions recorded in 2023/24. These extended transit times occurred regardless of the transport mode air, sea or land and were mainly caused by uncertain operational factors such as customs clearance backlog(especially at Djibouti port), vehicle shortages, poor coordination for consolidated cargo, or infrastructure bottlenecks.

The detailed data and operational insights obtained from Pave logistics have been instrumental in developing and validating the Agent based model used in this research. By incorporating real-world distance, transport speeds, vehicle availability, clearance durations, and mode choices, the model replicates actual operational dynamics. The clear structure of sourcing, routing, and delivery documented in pave’s operations makes it an ideal case for representing BLSEZ logistics in the simulation environments.

Table 4.3 the document review of pave logistics plc main supply chain route

Logistic segment	Smallest transit time (hrs)	Mostly frequent transit time(hrs)	Largest transit time(hrs)
Shanghai-Djibouti (ship)	496	502	506
Djibouti-BLSEZ(truck)	31	41	44
BLSEZ- Djibouti(truck)	31	41	44
Djibouti-UAE(ship)	146	147	154
Customs at BLSEZ	0.5	3	24
Customs at Djibouti entry	6	10	14
Customs at Djibouti exit	6	10	14
Customs at UAE	0.4	0.4	0.4
Production time	22	24	26
Store when truck available	48	48	48

CHAPTER FIVE: MODEL DEVELOPMENT AND VALIDATION

Agent based modeling (ABM) is developed to explore how the supply chain interaction can be optimize to reduce transit time and, in turn, minimize fashion obsolescence risk, the primary objective of this model is to demonstrate the feasibility and benefits of using ABM to simulate the behavioral dynamics among supply chain actors including manufacturers, logistics agents, and retailers as they respond to time sensitive demand in the fashion industry. Unlike traditional supply chain models that focus on inventory or transportation cost minimization, this model focuses on how efficient coordination and responsiveness can suppress the risk of product obsolescence, which is especially acute in fast moving consumer industries like apparel.

In this ABM, agents operate in a distributed logistics environment modeled as a dynamic network that allows interaction between production hubs, distribution intermediaries, and demand nodes. For the purpose of this research, the decision is interpreted as the agent's selection of the most time efficient routing strategy or logistical configuration, which is crucial in timely delivery of fashion goods before they become outdated. These individual decisions collectively shape the emergent system behavior, allowing us to observe both micro level (agent decision) and macro level (system performance) outcomes, such as total transit time.

The modeling process begins with constructing a conceptual model that comprises three major elements: defined agent roles, integration network topology, and decision making rule ser. The agents' retailers, manufacturers, logistics providers and geographic hubs are characterized by attributes such as demand urgency, transit time constraints and processing capacity. The interactions are shaped by a semi-hierarchical with flexible linkages representing transport and communication paths. The agents' decisions are guided by a flow base logic tree where inputs like volume, time delay and available transport capacity determine the routing and execution of each supply task. These decisions are modeled with deterministic rules that reflect real world constraints, such as customs processing time or vehicle availability.

To incorporate uncertainty in decision making an inherent aspect of supply chain operation some logic nodes integrate probabilistic or threshold based decisions. This allows agents to adopt a preferred path dynamically, based on a real time conditions such as congestion or transport delays.

The final model is validated through simulation runs that track delivery time distributions and identify key choke points that contribute to obsolescence risk.

Key assumptions of the model

- Retailers serve as demand nodes with strict delivery time preferences, mimicking the pressure of short fashion cycles and promotional windows.
- Manufacturers initiate raw material sourcing and production only when logistics resources are confirmed, to avoid overproduction and idle inventory.
- Logistics agents (e.g., trucks, ships, aircraft) act as dynamics connectors between geographic nodes and are limited in number, creating a resource competition effect that can simulate real world congestion.
- Geographic nodes such as ports and processing centers are static and imposed delay penalties (e.g., customs clearance), influencing agents' routing behavior.
- Delayed shipments increase the likelihood of fashion obsolescence, which is treated as a system-level cost to be minimized

5.1 Features of the agent-based model

Agent based Modeling (ABM) is a powerful simulation approach used to capture complex systems composed of interacting autonomous agents. In the context of global supply chain and logistics operations, ABMs provide insights into dynamic processes such as order fulfillment, transportation routing, and resource constraints. This model was developed for pave logistics plc to replicate and analyze international logistics operations spanning multiple geographical regions shanghai (china), Djibouti (east Africa), BLSEZ (Bole lemi special Economic Zone in Ethiopia), and UAE by simulating various stakeholders retailers, manufacturers, logistics operators, and suppliers. This ABM reflects the real world conditions of supply chains involving multimodal transportation, customs processing, and production scheduling.

The model incorporates temporal dynamics, geographic separation, and capacity constraints such as vehicle availability and storage delays. By using simple but realistic rules, agents in the model interact to generate emergent patterns that reflect real logistics bottlenecks, delays, and performance metrics though this modeling, pave logistics PLC can better understand lead times, infrastructure dependencies. And decision making tradeoffs in supply chain design.

5.1.1 Defining Agents

The effectiveness of any agent based model lies in how well its agents encapsulate real world roles and how meaningfully they interact. In this logistics ABM for pave logistics PLC, the four core agent types' retailers, manufacturers, logistics agents, and suppliers were selected to mirror critical actors in an international supply chain. Each agent is a computational abstraction that embodies specific capabilities, decision rules, and constraints. Their collective behavior creates emergent phenomena that can be used to understand delays, resource bottle necks, and network dynamics under various conditions.

1. **Retailers**

Retailers act as the initial demand nodes in the model. Positioned in the UAE, they represent individual customer entities or market clusters that place product orders. In most supply chain models, demand forecasting is probabilistic or dynamic, but in this simplified version, each retailer places a onetime deterministic order. This design simplifies tracking and performance evaluation, allowing modelers to isolate how logistics decisions impact delivery outcomes.

However, the retailer's role extends beyond merely triggering a product a production cycle. Retailers also function as observers and evaluators of the supply chain performance in the case of transit time performance. They record the transit time from order placement to delivery, serving as the key metric for system responsiveness. This feedback is crucial in simulations aiming to optimize logistics configuration, test new delivery routes, or assess the impact of infrastructure changes.

Retailers are assigned to manufacturers in a fixed manner, representing contractual or regional relationships. This reflects real world dynamics where companies often deal with specific vendors. This fixed assignment removes randomness and enhances comparability between simulation runs.

2. Manufacturers

Manufacturers located in the bole lemi special economic zone (BLSEZ) act as the core transformation agents in the model. Their responsibilities span order processing, material procurement, production management, and outbound logistics coordination. Each manufacturer maintains a queue of current orders, processing them in sequence. This queue is not just a storage mechanism but a reflection of production planning decisions that directly influence lead times.

When a new order is received, t6he manufacturer evaluates whether raw materials are on hand. If not, it immediately initiates a logistics request to shanghai, the origin point for raw materials. Once materials are delivered, the manufacturer begins productions, which are volume sensitive, larger orders take longer to produce. This introduces a dynamic link between order size and delivery time, critical for understanding tradeoffs in batch size in batch size and resource allocation.

Once production is completed, manufacturers again depend on available logistics agents to dispatch the final product to the United Arab Emirates retailers. This dual dependency on inbound and outbound logistics makes the manufacturers a synchronization point in the supply chain.

3. Logistics Agents

Logistics agents are arguably the most complex and dynamic agents in the system. They serve as the transportation backbone, executing both inbound (shanghai to BLSEZ) and outbound (BLSEZ to UAE) deliveries. Each agent is task-oriented, activated only when assigned a delivery by manufacturer. Once assigned, a logistics agent becomes temporarily unavailable until the task cycle is completed. What sets logistics agents apart is their conditional routing logic. They must determine the mode of transport air freight vs. sea plus truck combination based on the volume of cargo. This introduces variability in delivery times; resource consumption (e.g. truck allocation).agents must also navigate a predefined movement path involving multiple legs and location specific customs delays at nodes such as Djibouti and UAE.

Furthermore, logistics agents consume resources such as truck availability, a shared constraint that introduces system wide interdependence. For example, if multiple logistics agents are assigned large-volume delivers at once, the system may experience a truck shortage, causing cascading delays.

Their state transitions from idle to active to complete simulate the real world cycling of transport assets. Once a delivery task is finished, agents reset and become available for reassignment, enabling dynamic task allocation, and reflecting fleet utilization patterns.

4. **Suppliers**

The supplier agents differ from others in that they are static, non-interactive nodes. They represent the geographical landmarks shanghai rather than human or corporate actors. These nodes are essential to defining the spatial topology of the model. Every logistics movement originates from at this node.

While they do not possess decision making logic, suppliers play an important functional role, they act as location anchors for calculating distances, imposing customs delays, and structuring delivery paths. For example, Djibouti is the key transshipment point for sea freight, while shanghai is the origin of all raw materials. Each supplier node has a location specific customs delay introducing variability and realism into logistics calculation by embedding such delays, the mode simulates the regulatory and infrastructural friction present in real world logistics operations. By embedding such delays, the model simulates the regulatory and infrastructural friction. Even though suppliers are not agents in the decision theoretic sense, their inclusion as agent entities facilitates the modular design of the model, allowing them to interact with mobile logistics agents in a structural way.

