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RESEARCH PAPER

A Structural Equation Model For Adopting Additive Manufacturing in the Footwear Firms Supply Chains

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ABSTRACT

Goal: The objective of this research is to present a theoretical framework and explore how additive manufacturing (AM) techniques affect supply chain complexity (SCC) in the footwear sector.

Design/Methodology/Approach: This study developed theoretical framework that includes AM best practices and SCC through extensive literature review. Using 1-5 likert scale surveys, data were gathered from 205 professionals working in 29 Ethiopian footwear industries in the period October 20 to December 23, 2023. The collected questionnaires were tested for reliability and validity, measurement and structural model fit test were checked using confirmatory factor analysis. Structural Equation Modeling using AMOS v23 was used to evaluate the proposed correlations.

Results: The confirmatory factor analysis test result revealeld that measurement and structural equation model fit test fulfill the model fit test requirements, i.e. $\chi^2/df < 5$, CFI, GFI and TLI > 0.9, RMR and RMSEA < 0.08. The findigs of the study confirmed that additive manufacturing best practices (time, inventory, operation, and resource, energy and waste related factors) have positive effects on static and dynamic supply chain complexity.

Practical implications: This study helps the firm to focus on adoptation of AM for improving supply chain complexity. Furthermore, this study extended earlier research in the domains of SCM by building a theoretical framework that connects AM best practices with supply chain complexity factors.

Originality/value: This work bridges the scientific knowledge gap by combining supply chain complexity and AM best practices. Among others, it can contribute to the existing literature by illustrating the benefits of adopting AM technology particularly in footwear sector.

Keywords: Additive manufacturing; Footwear firms; Structural equation modeling; Supply chain complexity.

1 INTRODUCTION

The supply chain complexity (SCC) in manufacturing firms is caused by the process, product, market demand, and suppliers, which result in higher product manufacturing costs and lower firm profit. Consequently, it clears the benefits and drawbacks of switching to additive manufacturing (AM). A network of suppliers in a supply chain is not a simple linear structure; even minor changes can cause chain reactions.

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Monitoring and regulating the interplay of different aspects of the supply chain gets increasingly challenging as the supply chain's complexity develops. The structural complexity of supply chain networks substantially influences performance, resilience, and adaptation. Researchers such as Cheng et al. (2014) have explored all aspects of SCC using the entropy model based on information theory, the causes that contributed to it, and the consequences for enterprises and supply chain management methods.

The researchers Pérez-Gallardo et al. (2014) particularly focused on the footwear industry, which often has unique challenges to streamline operations, improve coordination, and improve the overall performance of the supply chain management (SCM) by focusing on collaboration, technology integration, process optimization, sustainability, and continuous improvement, businesses can create a more efficient and responsive supply chain. The analysis explored the structural factors that contribute to upstream SCC and examined the sourcing of raw materials and components that are often the most complex part of the supply chain due to their reliance on multiple suppliers, geographical dispersion, and variability in supply (Bode and Wagner, 2015). The automobile industry's supply chain is complicated due to a variety of factors, including various supplier networks, varying consumer expectations, and intricate logistics. To successfully manage this complexity, an integrated strategy combining Interpretive Structural Modeling and a Graph-Theoretic methodology can provide an effective basis for recognizing and quantifying SCC (Kavilal, et al., 2018). The authors Chowdhury and Islam (2021) developed a conceptual framework for the implementation of effective SCM practices that have a noteworthy influence on operating performance, by focusing on supplier management, inventory optimization, production planning, logistics efficiency, and IT integration of firms to improve their cost efficiency, quality management, flexibility, and supply chain resilience. Habib and Saleheen (2022) created the Integrated SC performance measurement model, which determines the performance of SC parameters and a performance index of measurement. This methodology integrates 10 supply chain performance assessment variables and uses quantitative methodologies to create a synergistic effect across all stakeholder problems. To address agile and global supply chain issues, Adam and Dandutse (2023) investigated and proposed a relationship-building methodology on Avakino Ltd. The study aimed to investigate qualitatively, how supplier sustainability affects wholesaler-distributor sustainability. Unsustainable supplier practices can cause wholesaler and supply chain disruptions (Rosa et al., 2019).

