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Studying the Moderating Effects of Additive Manufacturing Best Practices Between Supply Chain Complexity and Its Performance

Tekalign Lemma [1], Hirpa G. Lemu [2,*] and Endalkachew Mosisa Gutema [1,2]

[1] College of Engineering and Technology, Wollega University, Nekemte P.O. Box 395, Ethiopia; tekalignlemma507@gmail.com (T.L.); endalkem5@gmail.com (E.M.G.)
[2] Faculty of Science and Technology, University of Stavanger, 4036 Stavanger, Norway
* Correspondence: hirpa.g.lemu@uis.no

Abstract: *Background:* Supply chain performance (SCP) is impacted by complexity brought about by static and dynamic drivers. This study aims to investigate the effects of supply chain complexity (SCC) on SCP and ascertain whether additive manufacturing best practices have moderating effects on this relationship. *Methods:* Using data from 29 Ethiopian footwear industries and 205 respondents, the relationship established in the theoretical framework was validated using structural equation modelling (SEM). *Results:* The study's findings provided several important insights. First, upstream supply chain complexity (USSCC), midstream supply chain complexity (MSSCC), and downstream supply chain complexity (DSSCC) negatively affect SCP. Second, additive manufacturing best practices have significant moderation effects between supply chain complexity and supply chain performance. Third, the negative impacts of USSCC and MSSCC on SCP are reduced at a higher level of additive manufacturing adaptation. The findings of this study also revealed that the effects of DSSCC on SCP have no difference at both low and high levels of additive manufacturing best practices. *Conclusions:* This work offers the first empirical investigation to which the detrimental effects of SCC on SCP are mitigated or improved through the moderating role of additive manufacturing best practice.

Keywords: additive manufacturing; best practices; moderator; supply chain complexity; supply chain performance; structural equation modeling

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1. Introduction

In today's supply chain management, measuring and identifying factors that influence supply chain performance (SCP) is critical for success, and for strategically managing and continuously improving the achievement of firm's objectives. Among the factors that affect SCP, supply chain complexity (SCC) takes priority. Supply chain complexity is termed as condition of inter-dependence and inter-connectedness of entities across a network [1]. This complexity is created by the static and dynamic drivers within the supply chain network [2]. The level of SCC within the network is a significant performance bottleneck and one of the most pressing concerns confronting contemporary SCs Please check all author names carefully [3]. In particular, the number of levels created due to static and dynamic drivers like number and variety of products, supplier variety, number and reliability of supplier, customer heterogeneity, and demand uncertainty within supply chain (SC) network substantially affects the performance of supply chain and makes supply chain management more challenging.

According to Malina [4], increased complexity due to these drivers negatively affects the firms' efficiency in terms of cost, flexibility, and lead time. Studies also indicate that high levels of SCC have negative effects on performance [5]. Similarly, an increase in SCC leads to a more complex supplier network [6], higher SC costs [7], and poor customer service [8]. Higher levels of complexity significantly reduce competitiveness, cost efficiency, customer satisfaction, and market share [9]. Constantin et al. [10] reported the negative association between SCC and performance, while other researchers, for instance, Lu and Shang [11] and Pathak et al. [12], reported the positive effects of SCC on performance. Similarly, the study by Memiş [13] found that some of the supply base complexity drivers have positive effects in improving firm performance. According to Ates et al. [14], low levels of complexity improve the performance of those firms with long-term strategies. On the other hand, the study [15] indicated that the performance of supply chain depends on the degree of complexity found within the network. The level of these complexities varies between industries and countries due to cultural differences and customer requirements of management practices.

In this regard, different studies used different types of methodologies, procedures, or strategies to study the effects of SCC on SCP. Brandon et al. [16] used the moderating effects of slack resource to study supply chain base complexity on disruption and performance. The study by Ateş and Memiş [17] examined the moderating effects of strategic purchasing on the relationship between supply base complexity and performance. The study by Giannoccaro et al. [18] investigated the effects of the number of firm and level of the supply interaction on supply chain network performance by considering the scope of control as moderator, and their findings revealed the negative effects of complexity on SC network performance. Furthermore, other studies suggested qualitative techniques and tactics to show how to reduce SCC through lean manufacturing [19], flexibility [20], and operational strategy [21].

Other studies have also qualitatively verified the use of Industry 4.0 drivers like additive manufacturing (AM), to address the above-mentioned important concerns. Due to the emergence of AM, numerous industries' SCs are predicted to be significantly disrupted, and it is seen as a useful instrument in contemporary production because of its ability to reduce expenses, boost productivity, expand flexibility, and support sustainability. Accordingly, AM has much to offer in terms of lowering SC costs, as well as transportation and warehousing expenses. The empirical study by Oettmeier and Hofmann [22] revealed the positive effects of adopting AM technology to illustrate its potential cost savings, lead time reduction, and increased SC resilience. Similarly, the study by Yang et al. [23] indicated that digital technology significantly improves supply chain capabilities. According to Noorwali et al. [24], the adoption of AM technology reduces the number of suppliers and reduces the need for huge stocking, transportation, and raw material inventory [25]. This demonstrated that AM has the potential for enhancing or improving supply chain performance.

The effects of industry and cultural differences on SCC and performance interrelationships were not specifically explored in previous studies. In particular, key relationships were not established in the context of developing countries like Ethiopia, where their substantial influence on international markets is growing, a rapid growth in population can be observed, and an increasing number of customers are an unavoidable reality, specifically in the footwear industry. In some industries and countries, these relationships may differ due to differences in customer requirements and preferences or differences in manufacturing processes and SC management practices. In addition, even if the benefits of AM best practices in improving the negative impacts of SCC on SCP were indicated in the reviewed literature, the use of AM best practices as moderators between SCC and SCP is still not widely reported.

Thus, by taking these into consideration, this study is intended to fill the identified gaps by examining the moderating role of AM best practices between SCC and SCP of footwear industries in Ethiopia. From the context of industries in this category, the study aims to answer the following questions:

1. What are the moderating effects of AM between supply chain complexity and supply chain performance?
2. Which of the complexity types are altered in the presence of AM technology?
3. At what level of AM best practices are the negative effects of SCCs reduced?