5.1.2 Collective dynamics and agent interdependency

Together, these four agent types create a tightly interwoven system that mimics core elements of international logistics. The flow is initiated by retailers, processed and transformed by manufacturers, executed logistically by transport agents, and constrained by geographical suppliers.

The inter dependence among agent types leads to dynamic behaviors

- A retailer’s order timing affects when a manufacturer queues the task.
- A manufacturer’s ability to fulfill orders depends on the both raw material availability and transport resources.
- A logistics agent’s availability affects multiple manufacturers, leading to indirect coupling between seemingly independent retailer- manufacturer pairs.

- Supplier delays influence every step, functioning like environmental constraints that shape agent decisions.

These interactions collectively reflect the complex adaptive system nature of the supply chains, where decentralization decisions, local rules, and global constraints interact to produce emergent outcomes such as delays, idle time, and utilization bottlenecks.

5.2 Agent's Interaction Topology

In an agent based model (ABM), the interaction topology defines the rules and structure though which agents exchange information, share resources, and affect each other's state. Unlike centralized or fully distributed system, the topology in this logistics ABM is semi-hierarchical, combining clear upstream and downstream flows with decentralized decision-making and resource contention. This hybrid structure enables the model to reflect both the organizational formality of fixed contracts and the operational flexibility of real world logistics networks.

1. **Retailers and Manufacturers interaction**

At the top layer of the interaction topology lays the retailer-manufacturer relationship. Each retailer is statically assigned to a single manufacturer in the BLSEZ. This one to one mapping simulates long term business arrangements, such as exclusive supply contracts or regional partnerships. Because of this fixed relationship, the interaction is non-negotiable and deterministic retailers send orders only to their designated manufacturer in bole lemi special economic zone. From a topological standpoint, this layer forms a star-like structure, with manufacturers as the hubs and retailers as the spokes. The lack of cross linking among retailers or between manufacturers removes complexity and enforces a linear interaction chain. This simplicity facilitates clarity in the simulation; isolate the effects of manufacturing delays and logistics availability without introducing randomness in order allocation. Despite being static, it determines the initial load distribution among manufacturers, which in turn affects production, queuing delays, and eventual delivery times. Any imbalance in order size or timing across retailers translates into asymmetric workloads across manufacturers, which in turn affects production scheduling, queuing delays, and eventual delivery times. Ant imbalance in order sizes or timing across retailers translates into asymmetric workloads across manufacturer, which then propagates downstream through the system.

2. Manufacturers and logistics company interaction

The second layer introduces a dynamic and resource constrained interaction between manufacturers and logistics agents. Manufacturers do not possess inherent transportation capabilities; instead, they issue requests for logistics support whenever they need to ship raw materials from shanghai or finished products to UAE. Logistics agents, in turn, exist in a global idle pool and can be dynamically allocated based on availability.

This creates a many to many matching topology, where each manufacturer can interact with any logistics agent, but only on a temporary, task specific basis. The matching is opportunistic and synchronous there is no scheduling mechanism that reserves agents in advance, nor is there prioritization logic embedded in the model. As a result, manufacturers are subject to logistics bottlenecks, especially under high demand or constrained resource conditions.

3. Logistics company and supplier interaction

The third layer of interaction occurs between logistics agents and suppliers, forming the geospatial backbone of the model. Unlike previous layers, this interaction is not about communication or negotiation but about mobility and spatial traversal. Each logistics agent follows a path defined by its delivery type (raw materials and finished goods), volume, and mode of transport.

Suppliers' agents are static nodes at shanghai transport to Djibouti; manufacture at BLSEZ, and deliver to UAE each representing real world logistics landmarks. As logistics agents move between these locations, they experience distance dependent delays, customs processing times and resource specific constraints (e.g., truck unavailability). The directionality and irreversibility of movement agents cannot turn back or reroute mid-task mirror real world transportation constraints where shipments are often pre planned and difficult to modify once dispatched.

The sequential dependency in logistics and supplier interaction further constraints agent behavior, For example, an agent moving from shanghai to BLSEZ via Djibouti must complete each leg before initiating the next. Delays at any node are accumulative, and cannot be parallelized, which introduces further time sensitivity and bottlenecks.

4. Cross Agent Resource contention

Perhaps the most interesting aspect of this topology is the emergent interdependence created by resource constraints, particularly the logistics agents and trucks. Even though agents do not directly communicate or compete, they are bound by shared operational infrastructure. This creates a latent network of indirect interactions a form of competition that arises not from negotiation but from the temporal coincidence of demand. This interdependence forms a non-explicit interaction network, where an action by one agent (e.g., reserving a truck for a large shipment) influences the options available to others. The topology thus exhibits distributed coupling, where every action reverberates through the system via shared resource pools. For instance, under normal demand levels, logistics agents operate smoothly with minimal delays, but under peak conditions, such as simultaneous large volume orders, the system can enter a congestion phase, where logistics availability becomes the limiting factor for system throughput. This reflects real world logistics crises where transportation capacity, rather than production ability, becomes the bottleneck.

5.3 Agents' Rule and Decision making

The intelligence of the ABM lies in the decision rules that govern agent behavior. These rules are context sensitive and often depend on environmental parameters like order volume, available trucks and current simulation time.

Retailers operate with binary decision logic, if an order has not yet been placed and the retailer has a positive order volume, it triggers a purchase by notifying its manufacturer. The decision is one off, reflecting scenarios like batch procurement or demand fulfillment within a single time period.

Manufacturers have more complex behavior. Upon receiving an order, they append it to their queue and check for logistics availability. If a logistics agent has resource for transportation, they assign a raw material sourcing task, which includes choosing between air and sea transport based on container volume. Once raw materials arrive, the manufacture schedules production based on volume and a constant production rate dispatching goods to UAE.

Logistics agents follow a rule based execution plan, when assigned a task; they create a list of delivery steps customs delay, movement and further customs checks. They choose between air or sea and truck or train and routs based on the volume. The rules also consider resource consumption and release. Trucks are deducted from the global pool during a shipment and returned once the task is completed. Each task also accumulates total transit time.

5.4 Simulating the supply chain of BLSEZ garment industries

The simulation model is developed using Netlogo 6.4.0 with a focus on modeling a supply chain network for fashion logistics. The spatial grid in the interface represents a simplified geographic flow of goods, simulating critical logistics hubs such as Shanghai, Djibouti, BLSEZ (Bole lemi special economic zone), and the UAE. These points represent the major stages in the product flow from sourcing raw materials to delivering finished goods to retailers. Within this framework, seven retailers (labeled R0 to R6) are distributed vertically along the UAE node, each simulating a fashion enterprise capable of placing unique orders.

The simulation incorporates four types of agents: suppliers, retailers, manufacturers, and logistics agents. Suppliers, located in shanghai, serve as the origin of raw materials and are represented as red circular nodes. Retailers are the demand driving agents positioned in the UAE, represented as blue house shaped icons. These retailers have independent order volumes which can be adjusted via sliders in the interface. Manufacturers are based at the BLSEZ hub and are responsible for processing raw materials into finished products. Through they are not visualized in this version, they play a core role in the time required to fulfill orders. Logistics agents are abstracted into mathematical transit time calculations instead of animated movement, simulating the flow of materials between nodes by accounting for transport speed, distance, and potential delays.

Figure 5.1 2D view of the major route of BLSEZ garment industries supply chain

The distance between supply chain nodes are carefully chosen to reflect realistic values. For example, goods traveling by sea from Shanghai to Djibouti cover 11,000 kilo meters, while truck transport from Djibouti to BLSEZ is modeled as 1000 km, counted twice due to daytime only truck driver operation. Further distance includes 3,276 km by ship from Djibouti to the UAE, and air routes of 8,400 km (Shanghai to BLSEZ) and 2,011km from BLSEZ to UAE. These distances are converted to time using corresponding speeds, the average ship speed (22km/h), truck speed (50km/h), and air speed (800km/h).

In the simulation, geographic distances between supply chain nodes are not just spatial elements. They serve as the foundation for calculating time based logistics performance. The distance by each mode of transport (e.g., sea, land, or air), the model simulates how long it takes for goods to move between locations. This introduces temporal realism to the system and enables comparative evaluation of different transport strategies.

Beyond basic transit time, the model integrates a number of logistical constraints to mirror real world inefficiencies. Customs delays are imposed at key nodes (shanghai, Djibouti, BLSEZ, and UAE), with their magnitude dependent on the number of containers being processed. For large volume orders, these delays also increase during inspection and done all requirements of the customs officers. Production time is another major contributor, especially for bulk orders, calculated as the average production speed of bole lemi special economic zone depend of the workers and other resource of production and the volume of orders. The model also considers store delays, representing internal handling or warehousing processes before outbound delivery is initiated.