1.1. Supply Chain Complexity

Serdarasan (2013) divides SCC into two categories: (1) static and (2) dynamic. Static complexity, also known as detail or structural difficulty refers to the unique quantity of elements, operations, or sections that together make up a method. It is also measured by the number and variety of items, procedures, customers, and vendors. Furthermore, based on Cheng et al. (2014), this complexity is related to the SC's structure as well as its numerousness (number of customers, suppliers, commodities, etc.) and diversity of components (supply base, product varieties, markets serviced, etc.) inside the SC. Dynamic complexity, also known as operational complexity, termed as the unexpected character of a system's reaction to a given set of inputs, this is partly due to the system's interconnectivity and is connected to uncertainties associated with time and randomness. In contrast, Wilson and Perumal (2009) classified SCC into three categories: (1) organizational complexity, (2) product complexity, and (3) process complexity. According to them, organizational complexity is made up of multiple facilities, organizations, and systems that power a company's activities. Furthermore, product complexity refers to the variety of items available to clients, whereas process complexity refers to the number of business procedures and contact points used in delivering a product and its support. These SC difficulties are classified into three groups based on their position in the hierarchy: (a) upstream complexity, (b) internal manufacturing complexity (midstream complexity), and (c) downstream complexity (Hakimi et al., 2015).

1.2. AM in Supply Chain

Additive manufacturing is expected to have a disruptive influence on supply chains across several sectors. Its capacity to cut costs, improve efficiency, increase flexibility, and promote sustainability makes it a valuable tool in modern production. However, resolving issues like quality, scalability, intellectual property, and regulatory compliance is critical to fully fulfilling

AM's promise (Zijm et al., 2019). AM is transforming industrial processes, especially within the context of Industry 4.0, which focuses on digital transformation, connectivity, and smart production. The incorporation of AM into eco-friendly business strategies has extensive potential to increase economic, environmental, and social enhancement (Godina et al., 2020). An empirical analysis was performed by Oettmeier and Hofmann (2017) to investigate the determinants of AM technology adoption, focusing on both general and SC related factors to understand the factors that influence the potential for cost savings, lead time reduction, and increased SC resilience, allowing businesses to make more informed decisions about incorporating AM into their operations and supply chains. AM is rapidly being used in a variety of sectors due to its ability to transform traditional production and supply chain processes. The research reported by Thomas (2016) focused on the costs, advantages, and adoption aspects of AM from a supply chain viewpoint, offering a thorough grasp of its influence on contemporary manufacturing and logistics. AM is poised to have a transformative impact on the aviation industry, providing significant profits in terms of cost efficiency, personalization, and supply chain optimization (Wagner and Walton, 2016). The complexity of AM supply chains may be quantified in a variety of ways, reflecting the distinct qualities and problems inherent in AM processes. The article reported by Raihanian and Behdad (2017) explored key metrics and approaches for analyzing the SCC in AM complexity, offering a complete framework for understanding and managing this complexity. Haghighat (2020) developed a comprehensive strategy, combining technology innovation with strategic supply chain management.

As stated, AM is known to provide a disruptive prospect for supply chains by enabling decentralized, customizable, and on-demand production, complications such as product variability, material management, and technical integration. Accordingly, Velazquez et al. (2020) examined the implications of AM in reforming traditional SC and logistics operations to obtain a competitive edge by increasing agility, cutting costs, and meeting expanding customer expectations in a rapidly changing global market. An exploratory qualitative study technique was also used on 20 organizations, and workshops to outline the procedures and actions connected to AM, as well as to examine innovations in the supply chain. The study reported by Luomaranta and Martinsuo (2020) highlights real changes in SC as well as a need for supply chain advances pertaining to AM, and the outcomes that can help businesses guide their operations and collaborate with other enterprises in the AM SC. The theoretical models were developed to evaluate the SC costs of traditional and AM in a local, small-scale supply chain for producing, inventorying, and delivering highly individualized consumer products. The case study results reported by Cui et al.(2021) indicated that using AM can result in cost reductions of up to 31.46% . The researchers Rinaldi et al. (2021) used simulation to examine the adoption of AM methods and the factors that influence supply chain architecture, where the efficiency was evaluated for both conventional and AM. The results demonstrated that AM improves supply chain performance and offers significant advantages in the decentralized solution. The conceptual model case study developed by Alogla et al. (2021) showed the results of implementing AM on SC adabtabilityin key areas: quantity, mix, shipment, and novel item development. Comparison of processes was done utilizing data acquired from a manufacturing organization. A discrete event simulation model was designed to analyze the role in the supply chain, using five input elements, to test the reaction of the supply chain to varied beginning circumstances to evaluate supply chain performance (Rinaldi et al., 2022). The authors Akmal et al. (2022) proposed that potential decision making for the transition to industrial AM entails a systematic method to assess feasibility, minimize risks, and optimize supply chain integration. This strategy not only improves operational efficiency and flexibility but also prepares organizations to benefit from AM technology.