In this paper, these research questions are addressed by developing a conceptual framework and hypotheses based on the conducted literature review. To test the developed conceptual framework and developed hypotheses, data were collected from the footwear industry operating in Ethiopia and tested using a structural equation modelling (SEM) approach. This study is expected to contribute to the scientific knowledge of a new conceptual framework that will help practitioners measure and test the impacts of SCC on SCP through the moderation role of AM best practices. Through this conceptual framework, the industry can control the level of supply chain complexity to improve supply chain performance. Furthermore, this study intends to discuss managers and practitioners, how complexity within the firms SC network influences supply chain performance, and how the adoption of AM improves the negative relationship between SCC and SCP. Managers and practitioners can learn from this research about how the complexity of a company supply chain network affects the effectiveness and efficiency of their supply chain, as well as how the adoption of AM might mitigate the negative correlation between supply chain and performance.

The remainder of this article is structured as follows. In Section 2, a review of the literature on supply chain complexity and its types, the effects of supply chain complexity on performance, and additive manufacturing best practices in the context of supply chains are presented. Section 3 outlines the materials and methods, including a research model, sample and data collection, instruments, procedures followed to conduct reliability, measurement, and structural model fit tests. Then, the results are presented in Section 4, and the findings are further discussed in Section 5. Finally, the paper concludes with findings implications and suggestions for future research in Section 6.

2. Literature Review

This research was conducted based on a separate systematic literature review conducted by the authors and reported in [26]. In this section, the literature study is presented. The literature findings that illustrate the theoretical backgrounds of supply chain complexity, additive manufacturing best practices in the context of supply chains, and their impacts on supply chain performance, as well as the issues that clarify the research gap and enable hypotheses, are highlighted.

2.1. Supply Chain Performance Measurement

Different studies and scholars measure and define the performance of SC using different criteria. Pillai et al. [27] defined SCP in terms of cost, and they further segmented these costs into purchase order cost, setup cost, transportation cost, carrying cost, major cost, and shortage cost. On the other hand, customer satisfaction served as a metric for SC success and was considered to be a significant predictor of performance [28]. Panayides et al. [29] also reported customer satisfaction as an indicator of the supply chain. Fulfilling and meeting consumers' needs in terms of flexibility in product design, product quality, product delivery, and reliability is very important in the SC process. Furthermore, supply chain performance metrics pertaining to suppliers are crucial for customers and suppliers alike. Delivery performance, responsiveness, flexibility, and cost are among the most often measured characteristics of supplier performance [30]. Meeting changes in customer demand and specifications and shorter delivery time are also mentioned as performance measures of supply chain [31]. This performance measuring factor has the advantage of decreasing costs and time while increasing the value and quality of goods. Thus, supply chain performance measures need to be considered in terms of qualitative (flexibility in product design, product delivery, and customer satisfaction) and quantitative measuring factors (such as total supply chain cost, inventory levels, and resource utilization).

2.2. Supply Chain Complexity

Supply chain complexity is defined as a condition of inter-dependencies and interconnectedness of entities across a network [1]. The increasing interdependence and interconnection in the supply chain network creates challenges for the firms. Different factors or drivers affect SCs and make them extremely complex and interconnected. Complexity drivers are classified into different types based on their origin or sources. Based on this, Isik [32] classified complexity drivers according to their position into upstream, midstream, and downstream complexities.

Upstream supply chain complexity originates from the supplier's side and is caused by static and dynamic complexity. These types of complexities are characterized by supplier location, number and variety of suppliers, etc. [2], which are referred to as static supply chain complexities. On the other hand, dynamic complexity in this location is characterized by supplier reliability and variability [33], supplier resourcing risk, supplier competence [9], and supplier delivery unreliability [15]. Midstream supply chain complexity, on the other hand, is defined as the static and dynamic complexities found in manufacturing plants. According to Kunovjanek and Reiner [25], static complexity within the manufacturing plant refers to the distinct number of components or parts that make up a system, a number and variety of products, or processes and types of products. Similarly, dynamic complexity refers to operational complexity, and it is reflected by forecast inaccuracy and unstable production schedules, process uncertainties, process synchronization, employee induced variability, introducing new products in the system, etc. [2]. From the customer side, complexity within SCs is termed downstream supply chain complexity. These types of complexities within SCs occur due to the number of customers, the variety of customers, customer heterogeneity, and product lifecycles [33], which are classified under static complexity drivers. Accordingly, the dynamic complexity drivers in this location are caused by demand uncertainty, demand variability, market uncertainties, and the heterogeneity of customers' needs.

2.3. Supply Chain Complexity and Its Impacts on Performance

In previous studies on supply chain complexity, researchers have demonstrated the effects of SCC on performance. For instance, the study by [34] stated that longer supplier delivery time creates dynamic complexity; this in turn affects supply chain performance by forcing firms to adjust their planning and material management process. Higher number of suppliers increase static complexity due to an increased number of physical and information flow. And these increase management and control of their relationships, which in turn affect supplier relationships and increase costs (logistics and communication). Similarly, due to upstream supply chain complexity, firms are exposed to look beyond just price and fluctuation in currency, which results in increased cost to the firm and causes customer dissatisfaction. According to Kogan et al. [35], delivery uncertainties result either in inventory stock-outs or overstocks. A study by Xu et al. [36] revealed the negative effects of supply uncertainty on performance. Operations become more vulnerable and expensive due to supply chain interruptions brought on by uncertainties resulting from a variety of internal and external sources [37]. Supply base complexity can increase the frequency of disruptions and reduce performance [16]. According to Choi and Krause [3], supply chain complexity has several detrimental performance effects, including delivery speed and dependability and responsiveness. There is a greater chance of inconsistent delivery when there are more vendors. However, because of its limited flexibility, a very basic supply base with single sourcing may be quite risky.

According to Kunovjanek and Reiner [25] and Wu et al. [38], the degree of static and dynamic complexities in manufacturing plants affects the performance of firms supply chain. An increase in product variety increases internal operation cost (operational performance) [39]. Similarly, the studies by Wan et al. [40] and Wan et al. [41], illustrated that product variety negatively affects inventory turnover at high rate of demand variability. And an increase in product variety creates operational challenges and results in higher inventory levels, which in turn affects operational performance. A study by Thonemann and Bradley [42] expands this and includes supply chain costs. Increasing process changeover leads to longer manufacturing lead times and greater costs for firms due to increased product diversity. The amount and variety of parts also create detail complexity in the manufacturing environment, ultimately impacting performance [43]. According to Archie et al. [44], SC performance is improved by reducing process uncertainty.