Furthermore, the truck availability is modeled as a finite resource depend on the amounts of truck utilize in pave logistics plc operation, simulating capacity constraints in a ground logistics. If the number of trucks required for transport exceeds the available fleet, truck delays are introduced and representing queuing time or waiting periods for vehicles to return and become available. These design choices add operational constraints that simulate congestion, delays, and resource shortage, making the system more reflective of real supply chain behavior under stress or high demand.

One of the most important concepts in this simulation in the fashion period, set at 2,160 hours, which represents the threshold time before an order becomes obsolete. This value equates to three months (90 days) depend on the recent studied a cycle for fast fashion items. After which a product is considered outdated or undesirable. In the simulation, once a retailer place an order, the system computes its total transit time by summing all delays and transport segments. If this time is less than or equal to 2160 hours, the delivery is marked as on time; otherwise, it is categorized as obsolete. This captures the performance of fashion products and emphasizes the importance of fast and efficient logistics.

The visual layout of the model uses colors and shapes to distinguish agent roles and supply chain points. Red identifies shanghai (the main raw material supplier for BLSEZ garment manufacturers), yellow represents Djibouti port (transit hub), green is used for BLSEZ (Production site), and white denotes the UAE (retailers location). Retailers themselves are shown in blue, labeled R0 to R6 for easy tracking. These visual cues, combined with dynamic output such as monitors and plots, allow users to track the evaluation of in time and obsolete deliveries during the simulation.

5.4.1 Simulation variables of the supply chain

The Netlogo interface is equipped with a set of interactive sliders and output monitors that allow users to control the simulation's input variables and observe its outcomes dynamically. These sliders are crucial in shaping the initial configuration of the system. While the monitors provide feedback on the performance metrics. In the context of this simulation, the environment represents a fashion supply chain network involving several key logistical locations shanghai, Djibouti, BLSEZ, and the UAE and a set of retailers who place and receive fashion product orders.

The model features seven retailers, each represented by a corresponding slider: Vol-ro to Vol-r6. These sliders are used to assign the volume of 20 foot container ordered by each retailer, reflecting the diversity in demand levels across the in demand levels across the enterprise network. This modular input structure allows users to simulate a wide range of scenarios from low volume distributed demand to high volume concentrated orders by adjusting the values of individual sliders.

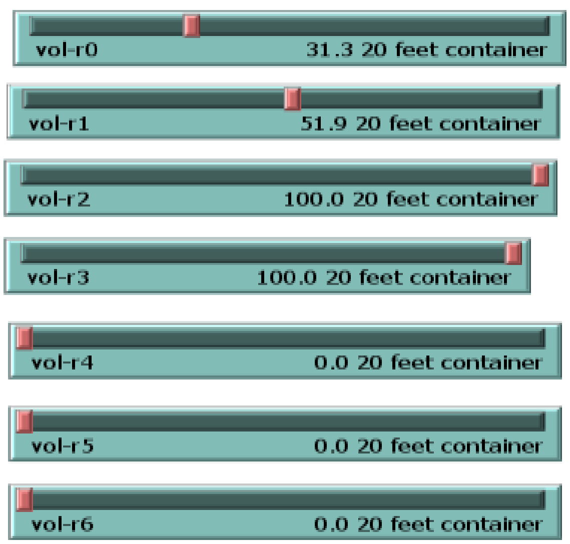

Figure 5.2 retailers order sliders

In the current configuration, as shown in the above image, the values of these sliders are unevenly distributed as example. Retailers R2 and R3 have the highest demand, each retailer can order until 100 containers, while R1 and R0 are set at 51.9 and 31.3 containers, respectively. Retailers R4, R5 and R6 are inactive, with their order volumes set to zero. This setup models a partially active fashion market, where only some enterprises are aggressively sourcing goods, while others are dormant or observing market trends. By controlling these sliders, the simulation captures variations in enterprise decision making.

To assess system performance, the model employs three output monitors, as shown in the third image. Total transit time, on time deliveries and obsolete deliveries.

- The total transit time sum the delivery duration for processed orders, incorporating all contributing factors transport time, customs delays, truck delay, and production time. It provides a cumulative measure of logistical effort and system load.

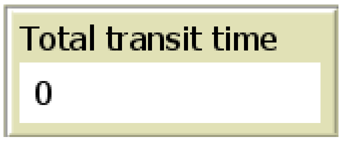

Figure 5.3 supply chain total transit time monitor

- The on-time deliveries monitor counts the number of retailers whose orders are completed within the fashion window of 2160 hours (equivalent to 90 days), this threshold represents the validity period of a fashion item, reflecting the urgency with which goods must be delivered to remain relevant in a rapidly changing market.

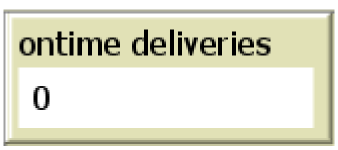

Figure 5.4 supply chain on-time deliveries monitor

- The obsolete deliveries monitor tracks how many orders exceed the 2160 hour limit. These deliveries are considered missed opportunities, as the fashion trend has already passed by the time they reach the market, rendering the goods unsellable or heavily discounted.

Figure 5.5 supply chain obsolete deliveries monitor

These three metrics provide a comprehensive performance overview of the supply chain under the current simulation configuration depend on the retailers order volume and the logistics agent decision for selection of mode of transportation. This simulation offers valuable insights into the relationship between order volumes, resource availability, route selection, and production time and delivery performance in a fast fashion supply chain. It highlights how small challenges in demand (as controlled by sliders) can have cascading effects on system performance, especially when resource constraints and time sensitive market conditions are present.

5.5 Model validation

Model validation was conducted to evaluate whether the simulation accurately reflects the real world behavior of transit times in the fashion supply chain. This validation process compared simulation's results with observed data collected from document review pave logistics plc operational performance. Which reported the smallest, most frequently achieved, and largest transit and customs times recorded during past one year operations involving the transportation of two 20 foot containers.

The real world supply chain scenario under consideration involves four key stages: shipment from shanghai to Djibouti, trucking from Djibouti to the BLSEZ, return from BLSEZ to Djibouti, and shipment from Djibouti to the UAE. In addition, customs clearance time was measured at both Djibouti and BLSEZ, and standard model based values were used for average production time (12 hours per containers) and store delay 48 hour after finished the production. The collected data are presented in table 4.3

Using this data, total transit time was calculated for three scenarios smallest possible, most frequently achieved, and largest possible. These were computed by summing the respective times for each segment.

- Smallest total transit time

Smallest transit time = smallest transit time b/n [customs at shanghai + (Shanghai-Djibouti) + (customs at Djibouti) + (Djibouti-BLSEZ) + (customs at BLSEZ) +

(production time) + store time + customs at BLSEZ + (BLSEZ -Djibouti)+ (customs at Djibouti)+(Djibouti-UAE)

Smallest total transit time = 0.5+496+6+31+0.5+24+48+0.5+31+6+146+0.4

=789 .9 hours

- Most frequently achieved total transit time

Most frequently achieved total transit time = mostly achieved transit time b/n [customs at shanghai + (Shanghai-Djibouti) + (customs at Djibouti) + (Djibouti-BLSEZ) + (customs at BLSEZ) + (production time) + store time + customs at BLSEZ + (BLSEZ -Djibouti)+ (customs at Djibouti)+(Djibouti-UAE)

Mostly achieved total transit time = 0.5+502+10+41+3+24+48+3+41+10+147+0.4

=829.9 hours

- Largest total transit time

Largest transit time = Largest transit time b/n [customs at shanghai + (Shanghai-Djibouti) + (customs at Djibouti) + (Djibouti-BLSEZ) + (customs at BLSEZ) + (production time) + store time + customs at BLSEZ + (BLSEZ -Djibouti)+ (customs at Djibouti)+(Djibouti-UAE)

Smallest total transit time = 0.5+506+14+44+24+24+48+24+44+14+154+0.4

=896 .9 hours

The model simulation result under the same conditions produced a total transit time of 834.709 hours. This values lies comfortably between the most frequently achieved total transit time and largest total transit time values, indicates that the simulation neither underestimates nor significantly overshoots the realistic logistic durations.

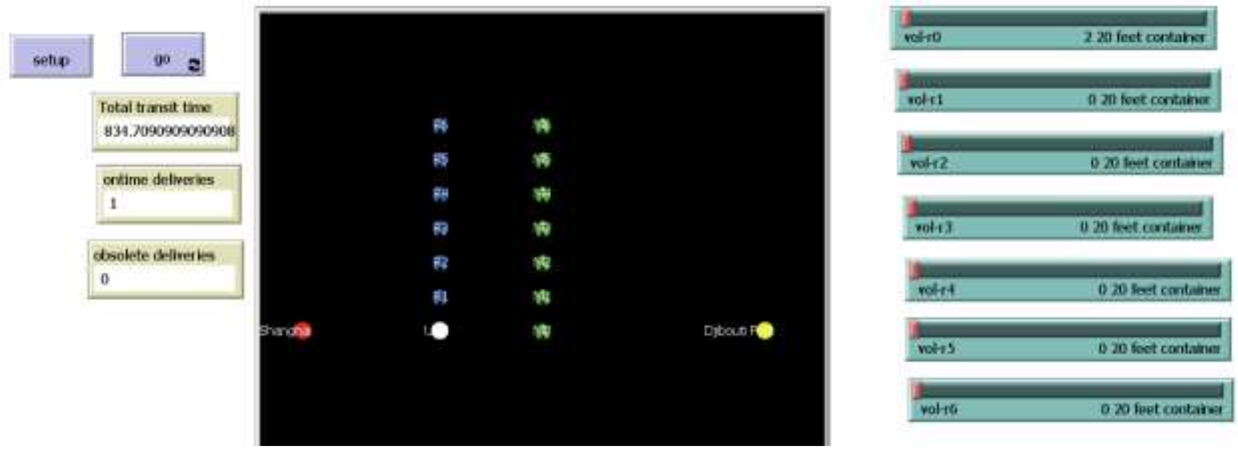

Figure 5.5 the simulation output at two 20 foot containers

To further assess the model accuracy statistically, a triangular distribution was assumed based on the three collected values. The expected (mean) value and standard deviation were estimated using the following.