Review of the existing literature indicates that the previous research focused on conceptual and qualitative study of the best practices of adopting AM technology to improve supply chain complexity. On the other hand, the AM adoption not only enables the SC to use fewer raw materials, but also removes the need for energy-intensive, ineffective, and environmentally harmful manufacturing processes (Evgeni et al., 2019). One of the main determinants of whether manufacturers will be able to compete and thrive in the era of Industry 4.0 is becoming the implementation of AM in the manufacturing process, where according to Rehman et al (2024), sustainable development like financial performance is increased by implementation of industry 4.0. However, there are limited quantitative studies that demonstrate the impacts of AM best practices to enhance SCC have been reported. Furthermore, no research has identified and correlated the AM optimal practices with SCC. Thus, this study was done in Ethiopia's footwear sector to bridge the gaps and quantitatively demonstrate the effects of implementing AM in SCC.

2 RESEARCH METHODOLOGY

2.1. Research Process

The best practices of AM and supply chain complexity drivers were discovered after exhaustive literature research. The present study implements the research procedure as illustrated in Figure 1. The selected AM best practices were divided into four categories: (a) factors relating to time, (b) inventory, (c) operations, and (d) resources, energy, and waste. In addition, the discovered supply chain complexity drivers are divided into static and dynamic complexities. From these findings, a theoretical framework and hypothesis were constructed, where 1-5 Likert scale questionnaires were developed based on the literature research, theoretical framework, and collaboration with professionals from the Ethiopian footwear firm. A preliminary investigation was conducted to evaluate the questionnaire's dependability, with 25 questionniers sent to respondents in the case industries. The reliability of each item was evaluated using the Cranach alpha (α) technique. Based on the pilot research findings, the questions were modified and 205 questionnaires were sent and collected from respondents from 29 footwear enterprises and one training institute that work on footwear and garment products between October 20 and December 12, 2023. A structural model was constructed with the SPSS Amos™ V 23 software using acquired data and a theoretical framework. Following that, confirmatory analysis (CFA), measurement, and structural model fit tests were carried out. The final structural equation model was built utilizing the outcomes of the CFA and the elements that fit the validity and discriminant analysis tests. The suggested hypothesis was subsequently tested using route analysis. Finally, the hypothesis test findings were compared to previous investigations, and a conclusions were drawn.

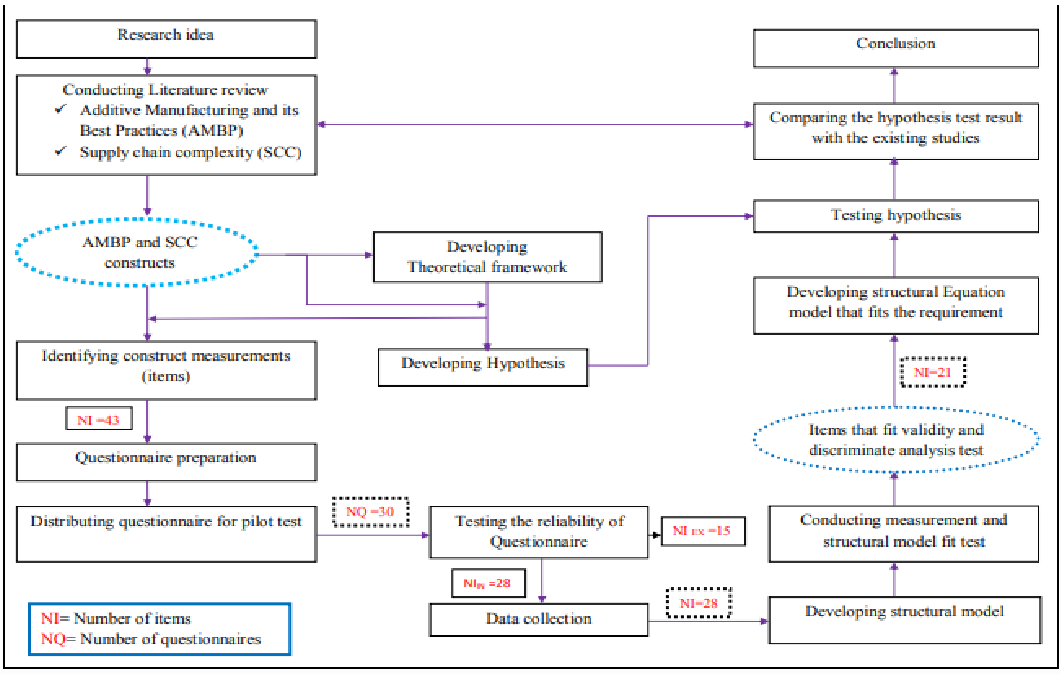

Figure 1 - Overview of research procedure

2.2 Reliability Test

The questionnaires were evaluated for reliability and validity. A higher computed dependability coefficient was obtained for more connected elements. For testing the reliability of constructs, Cronbach's alpha (□) value was employed to measure construct dependability, with a suggested reliability coefficient of 0.7 (Kline, 2023).