From the customer side of supply chain, the performance of a firm supply chain is affected due to the static and dynamic complexity drivers like the number and variety of customers, customer heterogeneity, and product life cycles [45]. Based on this, the study by Vollmann et al. [34] illustrated that, as the number and variety of customer increases, the magnitude of the customer relationship activity, the management of orders, and the demand increases. This creates the potential for conflicting manufacturing tasks and lower levels of manufacturing performance [46] and results in an imbalance between manufacturing capabilities and consumer needs [47]. Shorter product lifecycles and customer demand variability increases the number of parts and products; it introduces new products in the manufacturing system, and this in turn affects the cost of the firm, leading to the creation of significant fluctuations on supplier side. Suzan et al. [48] illustrated the negative impacts of demand variability on supply chain performance (operational cost, customer satisfaction, and environmental footprint). According to Madhusudanan et al. [49], a supply chain bullwhip effect creates a negative impact on the performance. Customer demand volatility frequently results in high capacity and inventory costs for the producer. The service level and overall cost of SCs are impacted by the fluctuation or volatility of customer demand [50].

The effects of SCC on performance were examined by Brandon et al. [16] in order to learn how companies could mitigate the effects of more frequent disruptions. They employed moderating impacts of slack resources between supply base complexity and performance. Their findings revealed that an increase in disruptions caused by supply base complexity can be mitigated through the moderation role of slack resources and visibility. In their research, Ateş and Memiş [17] looked at how strategic purchasing affected the link between supplier base complexity and performance. According to their findings, companies possessing significant strategic purchasing leverage are able to offset the adverse effects of supplier base complexity on their performance. The potential moderating role of supply chain visibility in the relationship between sustainable practices and sustainable performance was investigated by Zulkaif et al. [51]. Their study findings indicated that supply chain visibility moderates sustainable practices and firms' sustainability performances. Hugo et al. [52] looked at the moderating effects of inventory turns while examining the effects of static supply chain complexity (a company's number of goods, suppliers, and customers) on the performance of a company. A greater quantity of items, in their opinion, improves business performance. Furthermore, there is a favorable correlation between higher inventory turns and a higher number of suppliers and items. A study by Iftikhar and Ali [53] illustrated the moderating role of supply chain ambidexterity between SCC and performance. And their findings indicated the positive moderating effects of supply chain ambidexterity between the two distinct forms of SCC and a firm's performance.

On the other hand, the role of quality function deployment (QFD) and an integrated decision-making framework were proposed for the sustainability of the supply chain. For instance, a study by Karuppiah et al. [54] integrated customers and technical requirements in order to improve supply chain sustainability in a case study, where they demonstrated an improvement in supply chain sustainability by reducing carbon footprint, affordable cost, and on-time delivery, which are important customer requirements. In addition, financial strategy, green supply chain management, and government assistance were identified as technical requirements that play an important role for supply chain sustainability. Similarly, the study by Erdil [55] combined a QFD application with a supply chain management system to study its improvement in the outcomes of the manufacturing industry, in which potential applications were illustrated. Furthermore, Bhalaji et al. [56] developed an integrated decision-making framework to investigate the risks associated with cooperative supply chains and their interactions. This ensures the timely delivery of finished goods and the timely reception of raw materials and helps manufacturers build a robust and cooperative supply chain.

2.4. Moderating Role of Additive Manufacturing Best Practices

Additive manufacturing, also known as direct manufacturing, is classified as one of the drivers of Industry 4.0. It is a digital technology that produces physical objects layer by layer from a computer-aided, three-dimensional design file, contrary to conventional subtractive techniques [57]. AM is revolutionizing industrial processes, particularly in the context of Industry 4.0, which emphasizes smart production, connectivity, and digital transformation. According to Godina et al. [58], there is significant potential for improving economic, environmental, and social aspects of eco-friendly company strategies with the integration of AM. Oettmeier and Hofmann [22] conducted an empirical analysis to examine the factors that influence the adoption of AM technology. They focused on both general and SC-related factors to understand the factors that affect the potential for cost savings, lead time reduction, and increased SC resilience. This understanding enables businesses to make more informed decisions about integrating AM into their supply chains and operations. Because AM can revolutionize conventional production and supply chain procedures, it is quickly being implemented across a range of industries. Using a supply chain perspective, their study concentrates on the costs, benefits, and adoption elements of AM, providing a comprehensive understanding of its impact on modern manufacturing and logistics [59].

It is anticipated that additive manufacturing will significantly disrupt supply chains in several industries. It is an important instrument in contemporary manufacturing because of its ability to reduce costs, boost efficiency, increase flexibility, and support sustainability. Existing research demonstrated the simplicity of SC after implementing AM. According to Gimenez et al. [60], firm SC performance is improved through the implementation of AM due to its behavior in the effective use of resources and capabilities. It promotes rapid innovation and product design modifications, resulting in increased customer satisfaction and improved effectiveness, and it contributes to supply chain flexibility [61]. Additive manufacturing provides a quick response to customer demand uncertainty, enabling an organization to establish quicker designs and new product development, and hence reduces manufacturing cycles [62]. It reduces the need for diverse tools to fabricate geometrically complex components, and as a result, it reduces the cost of products. This results in reduced associated costs, lowering the requirements for tooling, and enables short and efficient production runs [58]. Shorter production times and the optimization of the material consumption behavior of AM results in fulfilling customer demand and reducing the number and variety of suppliers [63]. It satisfies customer needs by reducing SC lead time by reducing the need for logistics and inventories in the development of new products into the system. Through the implementation of AM, supply chain efficiency is improved by balancing inventory levels, increasing responsiveness (the ability to quickly react during demand uncertainty and forecasting errors), and by decreasing disruptions (by decreasing the number of interruptions of activities and processes) [64]. Manufacturing flexibility in AM applications positively influences performance by increasing the speed of material flow (reducing lead time) and by improving organizational efficiency [65].