$E = \frac{a+4m+b}{6} = \frac{789.9 + 4(829.9)+896.9}{6}$ = 834.4 hours and where a= smallest transit time

$S= \frac{b-a}{6} = \frac{896.9-789.9}{6}$ = 17.8333 m= most frequently transit time

b = largest transit time

The total transit time at 95 % of confidence level calculated

CI = E ± ZS The Z vale at 95% level of confidence =1.96

CI= 834.4 ± 1.96*17.833 = (799.44 hours and 869.35 hours)

The model's simulated result of 834.7 falls within this confidence interval, validating that the model out aligns with realistic expectations with 95% statistical confidence. The small deviation from the most frequent value suggests that the simulation captures logistical variability due to customs delays and transport dynamics accurately, especially under moderate to high load conditions.

In addition, the performance of 40 ft container transportation from raw material sourcing to delivery according to pave logistics experience and Netlogo based agent based simulation by two

20 ft containers had small difference due to the model assumption to reduce the complexity of dynamics and the above data based validation show the level error of assumption based modeling and actual performance had not greater than 5%.

5.6 Simulation Experiment

5.6.1 Adoption of an additional logistics agent at BLSEZ

In the baseline configuration of the model, only one logistics agent or Pave logistics plc is responsible for transporting raw materials from Djibouti to BLSEZ and finished products from BLSEZ to the UAE. As the simulation was scaled to represent the maximum possible combined order volume from all seven retailers, the system demonstrated full operational capability by handling a total of 269 twenty foot containers without triggering any fashion obsolescence with in 10,000 simulation hours. Each retailer placed between 30 and 46 containers, summing to a cumulative total transit time of 13,212.46. All seven orders were delivered within the 2,160 hour fashion lifecycle window.

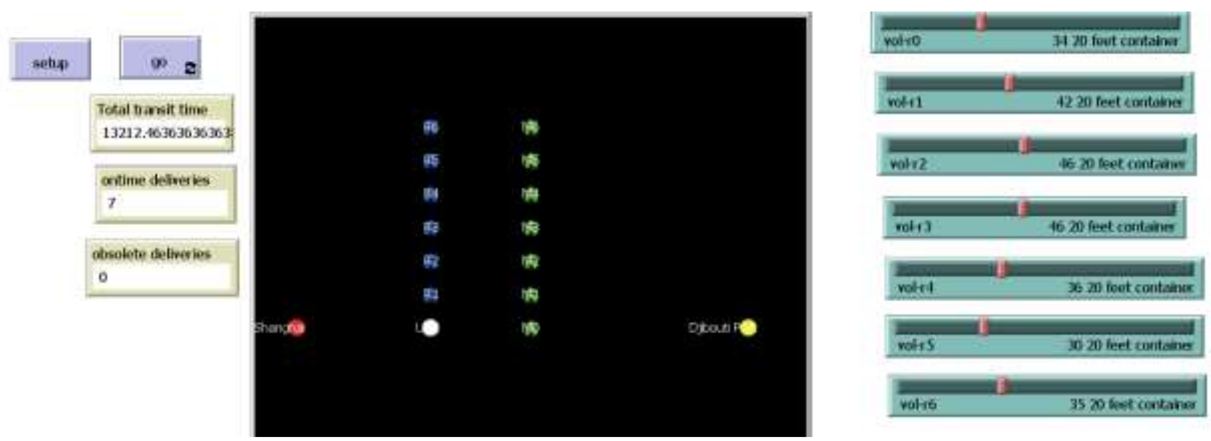

Figure 5.6 simulation result at the maximum order of seven retailers within fashion cycle window with one logistics agent

Despite achieving 100% on time delivery under this specific load, the result also revealed a critical capacity limitation. The cumulative total transit time exceeded or 1857 for each order transit time, suggesting that if any further load were added or if uncertain delays occurred in production, customs, or truck turn around fashion product obsolescence would become inevitable. This pointed to a saturation point of the logistics system, beyond which it cannot absorb additional demand without performance degradation.

To evaluate the effectiveness of capacity enhancement in reducing fashion obsolescence risk and improving logistics throughput, an experimental intervention was conducted using the existing net logo based supply chain simulation model by introducing a second logistics agent. This agent was identical capability or real competitor by each performance and resource with the first logistics agent pave logistics agent, to assign delivery tasks to the agent with more active trucks. This design aimed to reduce queuing time, balance the logistics workload, and improve overall system efficiency.

Using an input scenario of 269 containers distributed across seven retailers, the baseline model (with only one logistics agent) completed delivery in 13,212.46 hours. When the simulation was rerun with two agents in parallel operation, the total delivery time reduced to 12,125.46 hours.

Figure 5.7 simulation result at the maximum order of seven retailers within fashion cycle window with two logistics agent

- **Transit time reduction**

Reduced transit time = total transit time with one agent - total transit time with two agent.

Reduced transit time =13,212.46 hours - 12,125.46 hours.

Reduced transit time =1,087 hours

% reduction of total transit time= 8.23 %

- **Percentage of obsolescence Risk mitigation**

The fashion period is limited to 2,160 hours, beyond which deliveries become obsolete. In the baseline model, fashion obsolescence began once total container orders exceeded 269 containers. However, the two agent system successfully delivered up to 378 containers within the same threshold, with zero obsolete deliveries.

% of obsolescence risk mitigation = Capacity before Obsolescence by 2 agent- Capacity before Obsolescence by 1 agent/ Capacity before Obsolescence by 1 agent.

% of obsolescence risk mitigation = 378-269/269*100 = 40.52%

Experiment 2: supply chain delay reduction by 10 % across critical factors.

In the first experiment done the structural expansion and their result on the transit time reduction and mitigation fashion obsolescence. The second experiment was focused on intensive process optimization yielded significant improvements in supply chain; this experiment explores the supply chain optimization effects on the improvement across several key logistical components, each improved by 10%. The goal is to simulate realistic enhancements that can be achieved through modest technological upgrades, workforce adjusting, or operational streamlining, and observe how much moderate changes impact on total transit time and fashion obsolescence risk. This experiment keeps the system structure constant using only one logistics agent and focuses exclusively on improving internal efficiency.

These improvements expected inspired by realistic interventions, such as

- Investing in automation and extra labor at production facilities to reduce production time
- Upgrading to modern trucking fleets or improving driver logistics to increasing the truck speed.
- Implementing digital customs clearance systems and smart documentation to reduce port delays

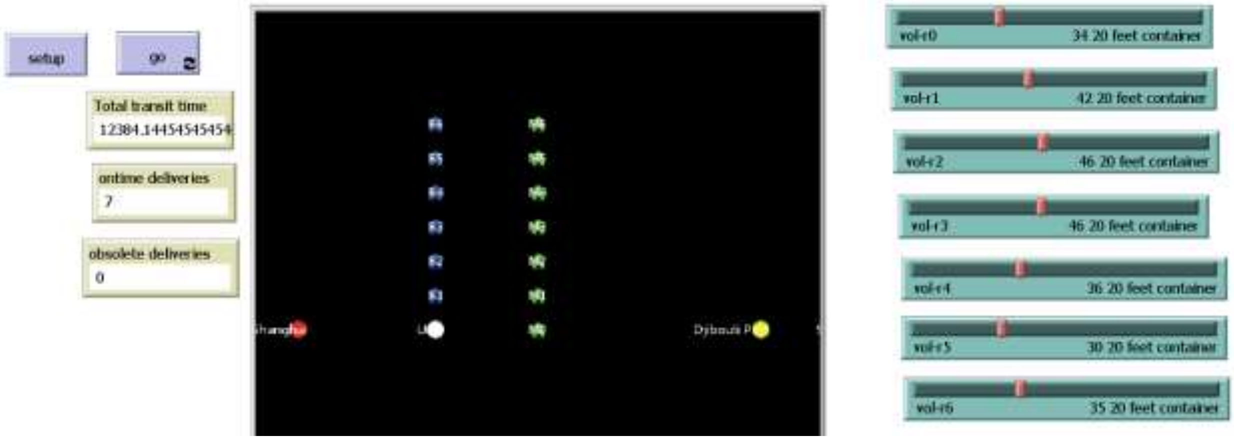

Figure 5.8 simulation result after improvement of supply chain delays after transporting 269 containers

- **Transit time reduction**

Reduced transit time = total transit time without improvement - total transit time with improvement

Reduced transit time =13,212.46 hours - 12,384.14 hours.