2.3 Measurement and Structural Model Fit Test

2.3.1 Convergent validity test

Correlation analysis provides a measure of convergence validity, which is the degree of agreement between various indicators of the same construct. To establish convergent validity, the items' factor loading (FL), composite reliability (CR), and average variance extracted (AVE) are considered. FL of 0.7 or above implies strong convergent validity, although FL of 0.5 or higher is acceptable. The composite dependability should be 0.7 or above. According to the author Joseph et al (2022), for sufficient convergent validity, the AVE value must be more than 0.50.

2.3.2 Discriminant Validity Test

Discriminant validity refers to how much the conceptions truly vary from one another through experimentation. It also determines the degree to which overlapping conceptions differ from one another (Joseph et al., 2022). 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 concept and other components (Hamid et al., 2017).

2.3.3 Confirmatory factor analysis

A confirmatory factor analysis is employed to assess the validity of the model's measurement. The validity is assessed using model fit indices. The author Brown (2015) recommended the following cutoff values for fit indices: Tucker–Lewis fit index (TLI) and comparative fit index (CFI) > 0.9, Relative/Normed chi-square ($\chi 2/df$) from $5.0 < \chi 2/df < 2.0$, Root mean square residual (RMR) and Root mean square error of approximation (RMSEA) < 0.08.

3 RESEARCH CONCEPTUAL FRAMEWORK AND HYPOTHESIS

Taking the preceding literature review into consideration, this study classified AM best practices into four categories.

(1). Time-related factors (TIMRF),

(2). Inventory related factors (INVRF),

(3). Operation-related factors (like manufacturing performance, manufacturing flexibility) (OPERF), and

(4). Resource, pollution and waste-related factors (REWRF) are considered exogenous variables.

Endogenous variables, on the other hand, describe SCC and can be classified as static (SSCC) or dynamic (DSCC) that are used as a basis to develop the theoretical framework depicted in Figure 2 by comparing AM best practices to supply chain complexity. Thus, based on literature study, the following hypotheses were developed:

Hypothesis 1: Time-related factor of AM has positive and significant effects on SSCC

Hypothesis 2: Time-related factor of AM has positive and significant effects on DSCC

Hypothesis 3: Inventory related factor of AM has positive and significant effects on SSCC

Hypothesis 4: Inventory related factor of AM has positive and significant effects on DSCC

Hypothesis 5: The operational factor of AM has positive and significant effects on SSCC

Hypothesis 6: The operational factor of AM has positive and significant effects on DSCC

Hypothesis 7: Resource, energy and waste related factor of AM has positive and significant effects on SSCC

Hypothesis 8: Resource, energy and waste related factor of AM has positive and significant effects on DSCC.

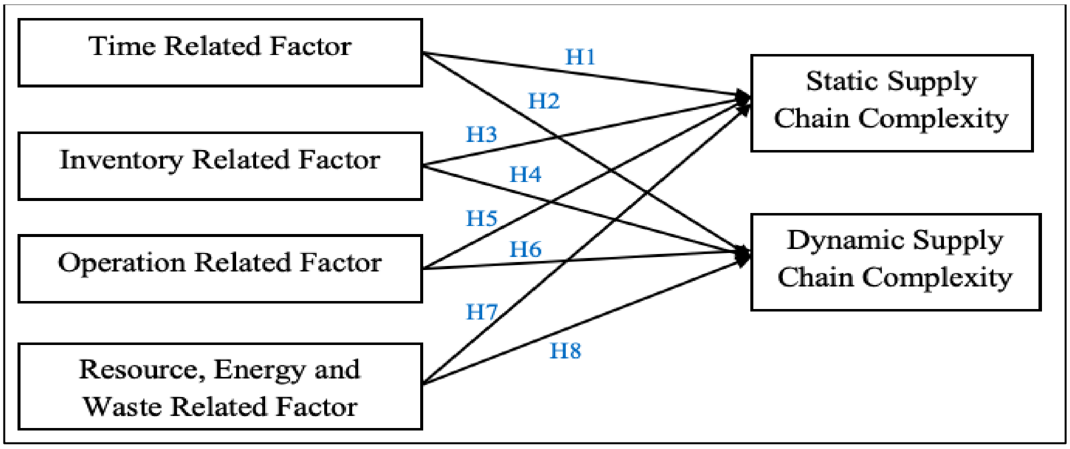

Figure 2 - Conceptual framework

4 RESULTS AND DISCUSSIONS

4.1 Demographic Characteristic

Table 1 shows the demographics of survey respondents. Gender, education level, age, respondents' employment position, and work experience were all identified among the 205 survey participants.