The literature reviewed above indicates that varied SCC drivers have different effects on determining the SCC level from sector to sector. The level of complexity and relevance of identified drivers on SCs vary depending on the industry and environment in which they operate. As such, management's attitude towards the complexity of drivers to mitigate their impact on SC performance may also differ. Based on the nature or dynamics of the industry, the number of SCC drivers may increase, decrease, or be rationalized. SCC drivers and sub-drivers might be dependent on one another. This indicates that identifying which supply chain complexity has a greater negative or positive effect than the others should be studied so that firms can focus on improving and controlling the complexities within their supply chain; this would result in fewer or no knock-on effects in performance. Based on this, the identification and development of industry-specific criteria, types of complexity drivers, decision-making approach proposals, and suggested strategies for particular industry sectors are needed.

3. Materials and Methods

3.1. Developing Conceptual Framework

Based on the literature review, the conceptual framework in Figure 1 was developed, which illustrates the impacts of the moderating role of AM best practices on supply chain complexity and its performance. The supply chain performance was measured in terms of quantitative measuring factors (QNMFs) and qualitative measuring factors (QLMFs), while supply chain complexities are represented using upstream supply chain complexity, midstream supply chain complexity and downstream supply chain complexity. In this relationship, AM best practices are considered moderating variables. It is assumed that there are no additional control variables in the developed model that may lead to wrong conclusions and affect the conceptual relationship created between constructs. This is also because including control variables does not accurately reflect the original model parameter estimates (path coefficients). Thus, to improve biases and errors that could affect the validity of the findings of the study model, relevant variables were compiled using a detailed literature review and in consultation with experts from the case study industry. In addition, sample selection was carried out in such a way that the research properly reflects the population under study.

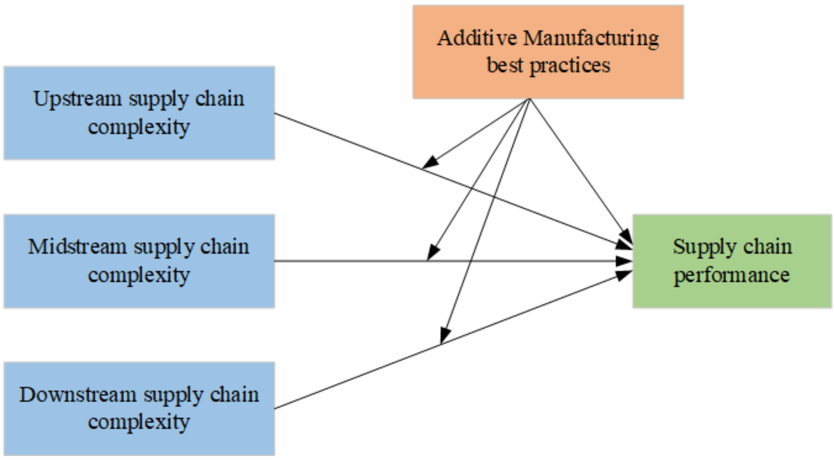

Figure 1. Research conceptual framework.

The developed model contains seven hypotheses: four direct (H1 to H4) and three moderating effects (H5 to H7). The suggested or developed hypotheses based on the literature review are as follows.

Hypothesis 1. *Upstream supply chain complexity has negative effects on supply chain performance.*

Hypothesis 2. *Midstream supply chain complexity has negative impacts on supply chain performance.*

Hypothesis 3. *Downstream supply chain complexity has negative impacts on supply chain performance.*

Hypothesis 4. *Additive manufacturing best practices have positive and significant effects on supply chain performance.*

Hypothesis 5. *Additive manufacturing has significant moderation effects between UPSCC on supply chain performance.*

Hypothesis 6. *Additive manufacturing has significant moderation effects between MSSC and supply chain performance.*

Hypothesis 7. *Additive manufacturing has significant moderation effects between DSSC and supply chain performance.*

3.2. Sample Data Collection

We used a purposive sampling method for selecting respondents involved in the survey for the purpose of data collection. Based on this sampling technique, 205 professionals from 29 footwear industries found in Ethiopia were selected who had direct contact with suppliers, manufacturers, and customers. As per Hair et al. [65], the minimum required sample size was taken into consideration while selecting data analysis type. An acceptable sample size of at least 100–200 is necessary for the structural equation modeling method that we intended to use [65,66]. Therefore, for this study, a sample size of 200 as a minimum requirement was determined. Permission to gather data was gained from each company before the questionnaires were delivered. The objective of the study was explained to the respondents, and they accepted our invitation to take part. The researchers physically visited the footwear companies to collect the data. The questionnaire used for data collection is provided in Appendix A.

As the demographic profiles of the respondents in Table 1 indicates, 50% of the respondents had work experience of 11–20 years. The majority of the respondents (33.17%) were supply chain and logistics workers, 62.43% of them had a BSc degree, 43.41% were aged between 31 to 35, 52.68% of them were male, and 47.31% were female. The demographic profiles of the participants of the survey revealed a heterogeneous collection of respondents with respect to age, gender, employment position, and work experience. People with various job positions and levels of experience contribute valuable information to the study because they have firsthand knowledge of the subject areas under investigation. This provides the study with a diverse range of viewpoints.

Table 1. Demographic description of respondents.

Description		Frequency	Percentage (%)
Gender	Male	108	52.68
	Female	97	47.31
Education level	Diploma	31	15.12
	Undergraduate	128	62.43
	Master's graduate and above	46	24.43
Age	20–30	33	16.09
	31–35	89	43.41
	>36	83	40.48
Respondent job position	Supply chain and logistic worker	68	33.17
	Production workers	58	28.20
	Top management workers	56	27.31
	Experts	23	11.21
Work experience	<5 years	5	2.43
	6–10 years	41	20
	11–20 years	103	50.24
	>21 years	56	27.31

3.3. Quantification of the Survey

All included measurement items in the survey, which was measured using 1–5 Likert scale questions (1 = strongly disagree; 2 = disagree; 3 = neutral; 4 = agree; and 5 = strongly agree), were developed through an extensive literature review of other studies. According to Phan et al. [67], the Likert scale is a commonly used quantitative research technique that offers a quantifiable measure for survey studies. It is used to gauge viewpoints and attitudes on a variety of issues. A pre-testing phase was carried out with the participation of 25 experienced professionals from a footwear firm to guarantee accuracy. The purpose of this pre-testing was to find and fix any problems with the phrasing and structure of the survey. Based on the feedback of the respondents who participated in the pilot study, the final questionnaire was revised. The initial version of the instrument consists of 26 items, and 21 items were retained using conducting factor reduction techniques. Thus, 2 items from MSSCC, 1 item from DSSCC, and 2 items from AMBP were eliminated. The final version and completed questionnaire items with their sources are shown in Table 2.