Reduced transit time =828.32 hours.

% reduction of total transit time= 6.27%

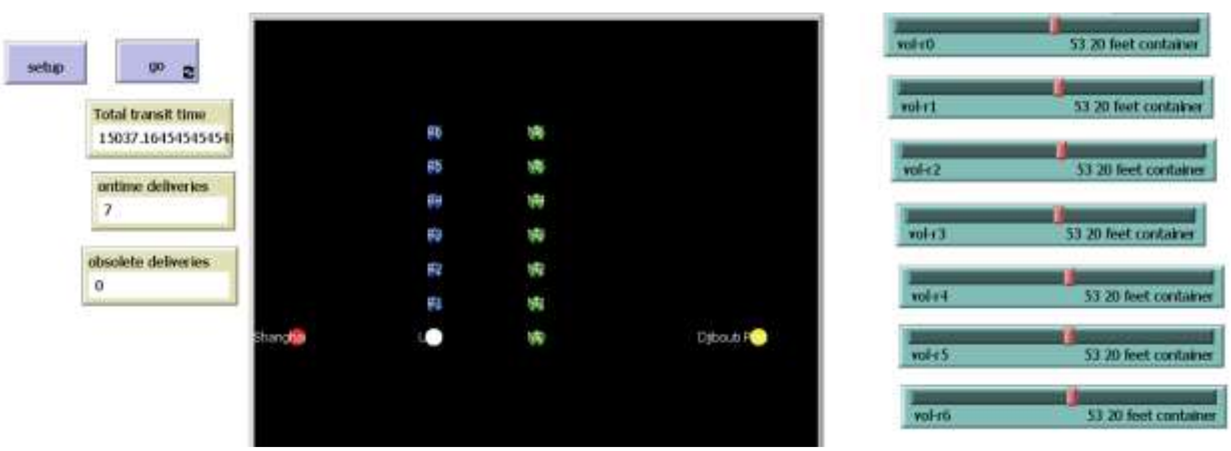

Figure 5.9 simulation result at the maximum order of seven retailers within fashion cycle window with improvement of supply chain

- **Percentage of obsolescence Risk mitigation**

Similarly the above, the fashion period is limited to 2,160 hours, beyond which deliveries become obsolete. In the baseline model, fashion obsolescence began once total container orders exceeded 269 containers. However, the supply chain system was improved by 10% and successfully delivered up to 371 containers within the same threshold, with zero obsolete deliveries.

% of obsolescence risk mitigation = Capacity before Obsolescence after improvement - Capacity before Obsolescence before improvement/ Capacity before Obsolescence before improvement

% of obsolescence risk mitigation = 371-269/269*100 = 34.45%

Experiment three

This experiment explores the compound effect of combining both strategies. Rather than relying on either agent expansion or process enhancement alone, this simulation synchronizes both the addition of a second logistics agent and a 10% improvement in critical operational parameters such as truck speed, customs clearance, and production time.

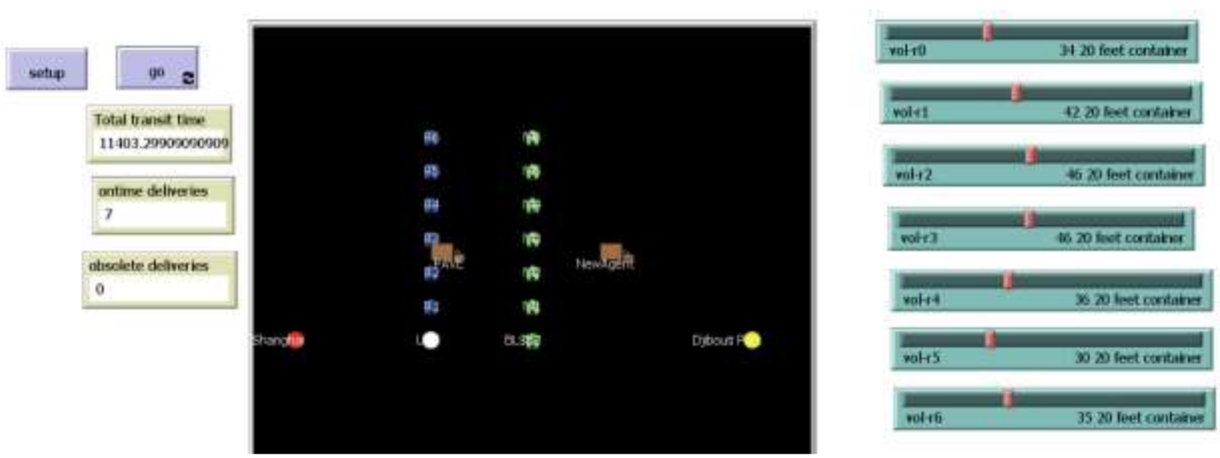

Figure 5.10 simulation result after combined improvement of supply chain delays and with two agents after transporting 269 containers

- **Transit time reduction**

Reduced transit time = total transit time without improvement and with one agent- total transit time with improvement and with two agents

Reduced transit time =13,212.46 hours - 11,403.3 hours.

Reduced transit time =1,809.16 hours.

% reduction of total transit time= 13.7%

- **Percentage of obsolescence Risk mitigation**

Similarly the above, the fashion period is limited to 2,160 hours, beyond which deliveries become obsolete. In the baseline model, fashion obsolescence began once total container orders exceeded 269 containers. However, the combined supply chain systems was improved by 10% and operate by two logistics agents are successfully delivered up to 427 containers within the same threshold, with zero obsolete deliveries.

% of obsolescence risk mitigation = Capacity before Obsolescence after combined strategies - Capacity before Obsolescence before combined strategies / Capacity before Obsolescence before combined strategies

% of obsolescence risk mitigation = 427-269/269*100 = 58.74%

5.7 Discussion

Logistics efficiency plays a pivotal role in the competitiveness of industrial parks, especially in time sensitive global value chains such as apparel and fast fashion. The Bole lemi special economic zone (BLSEZ) in Ethiopia has been established to anchor Ethiopia's position in the export textile sector. However the multiple bottlenecks including truck shortages, customs delays, underutilization of digital coordination etc are affect the operation of logistics to reach products under their fashion periods completed. To assess how different interventions affect fashion relevant delivery outcomes, this research modeled three logistics strategies under simulated conditions, using 2160 hours (approximately 3 months) as the standard fashion shelf life.

The first intervention evaluated the impact of introducing an additional logistics agent representing an expansion in transport capacity without major process changes result showed that by adding just one more agent, on time delivery volume increased from 269 containers to 378 containers improving performance by approximately 40.52%, in the context of BLSEZ, this is not only impactful but also highly feasible. The zone currently partners with pan Africa logistics plc as a dedicated transport service provider. Rather than building entirely new capacity, BLSEZ stakeholders can initially strengthen this existing agent's performance by expanding its truck fleet, improving scheduling discipline, and ensuring reliable dispatch from Djibouti. This can be achieved with modest capital investments and operational agreements. Thus, expanding or enhancing the capacity of pan Africa logistics plc is a practical short term solution that can be implemented within three months.

The second intervention involved achieving a 10% improvement across the entire supply chain. This includes customs clearance speed, manufacturer production lead time, logistics coordination, and even unloading time at the final retailer location. While this scenario offered less dramatic gains than the new agent strategy in high load conditions, it significantly reduced delivery variability and improved responsiveness, especially at moderate throughout levels. In BLSEZ, however, such improvement is challenging due to fragmented coordination among supply chain stakeholders. Customs processes at Djibouti and Djibouti border entry points often rely on manual paperwork, and Ethiopia border entry points often rely on manual paperwork, and communication, unwanted delay by the customs operation bureaucracy, and communication between BLSEZ manufacturers and logistics agents remains offline. Nevertheless, improvements are possible through digitalization, training, and policy alignment. For example digital retailers order and fashion period based production scheduling systems for manufacturers and service demand forecasting and resource scheduling tools can help achieve required the supply chain improvement. These initiatives, while requiring more time and institutional effort, provide a foundation or continuous, scalable improvement.

The third experiment combined both strategies; adding a logistics agent and improving the system by 10%. This hybrid model provided the highest performance or it can reduced the fashion obsolescence risk by 58.74%, enabling the system to deliver up to 427 containers before the fashion shelf life expired. This becomes a practical upper threshold for current BLSEZ capacity under optimized conditions. Beyond 427 containers per 10,000 hours, the model showed rising delivery delays and increased fashion obsolescence suggesting that syatem saturation also began at this point again when the production volume and the garment manufacturer increase above 427 containers. To accommodate this large and continuous production volume increment in the special economic zone will required, similarly introducing new additional agents or increase the capacity existing logistics agents and improving the supply chain performance continuously through a time by utilizing high speed transportation resource and routes, automating customs and gate operations etc.