Table 1 - Demographic description (n=205)

Description		Frequency	Percentage (%)
Sex	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
Respondents job position	Supply chain and logistic worker	58	28.20
	Production workers	68	33.17
	Top management workers	56	27.31
	Experts	23	11.21
Work experience	<5 years	5	2.43
	6-10years	41	20
	11-20years	103	50.24
	>21 years	56	27.31

4.2. Measurement Model Analysis

The values given in Table 2 demonstrate that every constructs have α-values ranging from 0.757 to 0.909. This means that Cronbach's α-values for all constructions superpassed the permissible limit of 0.70 (Kline, 2023). Therefore, all of the study's measurements have high consistency and reliability.

The CFA results in Table 2 show that the relative chi-square ($\chi 2$/df) value for all six constructs falls within 0.00 to 4.18; the goodness-of-fit statistic (GFI) within 0.968 to 1.00; Bentler's comparative-fit-index (CFI) within 0.982 to 1.00; and Tucker Lewis's goodness-of-fit-index (TLI) within 0.955 to 1.00. This demonstrates that the six structures fit fairly well, as suggested by (Brown ,2015).

The measurement model results in Table 2 reveal that all latent constructs meet the convergent validity requirement, which means that all variable factor loadings are greater than 0.7. Furthermore, the convergent validity test results in the same table revealed that all constructs have a CR higher than 0.70 and AVE higher than 0.50, indicating that both CR and AVE values corresponded to or exceeded the appropriate cutoff criteria (Joseph et al., 2022) and (Hamid et al., 2017).

In this work, measurement model fit tests for independent and overall constructs were done using CFA, and the results are given in Figures 3 and 4. In addition, the findings of CFA analysis for overall constructs shown in Figure 4 illustrated that the measurement model fits well with $\chi 2/df$ =2.288, GFI=0.855, IFI=0.905, TLI=0.882, CFI=0.908, RMR=0.063, and RMSEA=0.079.

Table 2 - Summary of measurement model test results

Latent variable	Items	FL	(α)	CR	AVE	χ^2/df	CFI	TLI	GFI	RMR	RMSEA
Time-related factor	TIMRF3	0.835	0.853	0.908	0.674		1.00	1.00	1.00	0.000	0.670
	TIMRF2	0.861									
	TIMRF1	0.764									
Inventory related factor	INVRF4	0.696	0.824	0.764	0.567		1.00	1.00	1.00	0.000	0.550
	INVRF2	0.799									
	INVRF1	0.762									
Operation related factor	OPERF3	0.549	0.757	0.864	0.580		1.00	1.00	1.00	0.00	0.00
	OPERF2	0.894									
	OPERF1	0.800									
Resource and energy-related	REWRF5	0.882	0.909	0.808	0.691	4.18	0.982	0.955	0.968	0.034	0.125
	REWRF4	0.808									
	REWRF3	0.691									
	REWRF2	0.907									
	REWRF1	0.851									
Static supply chain complexity	SSCC4	0.850	0.843	0.845	0.594	0.056	1.00	1.00	1.00	0.000	0.000
	SSCC3	0.719									
	SSCC2	0.852									
	SSCC1	0.642									
Dynamic supply chain complexity	DSCC3	0.967	0.861	0.892	0.686	0.000	1.00	1.00	1.00	1.00	0.711
	DSCC2	0.704									
	DSCC1	0.793									

α = Cronbach's, **FL**=factor loading, **CR=** composite reliability, **AVE=** average variance extracted, **χ2/df=** relative/normed chi-square, **CFI=**bentler's comparative-fit-index, **TLI=** tucker Lewis's goodness-of-fit-index,**GFI=** goodness-of-fit statistic, **RMR=** root mean square residual, **RMSEA=** root mean square error of approximation