Table 2. Items of constructs and their sources.

Variables	Items and Coding	Sources
Upstream supply chain complexity	Variety of suppliers	[2,33]
	Number of suppliers	[15,45,48]
	Reliability of suppliers	[33]
	Supplier variability	[33]
	Uncertainties in delivery	[15]
Midstream supply chain complexity	Number of products	[23]
	Varity of products	[40]
	Variety of processes	[23]
	Number of production lines	[23]
	Forecast inaccuracy	[38]
	Process synchronization	[2]
	Process uncertainties	[2]
Downstream supply chain complexity	Varity of customers	[33,45]
	Number of customers	[34]
	Demand variability (uncertainty)	[45]
	Heterogeneity of customer	[45]
Additive manufacturing best practice	Reduction in raw material variety	[22]
	Facilitate production closer to customer	[57]
	Reduce delivery times	[58]
	Reduce supplier lead times	[60]
	Manufacturing flexibility	[57]
Supply chain performance	Warehousing and inventory-holding cost	[27]
	Customer satisfaction (on-time delivery record to customers)	[31]
	Flexibility in product design, product delivery	[30]
	Satisfying customers' requirements	[29]
	Ability of suppliers to quickly respond to changes in market demand	[31]

3.4. Reliability Test

Before distributing the final refined questionnaires, pilot studies were conducted by distributing 25 questionnaires to the selected footwear companies to check the reliability of the questions for all measurement items. Upon testing the reliability of questionnaires using Cronbach's alpha (α) value, as recommended by Kline [68], items that fulfilled α value of > 0.7 were selected and retained. The final refined questionnaires were then distributed and the required information for testing the developed model was collected from 205 respondents from the considered case study industry.

3.5. Measurement and Structural Model Fit Test

To check the fitness test of the measurement, this study conducted convergent, discriminant, and validity tests, as recommended by Joseph et al. [69] and Hamid et al. [70]. The structural model fit test was then performed using the confirmatory factor analysis test.

Convergent validity refers to the degree of agreement between the different indicators of the same construct, as determined by correlation analysis. To establish convergent validity, the items' factor loading (FL), composite reliability (CR), and average variance extracted (AVE) were considered. A FL of 0.7 or above implies strong convergent validity, although a FL of 0.5 or higher is acceptable. The composite dependability should be 0.7 or above. According to Joseph et al. [69], for sufficient convergent validity, the AVE value must be more than 0.50. Discriminant validity refers to how much the conceptions truly vary from one another through experimentation. It also establishes the extent to which concepts that overlap differ from one another. The most rigorous and popular way of discriminant validity testing is to compare the square root of each concept's AVE value with the correlation estimate between that construct and other components [70]. Confirmatory factor analysis was used to assess the measurements of the model's validity. The validity was assessed using model fit indices. Brown [71] recommended the following cutoff values for fit indices:

- Tucker–Lewis fit index (TLI) and comparative fit index (CFI) > 0.9;
- Relative/normal chi-square (χ^2/df) from 2.0 < χ^2/df < 5.0;
- Root mean square residual (RMR) and root mean square error of approximation (RMSEA) < 0.08.

4. Results

4.1. Reliability and Validity Analysis

According to the analysis results presented in Table 3, the Cronbach's alpha (α) values for each construct ranged from 0.912 to 0.975. This finding shows that all constructs of Cronbach's alpha (α) values are higher than the value recommended by Kline [68] as an acceptable level of 0.70. This result showed that there is strong internal consistency among all the items in each of the study's constructs. Similarly, the factor loading results in the same table shows that the items under each relevant construct have stronger connections. The entire factor load is above 0.7 (ranging from 0.773 to 0.989), which shows a strong association with the construct.

Table 3. Reliability and convergent validity results.

Constructs	Items	Factor Loading	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
USSCC	USSCC5	0.860	0.942	0.996	0.769
	USSCC4	0.942			
	USSCC3	0.949			
	USSCC2	0.851			
	USSCC1	0.773			
MSSCC	MSSCC5	0.868	0.946	0.988	0.812
	MSSCC4	0.957			
	MSSCC3	0.894			
	MSSCC2	0.917			
	MSSCC1	0.867			
DSSCC	DSSCC3	0.924	0.912	0.991	0.787
	DSSCC2	0.908			
	DSSCC1	0.828			
AMBP	AMBP4	0.989	0.975	0.999	0.944
	AMBP3	0.961			
	AMBP2	0.965			
SCP	SCP5	0.928	0.958	0.994	0.807
	SCP4	0.925			
	SCP3	0.896			
	SCP2	0.886			
	SCP1	0.855			

Convergent and discriminant validity tests were run following the reliability analysis test. As a result, as demonstrated in Table 3, the values of average variance extracted (AVE) and composite reliability (CR) for each of the constructs, respectively, surpass the cutoff limits of 0.70 and 0.50, respectively, showing that convergent validity was guaranteed [70]. Additionally, the results of the discriminant validity test, which are displayed in Table 4, revealed that the square root of the AVEs is greater than the coefficients of interrelationships among the components. As a result, the discriminant validity is guaranteed and the Fornell–Larcker criterion is met [71].

Table 4. Discriminant validity test results.

	USSCC	**MSSCC**	**DSSCC**	**AMBP**	**SCP**
USSCC	0.877				
MSSCC	0.122	0.901			
DSSCC	−0.002	0.093	0.887		
AMBP	0.149	−0.086	0.169	0.971	
SCP	0.111	−0.237	−0.147	0.162	0.898

4.2. Structural Model and Path Analysis

The structural model and path analysis (hypothesis testing) were investigated using the structural modeling approach with AMOSE v23. The outcomes are displayed in Table 5 and Figure 2. As shown in Figure 2, the structural model fit result revealed that the created model fits well, meeting the recommended cutoff points [72] with the goodness of fit indices of CFI = 0.911, IFI = 0.911, TLI = 0.900, $\chi^2/\text{df} = 3.5$, and RMR = 0.02. These fit indices confirmed that there is a good fit between the collected data and the created conceptual framework.