Based on Ethiopia's context and BLSEZ's operational conditions, this study recommends a passed intervention strategy. First, the most feasible and impactful approach is to strengthen the current logistics partner (pan Affric logistic plc or introducing new logistics agent in the special economic zone). These improve truck allocation, route reliability, capacity scheduling and responsiveness in the logistics operation once agent performance is stabilized, then the supply chain agents should collectively target at least 10% of improvement at their operation. Finally the supply chain operation gain combined improvement by additional new agent and 10% of processes improvement in the special economic zone logistic operation can reduce the fashion obsolescence risk by more than 58% compared to the actual operation of BLSEZ. These cumulative efforts will ensure that BLSEZ remains competitive even as export volume increases and fashion cycles accelerate.

An important contextual insight from this research is the mismatch between assumed fashion shelf life and actual manufacturer perception. This model assumes that fashion value decays after 2160 hours or 3 months, which reflects global fashion calendar realities. However, 64.3% surveyed employees at BLSEZ manufacturers reported that their products typically remain in fashion between 3 to 5 months, 21.4% are below three or three months only and the rest respondent their product fashion period waiting for over one years. This finding positions the simulation's outcomes as a strategic warranty even though current products may have longer fashion windows period than 3 months, future shifts toward fast fashion (shorter cycles, tighter delivery windows) will demand higher logistics responsiveness. Therefore, this thesis not only provides evidence for improving current operations but also future proofs BLSEZ logistics strategy against anticipated shifts in the market expectations.

5.8 Implementation Framework

This framework provides a structured approach to improve logistics responsiveness and reduce fashion obsolescence risk among garment manufacturers in the BLSEZ. The stockholders in the fashion should following

1. **Strategic Scenarios**

Scenario 1: introduce competitive logistics providers to drive service innovation

Scenario 2: achieve a 10% performance improvement at pave logistics through training, system upgrades, and better coordination.

Scenario 3: combine new agent entry with internal process enhancement for broader efficiency gains.

2. **Stockholders Role**

- BLSEZ administration invite and provide incentive to new strong competitive logistics agent
- Pave logistics plc: upgrade fleet responsiveness, adopt digital tracking, improve loading/ unloading efficiency
- Government/ customs authorities; streamline clearance procedures, reduce port congestion, improve the road and rail facilities at least by 10% from now performance.
- Manufacturers: align the production schedule with logistics timelines, improve forecast sharing, and support digital collaboration platforms.

3. **Resource Requirements**

- Fleet and infrastructure upgrades(road, rail, warehousing)
- Investment in digital tracking platforms and automation
- Training program for fashion supply chain stockholder employees

4. Implementation Timeline

- Short term(less than one year): introducing competitor agent for sustainability of SEZs

    - Action: BLSEZ administrators to invite strong logistics competitor by offering strategic incentives to stabilize the logistics environment in the short term and maintain investor confidence by mitigating overdependence on single provider.

- Medium term (12-24 months): performance improvement across the supply chain

    - Once competition is introduced and operating, the focus shifts to improving supply chain performance by at least 10%through system wide optimization. key improvement areas include:

        - Customs clearance: streamline operations using electronic data interchange (EDI) systems, integrate pre clearance processes and automate paperwork to reduce delays.
        - Transportation infrastructure: upgrade and maintain road networks between Djibouti and BLSEZ and expand rail capacity and optimize schedules and speed on the Ethio- Djibouti corridor.
        - Government Role: provide policy stability, investor protections, and logistics infrastructure funding. And facilitate public private partnerships to accelerate development.
        - Manufacturers: optimize production planning to better align with shipment.
        - Training and Technology adoption(all stockholders) : adopt supportive technology and training to improve performance

- Long term(above months) continuous improvement and integration: fully implement data driven logistics system and foster a culture of collaborative improvement across BLSEZ's logistics ecosystem

5. Monitoring and Evaluation

- KPIs: average transit time, on time delivery rate, order rejection rate and obsolescence loss percentage.
- Tools: Monthly dashboards, quarterly performance reviews, and stockholder feedback loops

6. Expected Outcomes:

- Transit time reduction by up to **58.74%**.
- Enhanced delivery reliability and reduced inventory obsolescence.
- Strengthened competitive positioning of BLSEZ as a global apparel export zone.

CHAPTER SIX: CONCLUSITION AND RECOMMENDATION

6.1 CONCLUSITION

The global fashion industry is undergoing significant transformation, with trend cycles now evolving at a rapid pace often lasting no more than three to four months. This accelerated turnover, driven by social media and fast fashion consumption patterns, places extraordinary pressure on garment manufacturers to deliver products to market within increasingly narrow timeframes. The failure to do so results in fashion obsolescence, characterized by unsold inventory, markdowns, and financial losses. In this context, prolonged and unpredictable supply chain transit time emerge as a critical risk factor, particularly in developing and landlocked countries such as Ethiopia, where transportation infrastructure, customs operations, and technological integration remain underdeveloped.

This study focused on addressing these challenges within bole lemi special economic zone (BLSEZ), a key industrial area for textile and garment production in Ethiopia. Despites its strategic importance in attracting foreign direct investment, BLSEZ faces persistent logistics bottlenecks that undermine its ability to respond effectively to the rapid cycles of the global fashion market. The study's general objective was to mitigate the risk of fashion obsolescence by improving supply chain transit times. Specifically, the research sought to evaluate current logistics practices, the operational capacity of logistics agents, and the potential of various improvement scenarios to enhance supply chain responsiveness.

The analysis of existing logistics processes revealed that current systems within BLSEZ are poorly aligned with the dynamic requirements of the fashion industry. Outdated procedures, limited coordination among stakeholders, and delays in customs clearance contribute significantly to extend lead times, causing products to arrive late to market and miss critical sales windows. Furthermore, the evaluation of logistics agents; capacity indicated that many operators lack the responsiveness and spend required to meet fashion cycle demands, further exacerbating delivery challenges.

To address these issues, the study molded three distinct improvement scenarios. The first scenario introduced new, more capable logistics agents to the ecosystem, aimed at increasing operational speed and reliability. The second scenario focused on improving the performance of existing agents by 10%, targeting stockholders process improvement. The third and most comprehensive scenario combined both approaches introducing new agents and while simultaneously improving the performance of existing ones by 10%. Results from the simulations showed that all three contributed for mitigating fashion obsolescence risk 40.52%, 34.45% and 58.74 respectively. The integrated approach not only shortened delivery times more effectively but also enhanced overall supply chain reliability and positioning BLSEZ as a more viable and competitive hub for fashion related investment.

6.2 Recommendations

To address these challenges and position Ethiopia as more attractive destination for textile and garment investments, several recommendations are proposed. For policymakers, it is critical to invest in high speed and high capacity logistics infrastructure. The country needs multimodal transportation system that can efficiently move large volumes of cargo across boarders' and within its territory. Upgrading rail corridors, improving road connectivity, and ensuring seamless intermodal transitions will help mitigate the limitations of being landlocked and enable the faster movement of goods to and from ports.

In parallel, customs operations must be digitized and streamlined. This includes the implementation of digital technology systems. Automated clearance procedures, and integrated tracking platforms that allow for real time visibility and reduced human error by reducing fully paper work, manual inspection delays, and redundant processes. Policymakers should also consider introducing specific incentives or support schemes for logistics operators and exporters that meet international performance standards.

For garment manufacturers, it is essential to optimize production cycles to adapt to the fast pace of fashion trends. Investing in flexible manufacturing systems, lean inventory management, and closer supplier coordination can help reduce turnaround times and enable quicker responses to market demands. Manufacturers should also build stronger partnerships with logistics providers to align production schedules with delivery capabilities, leveraging real time data and digital tools to monitor and adjust operations dynamically.

Logistics service providers, meanwhile, must shift their focus toward offering time sensitive and reliable services. This means redesigning their service offerings to prioritize speed, reliability, and customer responsiveness. Using technology such as advanced route optimization, digital cargo tracking, and predictive delivery systems can greatly enhance performance and customer satisfaction. In a sector where delays can mean missed market windows and financial losses, logistics agents must evolve to meet the increasing expectations of both manufacturers and global buyers. By implementing these strategic improvements, Ethiopia can strengthen its logistics ecosystem, support the growth of its textile and garment industries, and enhance its appeal to international investors. A modern, efficient, and responsive logistics system is not fust an economic necessity. It is critical enabler of industrial competitiveness and sustainable development in a globalized market.

6.3 Future Research Direction

Future researchers are encouraged to explore the integration to explore the integration of artificial intelligence (AI) in modeling fashion demand and production cycles, particularly in the context of Ethiopia's growing garment industry. The fashion sector is highly dynamic, with demand patterns that shift rapidly due to social media influence, seasonal trends, and global consumer behavior.AI tools such as machine learning algorithms and predictive analytics can be employed to forecast demand more accurately, detect emerging trends in real time, and align production planning with market fluctuations. By building AI data driven model, it can simulate and gain better results and can forecast the future fashion demand and fashion cycle duration. Such research would contribute not only to academic knowledge but also to practical solutions that enhance the competitiveness of Ethiopia's textile and garment industries on the global stage.