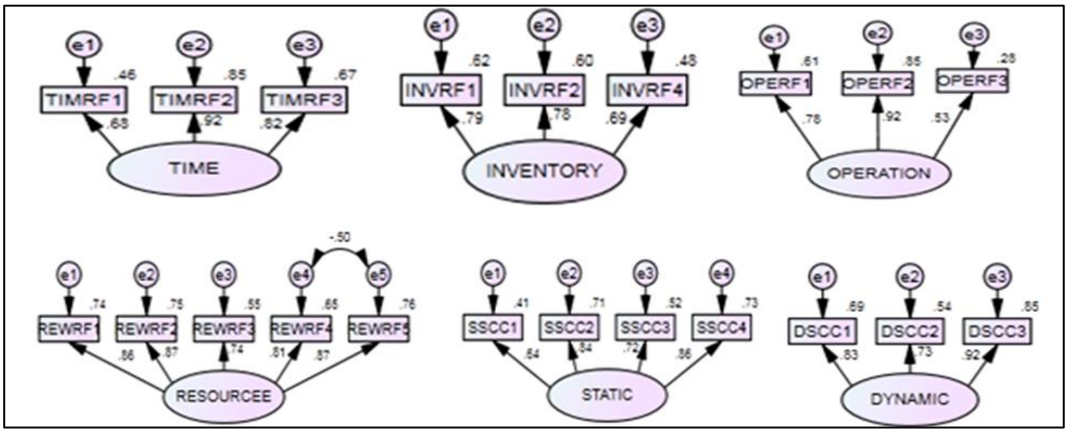

Figure 3 - Individual construct model fit test

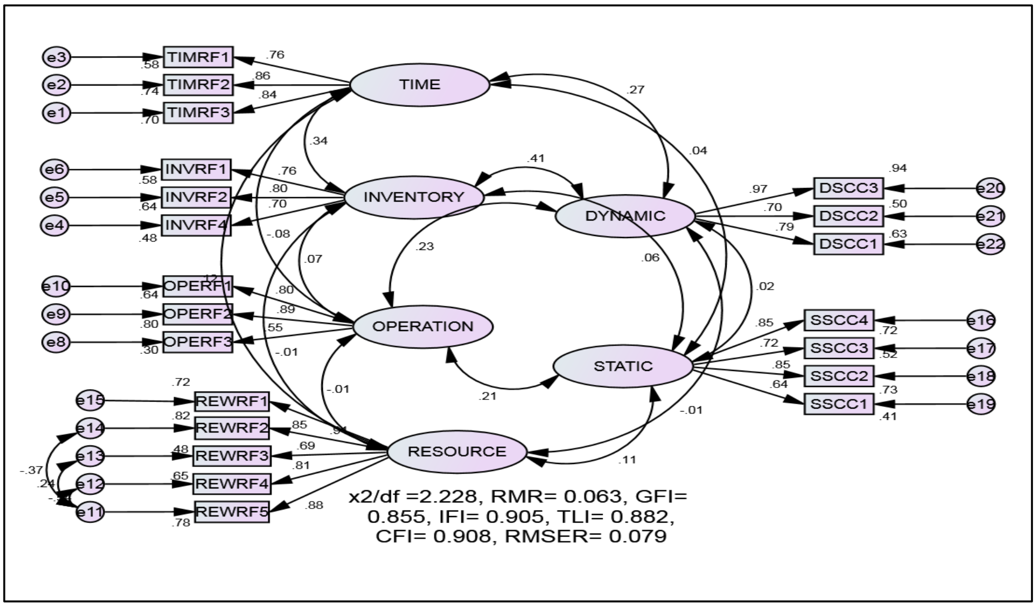

Figure 4 - Overall construct measurement model fit test

In addition, a discriminant validity test was performed to assess whether the AVE of each construct surpassed the maximum square correlation with other components. Based on this, the discriminant validity test, as shown in Table 3, demonstrated that the squared root of AVE for each latent variable is larger than the inter-construct correlation between each pair of latent variables in all cases. This revealed that the constructs were distinct and accurately characterized by their measurement scales. Hamid et al. (2017) found that convergent and discriminant validity were adequate for our measurement model.

Therefore, based on the results of reliability (Cronbach's alpha value), convergent validity (Factor loadings, CR, and AVE), and discriminant validity (squared root of AVE) test obtained by this study, concluded that the latent constructs found in the developed model in this study are reliable, internally consistent, convergent, and with a acceptable level of discriminant validity, and the developed model is acceptable or fit for structural model test or analysis.

Table 3 - Discriminant validity test or assessment

	TIRF	INRF	OPRF	RWRF	SSCC	DSCC
TIRF	**0.821**					
INRT	0.166	**0.753**				
OPRF	-0.056	0.111	**0.761**			
RWRF	0.020	0.029	-0.045	**0.831**		
SSCD	-0.002	0.097	0.181	0.016	**0.770**	
DSCC	0.046	0.102	0.010	0.083	0.216	**0.828**

4.3. Structural Model and Hypothesis Test

The measurement model's validity and reliability have been demonstrated; thus, the next step is to examine the structural model and validate the presented hypotheses using SEM (Malik et al., 2024) with AMOS. This study employed structural SEM as it allows for simultaneous analysis, which leads to more accurate estimations and is the highest probability approach for investigating the correlations between variables. Figure 5 displays the results of the structural model's goodness of fit assessment. The model has an excellent fit to the data, with a $\chi 2/df$ ratio of 2.27. This is below the usual criterion of fit (less than 5), indicating a robust fit. The model fit indices also offered corroborative evidence, with the root mean square error of approximation (RMSEA) at 0.063 and the root mean square residual (RMR) at 0.079, both considerably below the proposed limit of 0.08 as suggested by (Brown, 2015). Furthermore, the Tucker-Lewis index (TLI) was 0.887, approaching the cutoff point of 0.90, and the comparative fit index (CFI) was 0.903, reaching the minimal acceptance level of 0.90 (Brown ,2015). The goodness-of-fit statistic (GFI) was 0.854. When combined, these findings show the degree to which the SEM matches the empirical data, providing a solid foundation for the hypothesis' further evaluations.