Table 5. Path and moderation analysis results.

	Hypothesis	**Paths**	**β**	***p***	**Result**
Direct Effects	Hypothesis 1	USSCC → SCP	−0.030	0.643	Accepted
	Hypothesis 2	MSSCC → SCP	−0.309	0.405	Accepted
	Hypothesis 3	DSSCC → SCP	−0.102	0.039	Accepted
	Hypothesis 4	AMBP → SCP	0.167	0.000	Accepted
Interaction Effects	Hypothesis 5	MUSSCC_X_MAMBP → SCP	0.186	0.000	Accepted
	Hypothesis 6	MMSSCC_X_MAMBP → SCP	0.081	0.003	Accepted
	Hypothesis 7	MDSCC_X_MAMBP → SCP	−0.120	0.000	Accepted
β = standardized coefficients; *p* = significant value					

The direct and moderation effects of all the path analyses are displayed in Table 5. According to this study's findings, supply chain performance is negatively impacted by upstream supply chain complexity (β = −0.030, p = 0.643). This outcome validates Hypothesis 1. Thus, this shows that static and dynamic complexity found within upstream supply chain negatively affects supply chain performance. The second hypothesis, which claimed that midstream supply chain complexity has an adverse influence on supply chain performance, was confirmed (β = −0.309, p = 0.405). Furthermore, it was found that downstream supply chain complexity had a negative impact on supply chain performance (β = −0.102, p = 0.039). This outcome validated Hypothesis 3 and illustrated that the performance of the supply chain is negatively impacted by higher levels of static and dynamic complexity within the downstream supply chain. Nonetheless, the results given in Table 5 show that best practices for additive manufacturing have favorable and significant impacts on supply chain performance (β = 0.167, p = 0.000), which supports Hypothesis 4.

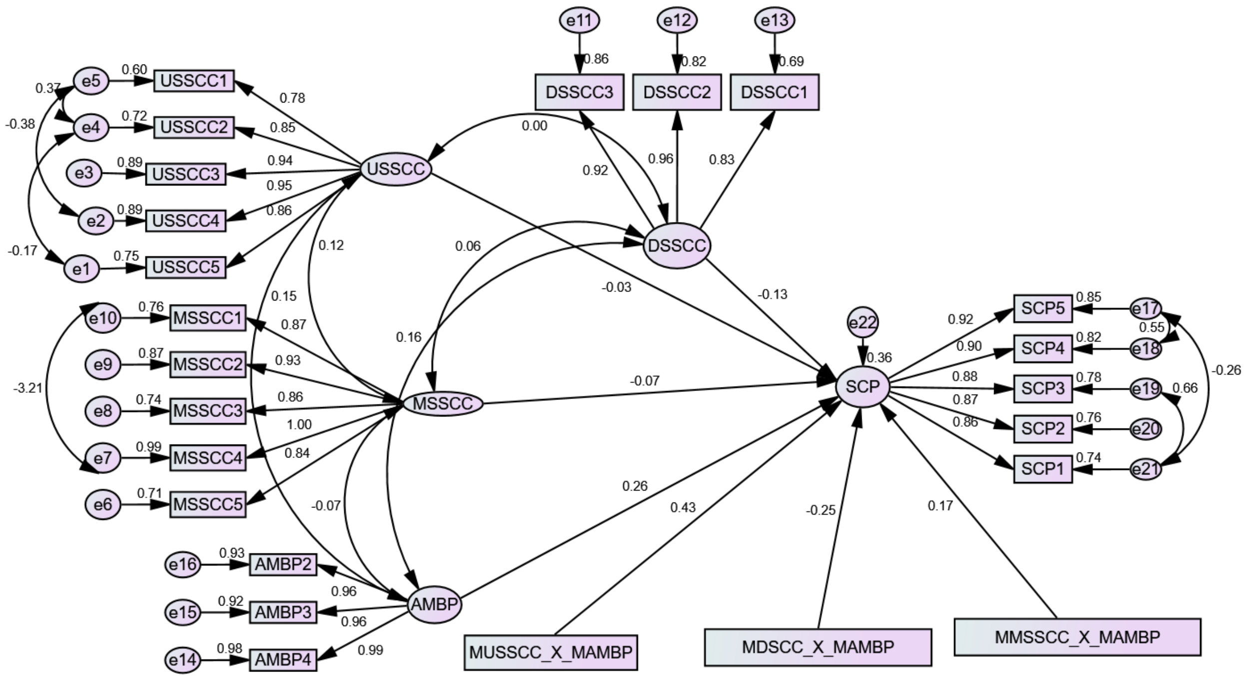

Figure 2. Structural equation modeling results (Note: e1—e25 stand for error terms).

This study assessed the moderating role of AM best practices on the relationship between SCC and SC performance. The interaction term between upstream supply chain complexity and additive manufacturing best practice (MUSSCC_X_MAMBP) has significant impacts on supply chain performance (β = 0.186, p = 0.000), indicating that the interaction between the two constructs significantly improves the performance of the supply chain. This result supports Hypothesis 5. In addition, to better understand the nature of the moderating effects of AMBP, a slope analysis was conducted. The slope analysis result, shown in Figure 3, indicates that the line is much steeper for low AMBP, implying that at low levels of additive manufacturing, the impact of USSCC on SCP is much stronger in comparison to high AMBP. From this, we can see that the more additive manufacturing practices in the case study industry, the fewer negative impacts of USSCC on SCP.

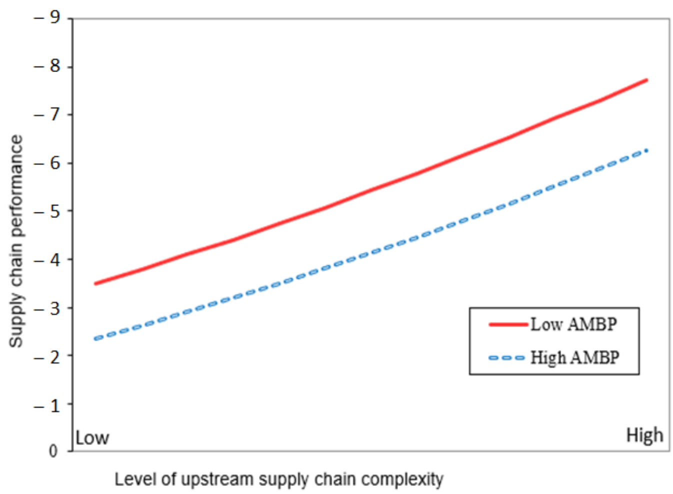

Figure 3. Slope analysis result for Hypothesis 5.