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ANNEX-A Data collection Tools

Questionnaires

Addis Ababa University

Addis Ababa institute of Technology

School of mechanical and industrial engineering

Dear Participant,

Greetings, As Mulugeta Fekade, a researcher at Addis Ababa University, conducting a study aimed at **mitigating fashion obsolescence risk** in garment manufacturing companies within the Bole Lemi Special Economic Zone (BLSEZ).

The goal of this research is to mitigate fashion obsolescence risk in garment manufacturing companies within BLSEZ by reducing the transit time of the supply chain. Your expertise as a key stakeholder in the management of garment manufacturing companies within BLSEZ is invaluable to this endeavor. Therefore, your participation is respectfully requested.

Your insights will significantly contribute to the development of a robust and practically applicable model. **All information provided will be treated with strict confidentiality** and used solely for academic research purposes. Participation is voluntary and may be withdrawn at any time without consequence. The survey/interview is estimated to require approximately 20-30 minutes of your time. Your candid responses are essential for accurately portraying the key issues pertinent to this research.

For any enquiry, please contact:

Researcher: MulugetaFekade +251-933729016 or mulugetafekade89@gmail.com

Advisor: Dr. Ameha+251-911948014

Thank you in advance for your time and genuine response!

Section 1: Background Information

1. Company Name: ____
2. Your Company Main product:
   - o Children's Wear
   - o Adult Wear
   - o Sportswear
   - o Formal Wear
   - o Work wear
   - o Other ____
3. Your Role
   - o General manager
   - o Supply chain manager
   - o Production manager
   - o Supply chain expert
   - o Other ____________________________________
4. Years of Experience in this Role
   - o Less than 1 year
   - o 1-3 years
   - o 4-6 years
   - o 7-10 years
   - o More than 10 years
5. Educational Qualification
   - o High School Diploma
   - o Bachelor's Degree
   - o Master's Degree
   - o PHD

<u>Section two: factors influencing product obsolescence</u>

Please rate how much each of the following factors affect your company's risk of fashion obsolescence by putting ***(X)*** *mark based on the following level of effect scale that affect your operation according to your experience.*

1. No Effect
2. Low
3. Moderate
4. High
5. Very High

No	**Descriptions of factors**	**1**	**2**	**3**	**4**	**5**
1	To what extent do delays in transit time contribute to fashion obsolescence?					
2.	How much do longer production times increase the risk of products becoming obsolete before reaching the market?					
3.	To what degree does the rapid pace of fashion trend cycles lead to a higher rate of obsolescence for products?					
4.	How essential is accurate forecasting in minimizing the risk of fashion obsolescence in offerings?					
5.	To what extent do changes in customer behaviors regarding fashion trends directly impact the obsolescence of products?					

<u>Section three: Logistics Overview</u>

In this section, please answer the questions based on your company's actual logistics operations and Mark (X) on the answer bullet

1. Do you have an agent to manage your logistics operations?
    - Yes
    - No
2. If you answered 'Yes' to Question 1, which logistics company is handling it?
    - Pave Logistics PLC
    - Africa Logistics PLC
    - Other (please specify):________________________________
3. Has your company experienced delays in shipments of finished garments due to transit time issues?
    - Yes
    - No
4. If you answered 'Yes' to Question 3, which of the following consequences have resulted from these transit time delays?
    - Increased inventory cost
    - Order rejection
    - Loss of customers
    - Reduced market share
    - Impact on cash flow
    - Other (please specify): ____
5. How long is the fashion cycle waiting period for your type of product manufactured?
    - Less than 3 months
    - 3-5 months
    - 5-7 months
    - 7-9 months
    - More than 1 year

Section Four: factors influencing Transit time delays

*Please rate for the following factors that affect your company's transit time performance by putting **(X)** mark based on the following level of agreement scale.*

1. Strongly Disagree
2. Disagree
3. Neutral
4. Agree
5. Strongly Agree

No	Descriptions of factors	1	2	3	4	5
1	Your company effectively utilizes different modes of transportation (e.g., road, rail, air, sea) to optimize transit times.					
2.	Geographic features in your region (e.g., urban density, road conditions) significantly impact our transit times.					
3.	The complexity of your chosen transportation routes leads to increased transit times					
4.	The efficiency of customs clearance processes significantly impacts our overall transit times.					
5.	Your team ensures that all customs documentation is accurate and submitted on time to avoid delays.					
6.	The skill level and training of your loading/unloading personnel directly affect your efficiency in meeting delivery schedules.					
7.	The use of technology in our logistics operations helps reduce transit times.					

Thank you!

Interviews

Semi structured Interview to reduce transit time to mitigate fashion obsolesce risk for pave logistics personnel

- What is the average transit time for shipments from BLSEZ to export ports, and what factors affect this time the most?
- How do you prioritize and allocate transport resources (e.g., trucks, containers) when handling multiple manufacturer orders?
- What are the common challenges you face in meeting delivery schedules, especially for fashion products?
- How flexible is your logistics operation in adapting to urgent or fast-cycle shipment needs?
- What types of transportation modes and routing strategies do you currently use, and how are decisions made between them?
- What logistics improvements (technology, coordination, capacity) do you believe are most urgently needed to reduce transit delays?

Semi structured Interview to reduce transit time to mitigate fashion obsolesce risk for Ethiopian Customs officials

- What are the typical steps involved in customs clearance for export shipments from BLSEZ?
- What are the main causes of delays during the customs process?
- How do variations in shipment documentation, inspection, or compliance affect processing time?
- Are there any efforts underway to digitize or streamline customs procedures at the BLSEZ or associated ports?
- How often do customs delays contribute to missed export deadlines, especially for time-sensitive products like garments?
- What recommendations would you give to improve customs efficiency and reduce clearance times?

Semi structured Interview to reduce transit time to mitigate fashion obsolesce risk for BLSEZ Manufacturer personnel

- From your experience, what are the main factors that contribute to delays in delivering your products to export destinations?
- How does transit time affect your ability to meet fashion cycle deadlines or market trends?
- What is the average shelf life or trend-relevance period of your fashion products, and how sensitive is your production to time-based delivery?
- In what ways do logistics delays impact your production planning and inventory management?
- Have you experienced instances where fashion products became obsolete due to late delivery? If so, what were the consequences?
- What interventions or improvements in logistics would most help your company reduce delivery delays and improve competitiveness?

ANNEX –B MODEL PROGRAMMING CODE

FOR ONE AGENT

```
breed [retailers retailer]
breed [manufacturers manufacturer]
breed [logistics logistics-agent]
breed [suppliers supplier]

globals [
  total-transit-time
  simulation-duration
  ship-speed
  truck-speed
  air-speed
  ship-distance-shanghai-to-djibouti
  truck-distance-djibouti-to-blsez
  ship-distance-djibouti-to-UAE
  air-distance-shanghai-to-blsez
  air-distance-blsez-to-UAE
  store-delay
  container-threshold
  location-blsez
  location-shanghai
```

```
  location-djibouti
  location-UAE
  fashion-period
  fashion-start-tick
  obsolete-deliveries
  on-time-deliveries
  max-trucks-per-location
]

retailers-own [
  order-volume
  transit-time
  fashion-obsolete?
]

to setup
  clear-all
  reset-ticks

  set total-transit-time 0
  set fashion-period 2160
  set obsolete-deliveries 0
  set on-time-deliveries 0
  set simulation-duration 10000

  set ship-speed 22
  set truck-speed 50
  set air-speed 800

  set ship-distance-shanghai-to-djibouti 11000
  set truck-distance-djibouti-to-blsez 1000
  set ship-distance-djibouti-to-UAE 3276
  set air-distance-shanghai-to-blsez 8400
  set air-distance-blsez-to-UAE 2011

  set store-delay 48
  set container-threshold 20
  set max-trucks-per-location 50

  set location-shanghai [-80 0]
  set location-djibouti [-20 0]
  set location-blsez [0 0]
  set location-UAE [60 0]

  ; Visual markers
  create-suppliers 1 [
    setxy item 0 location-shanghai item 1 location-shanghai
    set shape "circle" set color red set label "Shanghai"
  ]
  create-turtles 1 [
    setxy item 0 location-djibouti item 1 location-djibouti
    set shape "circle" set color yellow set label "Djibouti Port"
  ]
  create-turtles 1 [
    setxy item 0 location-UAE item 1 location-UAE
```

```
    set shape "circle" set color white set label "UAE"
  ]

  ; Create manufacturers at BLSEZ
  let j 0
  while [j < 7] [
    create-manufacturers 1 [
      setxy item 0 location-blsez (item 1 location-blsez + j * 2)
      set shape "house"
      set color green
      set label word "M" j
    ]
    set j j + 1
  ]

  ; Create retailers at UAE
  let vols (list vol-r0 vol-r1 vol-r2 vol-r3 vol-r4 vol-r5 vol-r6)
  let i 0
  while [i < length vols] [
    let vol item i vols
    create-retailers 1 [
      setxy item 0 location-UAE (item 1 location-UAE + i * 2)
      set order-volume vol * container-threshold
      set shape "house" set color blue
      set transit-time 0
      set fashion-obsolete? false
      set label word "R" i
    ]
    set i i + 1
  ]
end

to go
  if ticks >= simulation-duration [ stop ]
  ask retailers [ process-order ]
  tick
end

to process-order
  if order-volume = 0 [ stop ]

  let containers ceiling (order-volume / container-threshold)
  let delivery-time 0
  let truck-delay 0
  let trucks-needed ceiling (containers / 2)

  ; Air transport
  if containers <= 1 [
    set delivery-time
      (air-distance-shanghai-to-blsez / air-speed) +
      (air-distance-blsez-to-UAE / air-speed) +
      calculate-customs-delay "Shanghai" containers +
      calculate-customs-delay "BLSEZ" containers +
      calculate-customs-delay "UAE" containers +
      store-delay
```

```
  ]

  ; Sea + Truck transport
  if containers > 1 [
    if trucks-needed > max-trucks-per-location [
      set truck-delay (truck-distance-djibouti-to-blsez / truck-speed)
    ]
    set delivery-time
      calculate-customs-delay "Shanghai" containers +
      (ship-distance-shanghai-to-djibouti / ship-speed) +
      calculate-customs-delay "Djibouti" containers +
      (2 * (truck-distance-djibouti-to-blsez / truck-speed)) +
      calculate-customs-delay "BLSEZ" containers +
      (12 * containers) + ; production time
      store-delay +
      calculate-customs-delay "BLSEZ" containers +
      (2 * (truck-distance-djibouti-to-blsez / truck-speed)) +
      calculate-customs-delay "Djibouti" containers +
      (ship-distance-djibouti-to-UAE / ship-speed) +
      calculate-customs-delay "UAE" containers +
      truck-delay
  ]

  set transit-time delivery-time
  set total-transit-time total-transit-time + transit-time

  ifelse transit-time <= fashion-period [
    set fashion-obsolete? false
    set on-time-deliveries on-time-deliveries + 1
  ] [
    set fashion-obsolete? true
    set obsolete-deliveries obsolete-deliveries + 1
  ]

  set order-volume 0
end

to-report calculate-customs-delay [location containers]
  if location = "Shanghai" [ report containers * 0.5 ]
  if location = "Djibouti" [ report containers * 5 ]
  if location = "BLSEZ"    [ report containers * 3 ]
  if location = "UAE"      [ report containers * 0.4 ]
  report 0
end
```