The structural model evaluation results are given in Figure 5 and Table 4., which include the results of the hypothesis tests. The assessment results in Table 4 suggest that the path from time to static complexity (β= 0.028, p= 0.677) supports Hypothesis 1. This result is in line with the findings of Ming and Yi (2016). Additive manufacturing's time-dependent behavior has a favorable impact on static supply chain complexity. As a result, this AM behavior enables enterprises to reduce raw material delivery from suppliers to customers and product delivery from firms to end users by consolidating SC into a single entity.

Similarly, the path from time to dynamic complexity demonstrates a positive and statistically significant effect (β = 0.209, p = 0.005), entirely supporting Hypothesis 2. This finding is also supported by the Oettmeier and Hofmann (2017) study. It indicated that additive manufacturing's time-dependent nature minimizes demand uncertainty while balancing SCC produced by heterogeneous demands and demand amplification. Table 4 also shows that inventory-related AM best practices have positive but non-significant influence on static supply chain complexity (β = 0.030, p = 0.704), partially supporting Hypothesis 3. The findings for this hypothesis concur with the concepts raised by Thomas (2016), and they reveal that using additive manufacturing allows the company to make things on the customer's premises by converting physical inventory to digital inventory. It leads to reduction of static complexity generated by a larger number of inventories in the SC network. Furthermore, the inventory-related behavior of AM technology safety stock reduces the demand for storage, as well as the amount and diversity of objects handled. Thus, the results of Hypotheses 2 and 3 verify those of Marta et al. (2021) study outcome, who found that reducing production time and optimizing AM's material consumption behavior leads to meeting client demands while lowering the quantity and variety of suppliers. By cutting down the lead time for SC and the need for inventories and logistics while developing new items for the system, it meets client needs.

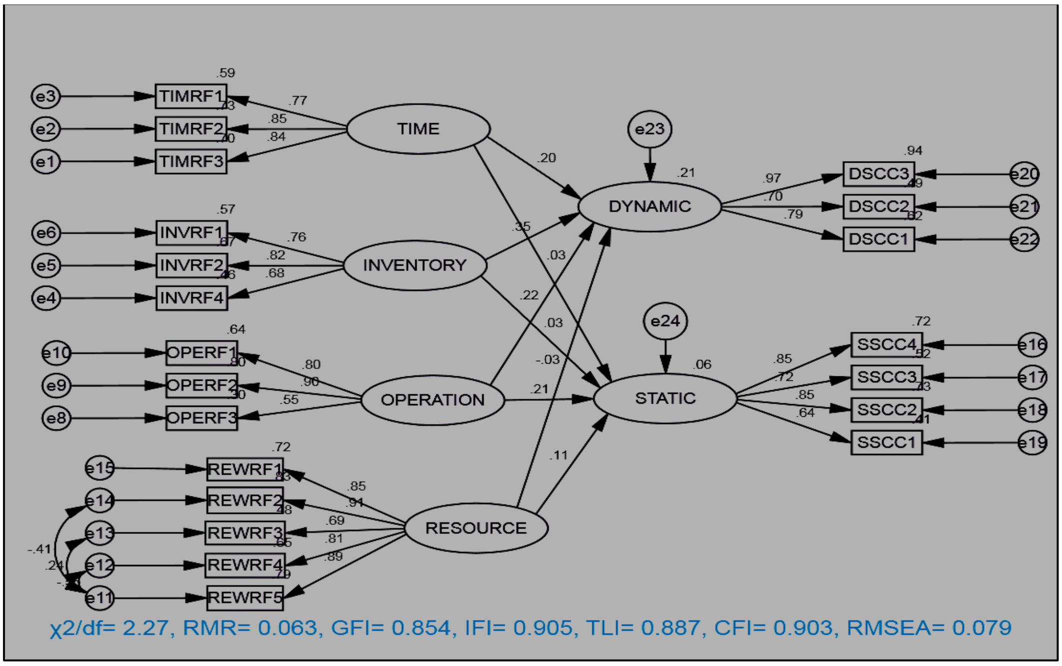

Figure 5 - Results of Structural model fit test

The path from INVRF to DSCC revealed that inventory-related AM best practices have optimistic and considerable influence on dynamic SCC (β = 0.426, p = 0.000), supporting Hypothesis 4. This study highlights the relevance of AM's inventory-related behavior in rising the dynamic SCC. AM technology reduces the complexity of the supply chain, which is caused by supplier unreliability, changing labor skill needs, supplier competency, and supplier resource risk (Velazquez et al., 2020).