The findings in Table 5 indicate that the negative effects of midstream supply chain complexity on supply chain performance are improved through the interaction or moderating effect of additive manufacturing best practices (MMSSCC_X_MAMBP) (β = 0.081, *p* = 0.003). This result also supports Hypothesis 6. Moreover, the plots in Figure 4 demonstrated that the moderating effects of additive manufacturing at lower level are stepper than at higher level of adaptation. This indicates that the negative impact of MSSCC on SCP is reduced at higher levels of AMBP. The more additive manufacturing practices, the lesser the negative impact of SCC in the midstream of the supply chain.

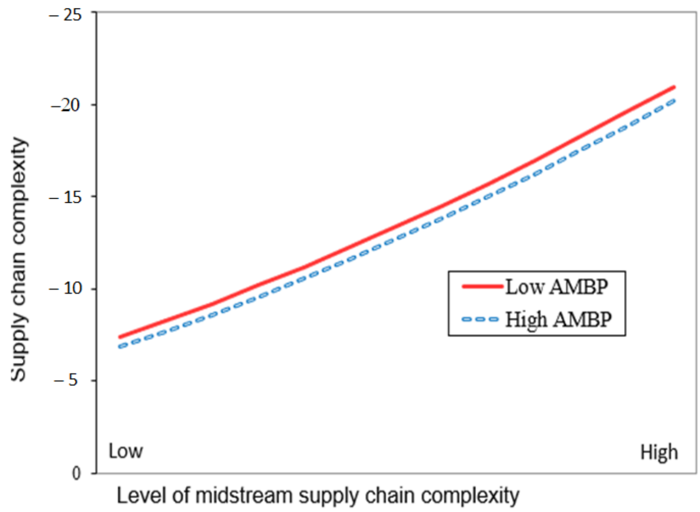

Figure 4. Slope analysis result for Hypothesis 6.

Similarly, as the results in Table 5 illustrate, the interaction effects of downstream supply chain complexity and AM best practices (MDSCC_X_MAMBP) significantly improve supply chain performance (β = −0.120, p = 0.000), which also supported Hypothesis 7. Nonetheless, the results of the slop analysis, as shown in Figure 5, indicate that at both low and high levels of AMBP adoption, the detrimental effects of DSSCC on SCP are not significantly different.

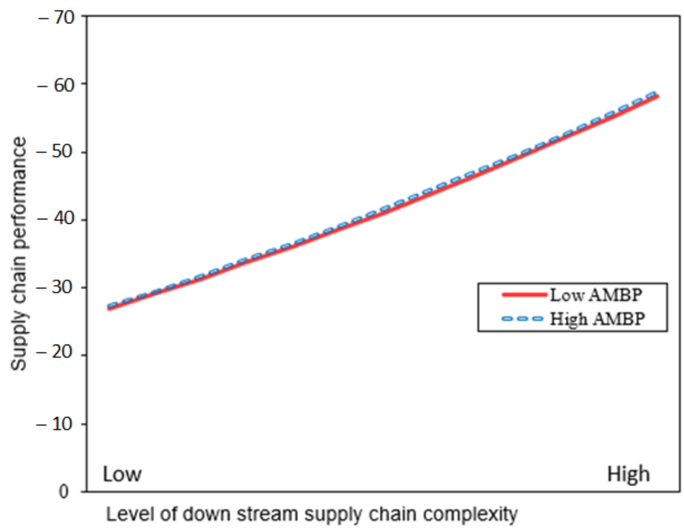

Figure 5. Slope analysis result for Hypothesis 7.

5. Discussions

There are several theoretical contributions addressed in this study, including investigations into how supply chain complexity affects supply chain performance and how AM best practices serve as moderators. The primary objective of this study was to demonstrate that SCC has a detrimental impact on SCP, and empirical approaches support this prediction. In accordance with the findings of this investigation, studies conducted by Brandon [16], Constantin et al. [10], and Kwabena et al. [5] similarly found and documented the existence of negative correlations between SCC and performance. The results obtained from the path analysis support our second hypothesis, which states that SCP is negatively impacted by upstream supply chain complexity. The findings are also consistent with the studies of Cecil et al. [15] and Vollmann et al. [34], which found that factors that contribute to upstream supply chain complexity, including delivery uncertainty, unreliable suppliers, and longer delivery times, have a negative impact on supply chain performance. Similar conclusions were also reached by Brandon et al. [16], who found that supply base complexity can lower performance and increase the frequency of disruptions. Furthermore, the idea that supply chain performance is negatively impacted by midstream complexity was investigated and shown to be empirically supported. According to studies conducted by Seyda [2], Patel et al. [39], Wan et al. [40], and Ramdas and Sawhney [43], a larger variety of products increases operation costs and the quantity of parts affects performance, which subsequently has an impact on the supply chain performance of businesses; these results are consistent with the findings of this study.

The empirical conclusion of this study validates (supports) the third hypothesis, which illustrates the detrimental effects of downstream supply chain complexity on supply chain performance. According to Hendrick et al. [33] and Bozarth et al. [46], for instance, SCP is significantly impacted by the rise in DSSCC due to demand volatility, uncertainty, and heterogeneity. Furthermore, the outcomes of studies by Alaswad et al. [48], Pillai et al. [49], and Georgel and Pillai [50] also align with our findings, which confirm that SCC negatively affects SCP because of supply chain volatility, demand variability, and the fluctuation or volatility of consumer demand. The hypothesis developed to determine the positive and direct impacts of AMBP on supply chain performance was supported. This outcome is consistent with the research conducted by Gimenez et al. [60] and Eyers [61], who found that AM behavior in maximizing resources and capabilities, encouraging quick innovation, and changing product designs improves SC performance. Furthermore, there was substantial evidence to support the hypotheses generated to investigate whether the moderating role of AMBP on SCC reduces the negative connection between SCC and SCP. Additive manufacturing can respond quickly to fluctuations in customer demand [62], decrease the number of processes [58], and balance inventory levels [59]—all of which can improve or lessen the detrimental effects of SCC on SCP.