FOR TWO AGENT

```
breed [retailers retailer]
breed [logistics logistics-agent]
breed [manufacturers manufacturer]
breed [suppliers supplier]

globals [
  total-transit-time
  simulation-duration
  ship-speed
  truck-speed
  air-speed
  ship-distance-shanghai-to-djibouti
  truck-distance-djibouti-to-blsez
  ship-distance-djibouti-to-UAE
  air-distance-shanghai-to-blsez
  air-distance-blsez-to-UAE
  store-delay
  container-threshold
  location-blsez
  location-shanghai
  location-djibouti
  location-UAE
  fashion-period
  obsolete-deliveries
  on-time-deliveries
]

retailers-own [
  order-volume
  transit-time
  fashion-obsolete?
]

logistics-own [
  agent-name
  active-djibouti-trucks
  active-blsez-trucks
]

manufacturers-own [
  assigned-retailer
]

to setup
  clear-all
  reset-ticks

  ;; Config
  set total-transit-time 0
  set simulation-duration 10000
  set fashion-period 2160
  set obsolete-deliveries 0
  set on-time-deliveries 0

  set ship-speed 22
```

```
set truck-speed 50
set air-speed 800

set ship-distance-shanghai-to-djibouti 11000
set truck-distance-djibouti-to-blsez 1000
set ship-distance-djibouti-to-UAE 3276
set air-distance-shanghai-to-blsez 8400
set air-distance-blsez-to-UAE 2011

set store-delay 48
set container-threshold 20

set location-shanghai [-80 0]
set location-djibouti [-20 0]
set location-blsez [0 0]
set location-UAE [60 0]

;; Display key locations
create-suppliers 1 [
  setxy item 0 location-shanghai item 1 location-shanghai
  set shape "circle"
  set color red
  set label "Shanghai"
]

create-turtles 1 [
  setxy item 0 location-djibouti item 1 location-djibouti
  set shape "circle"
  set color yellow
  set label "Djibouti Port"
]

create-turtles 1 [
  setxy item 0 location-blsez item 1 location-blsez
  set shape "house"
  set color green
  set label "BLSEZ"
]

create-turtles 1 [
  setxy item 0 location-UAE item 1 location-UAE
  set shape "circle"
  set color white
  set label "UAE"
]

;; Logistics Agents
create-logistics 2 [
  set shape "truck"
  set size 2
  set color brown
  if who mod 2 = 0 [
    set agent-name "PAVE"
    setxy -5 5
  ]
```

```
    if who mod 2 = 1 [
      set agent-name "NewAgent"
      setxy 5 5
    ]
    set label agent-name
    set active-djibouti-trucks 0
    set active-blsez-trucks 0
  ]

  ;; Retailers and Manufacturers
  let vols (list vol-r0 vol-r1 vol-r2 vol-r3 vol-r4 vol-r5 vol-r6)
  let i 0
  while [i < length vols] [
    let vol item i vols
    let y-offset i * 2

    create-retailers 1 [
      set order-volume vol * container-threshold
      setxy item 0 location-UAE (item 1 location-UAE + y-offset)
      set shape "house"
      set color blue
      set label word "R" i
      set transit-time 0
      set fashion-obsolete? false
    ]

    create-manufacturers 1 [
      setxy item 0 location-blsez (item 1 location-blsez + y-offset)
      set shape "house"
      set color green + 1
      set label word "M" i
      set assigned-retailer one-of retailers with [label = word "R" i]
    ]

    set i i + 1
  ]
end

to go
  if ticks >= simulation-duration [ stop ]
  ask retailers [ process-order ]
  tick
end

to process-order
  if order-volume = 0 [ stop ]

  let containers ceiling (order-volume / container-threshold)
  let trucks-needed ceiling (containers / 2)
  let delivery-time 0
  let truck-delay 0

  ;; Air Transport
  if containers <= 1 [
    set delivery-time
```

```
      (air-distance-shanghai-to-blsez / air-speed) +
      (air-distance-blsez-to-UAE / air-speed) +
      calculate-customs-delay "Shanghai" containers +
      calculate-customs-delay "BLSEZ" containers +
      calculate-customs-delay "UAE" containers +
      store-delay
  ]

  ;; Sea + Truck
  if containers > 1 [
    ;; --- Import ---
    let import-agent max-one-of logistics [50 - active-djibouti-trucks]
    if [active-djibouti-trucks] of import-agent + trucks-needed > 50 [
      set truck-delay truck-delay + (truck-distance-djibouti-to-blsez / truck-speed)
    ]
    ask import-agent [
      set active-djibouti-trucks active-djibouti-trucks + trucks-needed
    ]

    let import-time
      calculate-customs-delay "Shanghai" containers +
      (ship-distance-shanghai-to-djibouti / ship-speed) +
      calculate-customs-delay "Djibouti" containers +
      (truck-distance-djibouti-to-blsez / truck-speed)

    ;; --- Production ---
    let production-time (12 * containers)
    let blsez-delay calculate-customs-delay "BLSEZ" containers

    ;; --- Export ---
    let export-agent max-one-of logistics [50 - active-blsez-trucks]
    if [active-blsez-trucks] of export-agent + trucks-needed > 50 [
      set truck-delay truck-delay + (truck-distance-djibouti-to-blsez / truck-speed)
    ]
    ask export-agent [
      set active-blsez-trucks active-blsez-trucks + trucks-needed
    ]

    let export-time
      store-delay +
      blsez-delay +
      (truck-distance-djibouti-to-blsez / truck-speed) +
      calculate-customs-delay "Djibouti" containers +
      (ship-distance-djibouti-to-UAE / ship-speed) +
      calculate-customs-delay "UAE" containers

    set delivery-time import-time + production-time + export-time + truck-delay

    ;; Release trucks
    ask import-agent [ set active-djibouti-trucks active-djibouti-trucks - trucks-
needed ]
    ask export-agent [ set active-blsez-trucks active-blsez-trucks - trucks-needed ]
  ]

  ;; Final tracking
```

```
  set transit-time delivery-time
  set total-transit-time total-transit-time + transit-time

  ifelse transit-time <= fashion-period [
    set fashion-obsolete? false
    set on-time-deliveries on-time-deliveries + 1
  ][
    set fashion-obsolete? true
    set obsolete-deliveries obsolete-deliveries + 1
  ]

  set order-volume 0
end

to-report calculate-customs-delay [location containers]
  if location = "Shanghai" [ report containers * 0.5 ]
  if location = "Djibouti" [ report containers * 5 ]
  if location = "BLSEZ"    [ report containers * 3 ]
  if location = "UAE"      [ report containers * 0.4 ]
  report 0
end
```