Table 4 - Result of structural modeling test

Hypothesis	Paths			Estimate (β)	p	Remarks
Hypothesis1	STATIC	<---	TIME	0.028	0.677	Partially supported
Hypothesis2	DYNAMIC	<---	TIME	0.209	0.005	Fully Supported
Hypothesis3	STATIC	<---	INVENTORY	0.030	0.704	Partially supported
Hypothesis4	DYNAMIC	<---	INVENTORY	0.426	***	Fully supported
Hypothesis5	STATIC	<---	OPERATION	0.269	0.012	Fully Supported
Hypothesis6	DYNAMIC	<---	OPERATION	0.351	0.003	Fully Supported
Hypothesis7	STATIC	<---	RESOURCE	0.083	0.146	Partially Supported
Hypothesis8	DYNAMIC	<---	RESOURCE	-0.024	0.699	Not supported

The path from OPERF to SSCC demonstrated optimistic and statistically significant association between AM best practices and static supply chain complexity (β = 0.269, p = 0.012), supporting Hypothesis 5. Static complexity in the supply chain is produced by the increased amount of interdependence between pieces, the quantity and variety of suppliers, and their location. Furthermore, this level of complexity occurs as a result of the SC network's numerous components. However, according to Hypothesis 5, AM's operational behavior minimizes static supply chain complexity by lowering component variation and reducing the number and variety of providers. The path from OPERF to DSCC shows a positive and statistically significant association between operational factors of AM and dynamic supply chain complexity (β= 0.351, p= 0.033), supporting Hypothesis 6. This study also suggested that dynamic complexity induced by uncertainty within the SC, as well as the unpredictability of the supplier chain, is minimized by AM's operating behavior, which reduces supplier reliance. The results in Hypotheses 5 and 6 are also in line with concepts raised by Akmal et al. (2022).

AM's resource, energy, and waste variables have a positive but non-significant association with static supply chain complexity (β= 0.083, p= 0.146), partially supporting Hypothesis 7. This result is supported by the findigs of Evgeni et al. (2019). The use of AM technology decreases the amount of raw materials required, eliminates the need to produce undesirable parts (reducing waste), and delivers customized goods only when necessary. However, the path from REWRF to DSCC revealed that the resource, energy, and waste-associated factors of AM had a negative and non-significant association with dynamic supply chain complexity (β= -0.024, p= 0.699), rejecting Hypothesis 8. This demonstrated that AM's resource, energy, and waste-related best practices had little effect on improving supply chain complexity.

5 CONCLUSION AND IMPLICATIONS

5.1. Conclusions

This study illustrates the most effective AM strategies for improving supply chain complexity in the footwear sector. The study's unique contribution is identification of AM best practices and the evaluation of how they enhance supply chain complexity in the context of Ethiopia's footwear industry sector. Furthermore, thes study establishes a theoretical framework based on an extensive literature analysis and conversation with practitioners from the case industry, treating AM best practices as independent and SCC as dependent entities. The CFA and SEM were used to develop and validate measurement tools for supply chain complexity AM best practices. The SEM results show that TIMRF, INVRF, and OPERF have positive connections with static SCC and dynamic SCC, whereas REWRF has positive and negative associations with the same two variables, respectively. Thus, the deployment of AM reduces SCC by lowering uncertainty, unreliability, the quantity and diversity of SC pieces, and delivery time from the upstream and downstream supply chain networks. Based on the findings, this research offeres academics, and SC managers with a thorough understanding of AM technology's best practices for lowering supply chain complexity in the footwear sector.

As a recommendation, more research is needed to apply the findings to diverse industrial situations and to integrate best practices.

5.2. Implications and Future Research Directions

Theoretically, the findigs of this study is intended to contribute in closing the knowledge gap in the area by identifying the best practices of AM that affect supply chain complexity. In addition, it contributes the conceptual framework and empirically test how AM best practices improve the complexity of footwear industry supply chain. Therefore, researchers can base related investigations on this study model. Moreover, practically this research provides a basis for managers and practitioners in the footwear sector to successfully implement AM technology to address supply chain complexity-related issues and, consequently, to improve organizational performance. On the other hand, the study used data from a single industry sector (footwear industry), which can influence the generalizability of the findigs. Thus, forthcoming studies are encourage to use and empirically test the development of conceptual framework in other types of industries.

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