6. Conclusions

This study developed a theoretical framework regarding the role and performance of AM as a moderator in supply chain complexities. The framework was developed based on a literature review of studies examining supply chain complexities at three levels (USSCC, MSSCC, and DSSCC). The developed model was empirically tested using structural equation modeling by collecting data from the footwear industry in Ethiopia. The general results of the study show that SCC negatively affects SCP. Furthermore, the outcome of this study demonstrated that the relationship between SCC and SCP is moderated by AM best practices. Additionally, the results of the slope analysis showed that the detrimental effects of supply chain complexity found in the upstream and midstream supply chains on SCP decreased with increasing levels of AM implementation.

Theoretical and empirical implications: First, the work reported in this article is intended to contribute to closing the gap in the field of research regarding the moderating role of AMBP between supply chain complexity and supply chain performance of the footwear industry. Second, practitioners can be made aware of the detrimental effects of supply chain complexity on performance and the extent to which AMBP can mitigate these effects based on the study's findings. Thus, this research provides managers and practitioners with insights into how the complexity of a company's supply chain network affects the efficiency and effectiveness of supply chains, as well as how the adoption of AM may mitigate the negative correlation between supply chain complexity and its performance. Additionally, this study's findings can assist managers in limiting the level of SCC to avoid SCP being adversely affected.

Limitation and future research direction: Like any other research, this study also has several limitations. Primarily, the study's conclusions were restricted to a sample of data from the footwear businesses; while it is understood that SCC drivers vary depending on the types of industry and nature of products, this study was limited to the footwear industry supply chain. Thus, additional research in other industries will be required in order to compare the results of this study with data from other areas. Secondly, although several driver types can induce SCC, this study only included a few drivers when constructing the theoretical framework. Furthermore, this study only looked at the negative impacts of SCC on SC performance, even though other research shows that it has both positive and negative effects. Thus, further research will be needed to illustrate the positive effects of SCC on SC performance by including additional drivers when considering AMBP as moderator. In addition, there are other variables, such as culture and geographical environment, that directly or indirectly influence the impact of SCC on SC performance and create limitations in research conducted in specific areas. These variables are not considered in the present research and are potential subjects in our continuing study of this topic.

In addition to AM best practices, the application of QFD and the integration of the decision-making framework into the cooperative supply chain play a vital role in SC sustainability. Therefore, future research should expand this analysis by including QFD and a decision support model when evaluating supply chain performance in the footwear industry and comparing the results with the present study.

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Institutional Review Board Statement: Prior to the study, formal written permission was obtained from the research ethical committee of Wollega University, and the permission letter was attached to the questionnaire and distributed to the participants. After all participants had been fully informed about the objectives of the study and how the collected data would be used, verbal informed consent was obtained from each study participant. Verbal rather than written consent was obtained because of the very low sensitivity of the information that needed to be collected. For the confidentiality of the participants, no personal identifiers were used in the data collection questionnaire, and the data obtained from the study participants were not accessed by anyone except the authors. In addition, participants' names and other personal identifiers were not used in any sections of the manuscript.

Data Availability Statement: The original contributions presented in the study are included in the article; further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

AM	Additive manufacturing
AMBP	Additive manufacturing best practices
AVE	Average variance extracted
CFI	Comparative fit index
CR	Composite reliability
DSSCC	Downstream supply chain complexity
FL	Factor loading
MDSCC	Mean of downstream supply chain complexity
MMSCC	Mean of midstream supply chain complexity
MSSCC	Midstream supply chain complexity
MUSCC	Mean of upstream supply chain complexity
SEM	Structural equation modeling

SCC	Supply chain complexity
SCP	Supply chain performance
QLMF	Qualitative measuring factor
QNMF	Quantitative measuring factor
RMR	Root mean square residual
RMSEA	Root mean square error of approximation
TLI	Tucker–Lewis fit index
USSCC	Upstream supply chain complexity

Appendix A

Section I: Personal Details and Demographic Information

1. **Gender:** ☐ Male, ☐ Female
2. **Age:** ☐ 20–30, ☐ 31–35, ☐ 36–45
3. **Year of working experience:** ☐ Less than 5 years, ☐ 6–10 years, ☐ 11–20 years, ☐ 16–20 years, ☐ 21 years and above
4. **Level of education:** ☐ Diploma, ☐ Undergraduate, ☐ Master's graduate and above
5. **Respondents job position:** ☐ Supply chain and logistic worker, ☐ Production workers, ☐ Top management workers, ☐ Expert

Section II: Questions Related to Study Constructs

Table A1. Question Related with the Study Constructs. Please respond by marking X the number that represents the extent to which you agree or disagree about the following statements. Use the following guide 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

Codes	Descriptions	1	2	3	4	5
USSCC1	Our organization has a variety of suppliers.					
USSCC2	We have a lot of suppliers (number of suppliers).					
USSCC3	Our supplier variability (inconsistency) vary from time to time					
USSCC4	Comparatively our supplier uncertainty of delivery is poor					
USSCC5	Reliability of our supplier is poor					
MSSCC1	Our company has high number of products					
MSSCC2	Our company handled high Varity of items					
MSSCC3	The variety of processes and production lines in our plant is higher					
MSSCC4	In our company process uncertainties more frequently happened					
MSSCC5	Our company forecast inaccuracy is more or high					
DSSCC1	Our company has high number of customers					
DSSCC2	Our company served high Varity of customers					
DSSCC3	In our company the total demand volume of all products is significantly unstable from time to time					
AMBP1	Adaptation of additive manufacturing technology reduce raw material Varity					
AMBP2	Adaptation of additive manufacturing technology reduce delivery times					
AMBP3	Adaptation of additive manufacturing technology quickly respond to customer demand and facilitate production closer to customer					
SCP1	Additive manufacturing supply chain system reduces inventory-holding and warehousing costs					
SCP2	Additive manufacturing supply chain can quickly modify products to meet customers' requirements					
SCP3	Additive manufacturing supply chain can quickly introduce new products into the market					
SCP4	In additive manufacturing supply chain the time between the receipt of customer's order and the delivery of the goods is short					
SCP5	Through adaptation of additive manufacturing suppliers can quickly modify products to meet supply chains requirements					

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